ARTIFICIAL INTELLIGENCE-DRIVEN DECISION SUPPORT SYSTEMS IN EDUCATIONAL GOVERNANCE AND QUALITY ASSURANCE

Deepak Gupta, Devansh Jha, Aditya Sikarwar
Department of CSE-Data Science
Institute of Technology & Management, Gwalior, MP, India
Vugar Abdullayev
Azerbaijan University of Architecture and Construction, Baku, Azerbaijan
https://doi.org/10.5281/zenodo.23096133

Abstract. *This paper examines the role of artificial intelligence-based decision support systems (AI-DSS) in the governance and quality assurance processes of higher education institutions. Drawing on empirical studies of predictive analytics in accreditation, admissions, and student-performance monitoring, together with the broader literature on trustworthy and interpretable AI, the paper analyzes how such systems are reshaping institutional decision-making while introducing new risks of algorithmic opacity and automation bias. It concludes with governance recommendations — human-in-the-loop review, interpretability standards, and periodic auditing — for the responsible use of AI-DSS in high-stakes educational governance contexts.*

Keywords: *artificial intelligence, decision support systems, quality assurance, educational governance, accreditation, predictive analytics, trustworthy AI*

1. Introduction

Quality assurance and institutional governance in higher education have traditionally relied on periodic self-assessment, external accreditation review, and manually compiled performance indicators. The growing availability of institutional data, combined with advances in machine learning, has led to the emergence of AI-based decision support systems (AI-DSS) designed to assist administrators and quality assurance bodies in monitoring institutional performance in near real time. Systematic reviews of AI research in higher education document a steady expansion of applications in exactly this space — profiling and prediction, intelligent tutoring, and assessment and evaluation — even as the review authors note that critical reflection on the risks of such systems has lagged behind their adoption [Zawacki-Richter et al., 2019; 15].

These systems promise to reduce the administrative burden of quality assurance processes and to surface performance issues earlier than traditional periodic review cycles allow. At the same time, their use in governance contexts raises important questions about transparency, accountability, and the appropriate balance between algorithmic recommendation and human judgment — questions that have become more pressing as regulatory frameworks for AI systems have matured internationally [Poncibò and Ebers, 2025].

This paper is organized as follows. Section 2 reviews applications of AI-DSS in accreditation and quality assurance. Section 3 examines their use in admissions, enrollment, and student-performance monitoring. Section 4 discusses the risks of algorithmic opacity and bias. Section 5 sets out governance recommendations, and Section 6 concludes.

2. AI-DSS in Accreditation and Quality Assurance

One of the most concrete applications of AI-DSS in educational governance is in accreditation support. Kawesha and Phiri [2024] developed a predictive model using data mining and machine learning techniques to support decision-making in the accreditation of learning programmes at a national higher education authority, demonstrating that such models can flag programmes likely to fall short of accreditation criteria well before a formal review cycle begins. Their approach draws on a long institutional-research tradition concerned with the assessment context of accreditation, accountability, and performance measurement [Volkwein, 2010; 5], and it responds directly to longstanding critiques that traditional accreditation processes struggle to keep pace with the scale and complexity of modern higher education systems [Dill et al., 1996; 19].

This tradition is significant because it shows that the introduction of AI-DSS into accreditation is not a rupture with prior quality-assurance practice but an extension of a decades-long effort to make accreditation more evidence-based and less reliant on episodic, resource-intensive institutional self-studies. Gaston [2023] documents how accreditation itself has been undergoing significant structural change in response to pressures for greater accountability, cost control, and responsiveness to student outcomes — pressures that AI-DSS are increasingly positioned to help address, provided institutions can supply the data these systems require.

At the same time, the accreditation-support literature is candid about limitations. Kawesha and Phiri [2024] note that model performance is constrained by the quality and completeness of historical programme-level data, and that predictive outputs should inform, rather than substitute for, the judgment of accreditation panels — a caveat consistent with the broader argument, discussed in Section 4, that high-stakes educational decisions warrant interpretable rather than purely predictive tools.

3. AI-DSS in Admissions, Enrollment, and Performance Monitoring

Beyond accreditation, AI-DSS are widely applied to admissions and enrollment planning, both of which have direct implications for institutional governance and resource allocation. Cirelli et al. [2018] developed predictive analytics models for student admission and enrollment forecasting, finding that such models could materially improve institutions' ability to plan capacity and financial-aid budgets, provided that historical admissions data were consistently recorded across cohorts. Namoun and Alshanqiti [2020; 4] conducted a systematic literature review of data-mining and learning-analytics techniques for predicting student performance and found substantial heterogeneity in model accuracy across studies, attributing much of this variance to differences in data quality and feature selection rather than to the underlying algorithms themselves.

Complementary work on data-driven personalization of student learning support shows how predictive outputs are increasingly embedded into the everyday operational decisions of universities — from targeted academic advising to the allocation of support-service resources — rather than being confined to periodic strategic reviews [Liu et al., 2017; 148]. This integration of AI-DSS into routine governance processes strengthens the case that such systems now function as ongoing institutional infrastructure rather than as occasional analytical exercises, which in turn raises the stakes of getting their governance right.

Nieto et al. [2019; 75013] applied similar machine-learning techniques directly to strategic decision-making at higher education institutions and found that models trained on integrated student, financial, and academic datasets outperformed those relying on any single data source — reinforcing, from a different angle than the accreditation literature, that AI-DSS

effectiveness in governance settings is fundamentally a data-integration problem before it is an algorithmic one.

4. Algorithmic Opacity, Bias, and Automation Risk

Despite these benefits, the literature identifies significant risks associated with AI-DSS in governance contexts. A primary concern is algorithmic opacity: many predictive models, particularly those based on ensemble or deep-learning methods, operate as effective 'black boxes,' making it difficult for quality assurance committees to interrogate the basis for a given recommendation. Rudin [2019; 206] argues forcefully that in high-stakes decision domains — explicitly including areas closely analogous to educational governance, such as criminal justice and healthcare — the appropriate response is not to develop better explanations for opaque models but to prefer inherently interpretable models from the outset, since post-hoc explanation methods can themselves be unreliable or misleading about a model's true reasoning.

A second risk concerns data bias. Where historical institutional data reflect prior inequities — for instance, in resource allocation across departments or in disparities in recorded student outcomes — AI-DSS trained on this data risk reproducing or amplifying those inequities in their recommendations. This concern is reinforced by broader work on trustworthy AI, which identifies fairness and robustness, alongside transparency, as core pillars that governance frameworks must operationalize rather than treat as abstract aspirations [Kowald et al., 2024].

A third risk is automation bias: the tendency of decision-makers to defer excessively to algorithmic outputs even in cases that warrant contextual human judgment. This risk is amplified in educational governance settings precisely because AI-DSS outputs often arrive with a veneer of objectivity that can discourage the kind of critical scrutiny that quality-assurance processes are designed to provide. The historical scholarship on AI in education cautions that this dynamic is not new — earlier waves of educational technology adoption have repeatedly shown a gap between the confidence placed in automated tools and their demonstrated reliability [Doroudi, 2023].

A fourth, increasingly salient risk concerns regulatory exposure. Comparative legal analysis of AI regulation shows that jurisdictions are converging on requirements for documentation, explainability, and avenues for redress when algorithmic systems materially affect individuals' opportunities — a category that plainly includes admissions, financial aid, and accreditation-linked decisions [Poncibò and Ebers, 2025]. Institutions that treat AI-DSS governance purely as an internal, technical matter risk being caught unprepared as these regulatory expectations formalize.

5. Governance Recommendations for Responsible Implementation

To mitigate these risks while retaining the efficiency benefits of AI-DSS, this paper recommends four governance safeguards, each grounded in the literature reviewed above. First, institutions should maintain human-in-the-loop protocols requiring that AI-generated recommendations affecting programme accreditation status, admissions decisions, or resource allocation be reviewed and approved by a designated human decision-maker before implementation, consistent with the caution urged by Kawesha and Phiri [2024] regarding the proper role of predictive outputs in accreditation panels.

Second, institutions should adopt explainability and interpretability standards, favoring, where feasible, model architectures that are inherently interpretable rather than relying solely on post-hoc explanation techniques for opaque models, following Rudin's [2019; 210] argument that

interpretable models are preferable in high-stakes settings even where they involve some trade-off in raw predictive accuracy.

Third, institutions should invest in integrated, well-governed data infrastructure as a precondition for AI-DSS deployment, since the accreditation, admissions, and strategic-planning literature converge on the finding that model reliability depends more on data quality and integration than on algorithmic sophistication [Nieto et al., 2019; Namoun and Alshanqiti, 2020; Liu et al., 2017].

Fourth, institutions should establish periodic bias and robustness audits of the data and models underlying their AI-DSS, conducted by an independent internal or external body, both to identify and correct systematic distortions before they affect governance outcomes and to build the kind of documentation trail that an evolving regulatory environment is likely to require [Kowald et al., 2024; Poncibò and Ebers, 2025].

6. Conclusion

AI-driven decision support systems offer higher education institutions a valuable tool for strengthening the timeliness and evidentiary basis of governance and quality assurance processes, from accreditation review to admissions planning and student-performance monitoring. However, the literature reviewed in this paper indicates clearly that their responsible use requires deliberate safeguards against algorithmic opacity, data bias, and automation bias, and that these safeguards must be designed with an eye toward a maturing international regulatory landscape. Institutions that combine the analytical capacity of AI-DSS with robust human oversight, interpretable model design, and sound data governance are best positioned to realize the benefits of these systems while preserving the accountability and fairness that effective educational governance requires. Future empirical research should track how accreditation bodies and university governance structures adapt these recommendations in practice, and with what measurable effect on the accuracy, fairness, and legitimacy of AI-supported governance decisions.

REFERENCES

1. Kawesha, F., & Phiri, J. (2024). Data mining and machine learning-based predictive model to support decision-making for the accreditation of learning programmes at the Higher Education Authority. In Proceedings of the Ninth International Congress on Information and Communication Technology (ICICT 2024), Lecture Notes in Networks and Systems, Vol. 1000. Singapore: Springer. https://doi.org/10.1007/978-981-97-3289-0_29

2. Volkwein, J. F. (2010). The assessment context: accreditation, accountability, and performance. New Directions for Institutional Research, 2010(S1), 3–12. https://doi.org/10.1002/ir.327

3. Dill, D. D., Massy, W. F., Williams, P. R., & Cook, C. M. (1996). Accreditation and academic quality assurance: can we get there from here? Change: The Magazine of Higher Learning, 28(5), 17–24. https://doi.org/10.1080/00091383.1996.9937136

4. Gaston, P. L. (2023). Higher Education Accreditation: How It's Changing, Why It Must. New York: Taylor & Francis.

5. Cirelli, J., Konkol, A. M., Aqlan, F., & Nwokeji, J. C. (2018). Predictive analytics models for student admission and enrollment. In Proceedings of the International Conference on Industrial Engineering and Operations Management, 1395–1403.

6. Namoun, A., & Alshanqiti, A. (2020). Predicting student performance using data mining and learning analytics techniques: a systematic literature review. Applied Sciences, 11(1), 237. https://doi.org/10.3390/app11010237
7. Liu, D. Y. T., Bartimote-Aufflick, K., Pardo, A., & Bridgeman, A. J. (2017). Data-driven personalization of student learning support in higher education. In Learning Analytics: Fundaments, Applications, and Trends (pp. 143–169). Cham: Springer.
8. Nieto, Y., García-Díaz, V., Montenegro, C., González, C. C., & Crespo, R. G. (2019). Usage of machine learning for strategic decision making at higher educational institutions. IEEE Access, 7, 75007–75017. https://doi.org/10.1109/ACCESS.2019.2919343
9. Rudin, C. (2019). Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. Nature Machine Intelligence, 1(5), 206–215. https://doi.org/10.1038/s42256-019-0048-x
10. Kowald, D., et al. (2024). Establishing and evaluating trustworthy AI: overview and research challenges. Frontiers in Big Data, 7, Article 1467222. https://doi.org/10.3389/fdata.2024.1467222
11. Poncibò, C., & Ebers, M. (2025). Comparative perspectives on the regulation of large language models. Cambridge Forum on AI: Law and Governance, 1, e10. https://doi.org/10.1017/cfl.2024.14
12. Doroudi, S. (2023). The intertwined histories of artificial intelligence and education. International Journal of Artificial Intelligence in Education, 33(4), 885–928.
13. Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? International Journal of Educational Technology in Higher Education, 16(1), Article 39. https://doi.org/10.1186/s41239-019-0171-0
14. Khairullah, S. A., Harris, S., Hadi, H. J., Sandhu, R. A., Ahmad, N., & Alshara, M. A. (2025). Implementing artificial intelligence in academic and administrative processes through responsible strategic leadership in the higher education institutions. Frontiers in Education, 10, Article 1548104. https://doi.org/10.3389/feduc.2025.1548104
15. Williamson, B., & Eynon, R. (2020). Historical threads, missing links, and future directions in AI in education. Learning, Media and Technology, 45(3), 223–235. https://doi.org/10.1080/17439884.2020.1798995
16. Holmes, W., Bialik, M., & Fadel, C. (2019). Artificial Intelligence in Education: Promises and Implications for Teaching and Learning. Boston, MA: Center for Curriculum Redesign.
17. Selwyn, N. (2019). Should Robots Replace Teachers? AI and the Future of Education. Cambridge: Polity Press.
18. Middlehurst, R. (2004). Changing internal governance: a discussion of leadership roles and management structures in UK universities. Higher Education Quarterly, 58(4), 258–279.
19. Mongeon, P., & Paul-Hus, A. (2016). The journal coverage of Web of Science and Scopus: a comparative analysis. Scientometrics, 106(1), 213–228. https://doi.org/10.1007/s11192-015-1765-5
20. Chiu, T. K., Xia, Q., Zhou, X., Chai, C. S., & Cheng, M. (2023). Systematic literature review on opportunities, challenges, and future research recommendations of artificial intelligence in education. Computers and Education: Artificial Intelligence, 4, Article 100118.