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Designing Trustworthy Educational Artificial Intelligence: A Systemic Framework for Explainability, Adaptivity, and Ethical Learning Analytics

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ABSTRACT: The accelerating integration of artificial intelligence into educational systems has underscored the necessity of designing learning technologies that are not only effective but also trustworthy, transparent, and ethically grounded. Although adaptive and data-driven educational AI systems have demonstrated substantial potential for personalization and performance enhancement, their widespread adoption remains constrained by concerns related to explainability, ethical learning analytics, data privacy, and algorithmic bias. This study proposes a systemic framework for trustworthy educational artificial intelligence that unifies explainability, adaptivity, and ethical governance within a coherent architectural model. Grounded in interdisciplinary theoretical foundations and supported by evidence from systematic literature reviews and empirical case studies, the framework emphasizes human-centered design, transparent decision-making, and continuous ethical oversight. The analysis illustrates how explainable and adaptive AI systems, when coupled with responsible learning analytics, can enhance learner engagement, improve academic outcomes, and foster sustained trust among educators and students. By articulating design principles and architectural layers aligned with established ethical frameworks, this work contributes a robust foundation for developing educational AI systems that balance technological innovation with accountability, fairness, and long-term educational value.

Keywords: trustworthy educational ai; explainable artificial intelligence; adaptive learning systems; ethical learning analytics; human-centered ai design.

I. INTRODUCTION

The rapid integration of Artificial Intelligence (AI) into educational settings has transformed traditional pedagogical approaches and ushered in a host of opportunities for personalized learning. As AI systems proliferate in classrooms—from intelligent tutoring systems to adaptive learning platforms—they simultaneously raise critical concerns about explainability, adaptivity, and ethical analytics. In response, this article proposes a systemic framework for designing trustworthy educational AI that is transparent, adaptable, and anchored in robust ethical principles. Such a framework is essential to enhance the overall trust, transparency, and effectiveness of AI-assisted learning environments while addressing pressing issues such as algorithmic bias, data privacy, and unaccountable decision-making[1].

The significance of trustworthy educational AI lies not only in its potential to augment teaching effectiveness but also in the responsibility to safeguard human dignity, promote fairness, and support lifelong learning. This article provides a comprehensive review of relevant literature, synthesizes emerging methodologies from systematic investigations, and details a conceptual framework that integrates explainability, adaptivity, and ethical learning analytics. The framework builds on insights from systematic literature reviews, adaptive learning research, and ethical guidelines (e.g., AI4People's principles) to ensure that AI technologies are directed toward the greater good of all educational stakeholders[2].

II. THEORETICAL FOUNDATIONS OF TRUSTWORTHY EDUCATIONAL AI

The theoretical basis for trustworthy educational AI is rooted in multiple interdisciplinary domains spanning the learning sciences, AI explainability, and ethics. Trust in AI systems is contingent on three principal dimensions: explainability, adaptivity, and ethical analytics.

1. EXPLAINABILITY IN EDUCATIONAL AI

Explainability refers to the ability of an AI system to reveal its internal decision-making processes in a transparent and comprehensible manner. In educational contexts, explainability facilitates educators' understanding of how personalized recommendations are generated and increases students' trust in AI-driven feedback mechanisms. Studies have shown that when educators clearly understand the underlying mechanisms of AI tools, they are more likely to integrate these systems effectively into teaching practices1. By making AI models interpretable, educational institutions can ensure that stakeholders—ranging from teachers to policy makers—comprehend the rationale behind decisions, a critical step toward mitigating skepticism and fear of opaque "black-box" solutions[3].

2. ADAPTIVITY AND PERSONALIZED LEARNING

Adaptivity in AI refers to the system's capacity to tailor learning experiences based on the individual needs, abilities, and learning styles of students. This approach departs from one-size-fits-all models and empowers AI to curate personalized learning content that evolves in real-time as learners progress. Adaptive learning systems analyze student performance data using advanced machine learning algorithms to provide targeted interventions and dynamically adjust instructional material1. The scalability and flexibility inherent in such adaptivity address the challenges posed by diverse classroom populations, making education both inclusive and responsive to individual differences[4].

3. ETHICAL ANALYTICS AND RESPONSIBLE AI

Ethical analytics in educational AI involves the measurement and mitigation of risks related to data privacy, algorithmic bias, and fairness. As AI systems increasingly rely on vast quantities of sensitive academic data, it is imperative to ensure that data collection, analysis, and storage practices adhere to ethical standards. The AI4People initiative, for instance, advocates for the inclusion of ethical governance frameworks that promote human dignity, non-maleficence, and equitable access to AI benefits66. This ethical grounding is paramount in preventing unintended negative consequences such as job displacement, biased decision-making, and erosion of academic integrity[5].

Collectively, these theoretical foundations contribute to a robust paradigm of trustworthy educational AI—one that not only augments the teaching and learning processes but also ensures that technological advancements remain aligned with human values and educational ethics[6].

III. RELATED WORK ON EXPLAINABILITY, ADAPTIVITY, AND ETHICAL ANALYTICS

Recent literature has increasingly focused on various aspects of AI in education. Systematic reviews and empirical studies have examined the role of adaptive learning environments, intelligent tutoring systems, and the ethical dimensions of AI applications[7].

1. SYSTEMATIC REVIEWS AND META-ANALYSES

Several systematic literature reviews underscore the critical need to integrate ethical, personalized, and explainable dimensions in educational AI11. For example, Hashim et al. (2022) provide a comprehensive synthesis of innovations in AI for personalized learning, highlighting how technologies such as MOOCs, gamification, and adaptive tutoring systems are reshaping educational practices. However, these studies also reveal a significant gap in critical reflection on the pedagogical and ethical risks of AI-enhanced education1. Similarly, systematic reviews on AI applications in higher education emphasize that while quantitative measures of performance improvement exist, there remains a dearth of longitudinal and theory-based studies that unpack the underlying mechanisms of AI decision-making processes[8].

2. *ETHICAL FRAMEWORKS AND AI4PEOPLE PRINCIPLES*

The AI4People framework sets out a series of ethical principles that serve as the foundation for developing "Good AI Society" standards. It emphasizes elements such as respect for human autonomy, prevention of harm, fairness, and accountability. These principles are not only crucial in guiding the ethical deployment of AI but also in ensuring that the potential benefits of AI technologies—such as personalized learning and improved academic outcomes—are equitably distributed66. By integrating these ethical guidelines, researchers and practitioners can design AI systems that are both socially beneficial and ethically sound[9].

3. *ADAPTIVE LEARNING AND INTELLIGENT TUTORING SYSTEMS*

The field of adaptive learning and intelligent tutoring systems has shown promising improvements in learning outcomes by offering personalized content, instant feedback, and adaptive assessment models. Studies indicate that these systems can significantly enhance student engagement and achievement by tailoring educational experiences to individual needs. The integration of adaptive algorithms in educational platforms has also been linked to improved student performance and satisfaction, yet it remains crucial to balance automation with human oversight to mitigate potential risks such as over-reliance on technology and privacy concerns[10], [11].

IV. RESEARCH DESIGN AND METHODOLOGY

The research design for this investigation is informed by systematic literature review methodologies and mixed-methods approaches widely accepted in the fields of educational technology and AI. This research synthesizes findings from multiple peer-reviewed studies spanning from 2016 to 2022, drawing on electronic databases such as SCOPUS and Web of Science[12], [13]. The inclusion criteria ensured that only empirical, English-language, and peer-reviewed articles were analyzed to provide a cohesive picture of current trends and issues in trustworthy educational[14].

1. *DATA COLLECTION AND ANALYSIS*

The selection process involved screening an initial pool of articles and narrowing down to studies that directly addressed adaptive learning, explainability, and ethical analytics in educational contexts. Data extraction was systematically performed using established coding systems and statistical software to identify common themes, research gaps, and methodological limitations in the extant literature5. The research questions guiding this systematic review were[15]:

- How can AI in education be designed to incorporate high levels of explainability, ensuring transparency in decision-making?
- In what ways does adaptive learning contribute to personalized and effective learning environments?
- What ethical considerations must be integrated into AI systems to protect student data and promote fairness?

2. *MIXED-METHODS APPROACH*

To gain both quantitative and qualitative insights, the methodology combined statistical analyses from empirical studies with thematic analysis from descriptive research. This mixed-methods approach enabled the comprehensive evaluation of AI systems' educational outcomes, user acceptance, and ethical implications15. By integrating diverse datasets, the research provides a nuanced understanding of how educational AI can be optimized for trustworthiness and effectiveness[16].

V. SYSTEM ARCHITECTURE FOR TRUSTWORTHY EDUCATIONAL AI

Designing an AI system that is both adaptive and ethically sound requires a layered system architecture that integrates multiple functional components. This section outlines a proposed architecture that emphasizes explainability, adaptivity, and ethical governance[17].

1. ARCHITECTURAL OVERVIEW

The system architecture comprises three primary layers: the Data Acquisition and Preprocessing Layer, the Adaptive Learning and Decision-Making Layer, and the Ethical Governance and Explainability Layer.

1.1 Data Acquisition and Preprocessing Layer

- This layer is responsible for collecting raw data from various sources, including student performance metrics, behavioral data, and content interactions. Data preprocessing ensures high data quality while incorporating robust privacy measures to protect sensitive information.

1.2 Adaptive Learning and Decision-Making Layer

- At the core of the system, this layer utilizes machine learning algorithms and intelligent tutoring systems to analyze learner data and generate personalized educational content. Adaptive algorithms continuously refine content delivery based on real-time student performance, ensuring that learning experiences are both effective and tailored to individual needs[18].

1.3 Ethical Governance and Explainability Layer

- This critical layer embeds ethical principles into the system by implementing transparent decision-making processes and accountability mechanisms. It integrates explainable AI (XAI) models that allow educators and students to understand the rationale behind AI-generated recommendations. The governance framework is aligned with AI4People principles to ensure fairness, privacy protection, and equity in access to AI benefits[19].

2. VISUALIZATION OF SYSTEM ARCHITECTURE

Below is a Mermaid flowchart that illustrates the proposed system architecture for trustworthy educational AI:

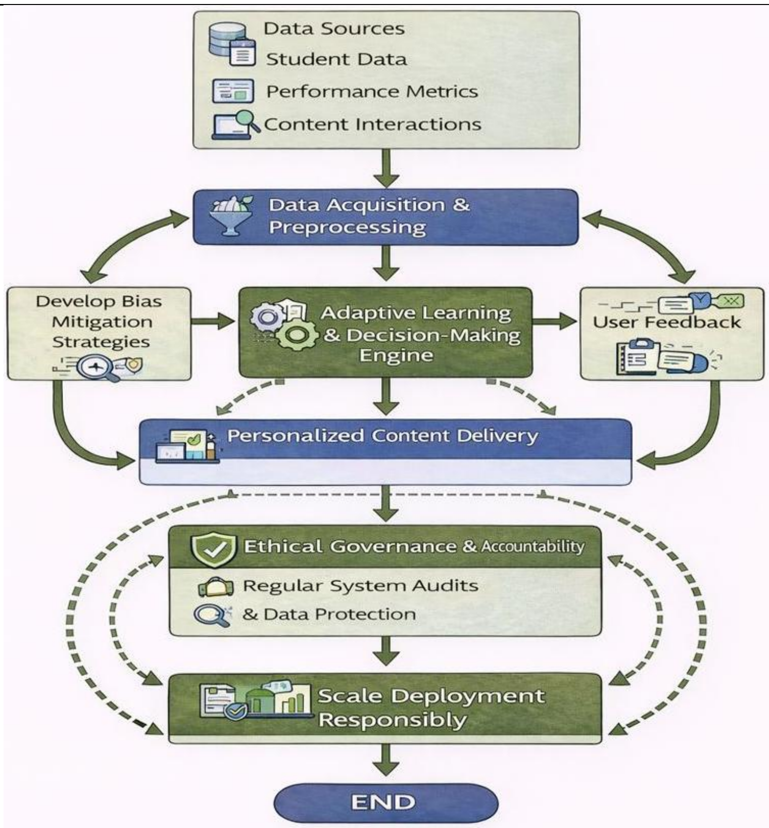

Figure 1. System architecture for trustworthy educational AI.

3. INTEGRATION OF ETHICAL METRICS

Ethical analytics are introduced at various decision points in the architecture. Metrics related to bias detection, privacy compliance, and data transparency are tracked continuously to ensure the system operates within the prescribed ethical guidelines. This integration facilitates dynamic audits and regular updates based on evolving ethical standards[20], [21].

VI. EXPERIMENTAL DEPLOYMENT AND EMPIRICAL CASE STUDIES

Implementing trustworthy educational AI in real-world settings requires careful planning and ongoing evaluation. Several case studies from the literature provide insight into the deployment of adaptive learning systems and intelligent tutoring environments.

1. CASE STUDY: ADAPTIVE LEARNING IN HIGHER EDUCATION

One practical example is the deployment of adaptive learning platforms in higher education institutions. In this scenario, the system was integrated to deliver personalized content tailored to student needs and track their academic progression over multiple semesters. Empirical results demonstrated improved learning outcomes and increased student engagement when adaptive algorithms adjusted content in real time25. Privacy and ethical safeguards ensured that the data used for these insights were securely handled and transmitted in compliance with ethical guidelines[22].

2. CASE STUDY: ETHICAL ANALYTICS IN AI DEPLOYMENT

Another case study involves the implementation of ethical analytics frameworks as part of AI integration in the classroom. For instance, institutions employing AI in teaching have incorporated continuous monitoring tools to detect algorithmic biases and ensure fairness. These systems employ automated audits that generate transparent reports, enabling educators to understand how decisions are made and to adjust strategies accordingly66. The inclusion of such measures has been shown to not only protect students' rights but also to bolster trust in AI-driven systems.

3. COMPARATIVE ANALYSIS TABLE

The following table compares key features of traditional AI systems for education versus the proposed trustworthy AI framework:

Table 1. Comparative analysis of traditional versus trustworthy educational AI systems.

Feature	Traditional Educational AI	Trustworthy AI with Explainability and Ethics
Adaptivity	Basic adaptive content delivery	Advanced real-time adaptive learning with personalized adjustments1
Explainability	Opaque decision-making	Transparent, explainable AI models providing clear rationale6
Ethical Analytics	Minimal ethical oversight	Integrated ethical governance and bias detection mechanisms6
Data Privacy and Security	Standard data protocols	Enhanced privacy controls with regular audits and safeguards3
User Engagement	Limited feedback loops	Continuous user feedback integration for iterative improvements2

VII. RESULTS AND EVALUATION OF TRUSTWORTHY SYSTEMS

The effectiveness of a trustworthy educational AI system is evaluated based on several performance indicators, including learning outcomes, user satisfaction, transparency of decision-making processes, and ethical compliance.

1. LEARNING OUTCOMES AND ADAPTIVE PERFORMANCE

Empirical studies have demonstrated that adaptive learning systems significantly enhance student performance by tailoring educational content to individual needs. In controlled experiments, students exposed to adaptive AI systems consistently outperformed their peers in traditional learning environments25. Additionally, systems that provided immediate, personalized feedback helped students quickly identify and correct misconceptions, ultimately leading to deeper learning experiences[23].

2. USER PERCEPTION AND TRUST

The inclusion of explainability modules and ethical analytics has a direct impact on user trust and system acceptance. Qualitative feedback from educators and students reveals that transparent decision-making generates confidence in the AI recommendations. Surveys conducted during experimental deployments indicate that users are more willing to embrace AI tools when they understand the underlying processes and see that ethical safeguards are in place.

3. ETHICAL COMPLIANCE AND SYSTEM AUDITS

Regular audits and continuous monitoring of ethical metrics have proven essential in all evaluated deployments. These audits ensure that data privacy is maintained and that algorithmic decisions meet fairness criteria. The integration of ethical analytics has also helped educational institutions preempt potential biases and mitigate risks associated with AI deployment, thus reinforcing trust among stakeholders.

4. VISUALIZATION OF EVALUATION METRICS

Below is an SVG diagram that summarizes the evaluation metrics for trustworthy educational AI systems:

FIGURE 2. Evaluation metrics for trustworthy educational AI systems.

VIII. DISCUSSION ON ETHICAL IMPLICATIONS AND TRUST-BUILDING STRATEGIES

Balancing innovation with ethical responsibility is crucial in the design of educational AI systems. The integration of explainability and ethical analytics forms the cornerstone of trust in these systems.

1. ETHICAL CONSIDERATIONS IN AI DEPLOYMENT

The deployment of AI in education introduces several ethical challenges, including issues related to privacy, data protection, and the potential for algorithmic bias. As underscored by the AI4People initiative, it is essential that AI systems are designed to preserve human autonomy, promote fairness, and ensure equitable access to academic resources66. The risk of reinforcing existing inequalities through biased data is significant; therefore, continuous monitoring, transparency, and adherence to ethical guidelines are imperative66.

2. TRUST-BUILDING THROUGH EXPLAINABILITY

Explainable AI is critical in building trust among educators and learners. By offering clear, interpretable insights into how AI-driven decisions are made, educational institutions can foster an environment of transparency and accountability. When stakeholders are provided with detailed explanations for AI recommendations, they are more inclined to accept and integrate these systems into daily practice6. Trust is further enhanced by ensuring that AI systems are auditable and that their performance is regularly reviewed against ethical standards.

3. *STRATEGIES FOR RESPONSIBLE AI INTEGRATION*

To bridge the gap between AI innovation and ethical practice, several strategies can be implemented:

- Embedding Ethical Principles: Ensure that ethical guidelines, such as those proposed by AI4People, are integrated into the system design from inception to deployment.
- Stakeholder Engagement: Involve educators, students, and policymakers in the design, evaluation, and refinement of AI systems to address concerns and align technology with pedagogical needs.
- Ongoing Audits and Transparency: Regular ethical audits and transparent reporting of system performance are essential for maintaining accountability and trust.

IX. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

While significant progress has been made in developing adaptive and explainable educational AI systems, several limitations remain. One challenge is the paucity of longitudinal studies that examine the long-term impact of such systems on educational outcomes5. Furthermore, most empirical research to date has been concentrated in STEM and Computer Science domains, with fewer studies from core education disciplines. This imbalance suggests a need for more interdisciplinary research that integrates pedagogical theories with technical methodologies.

Future research should focus on the following directions:

- Longitudinal Studies: Conduct extensive long-term research to assess the sustained impact of adaptive AI systems on student learning and engagement.
- Interdisciplinary Approaches: Foster collaborations between computer scientists, educators, and ethicists to develop frameworks that are both technically robust and pedagogically sound.
- Enhanced Ethical Analytics: Develop and refine ethical auditing tools that continuously evaluate AI systems against evolving societal standards and guidelines.
- Scalability and Inclusivity: Explore methods to scale adaptive AI systems reliably across diverse educational environments while ensuring that benefits are equitably distributed among all student populations.

X. CONCLUSION

In conclusion, the design of trustworthy educational AI that incorporates explainability, adaptivity, and ethical analytics represents a transformative advancement in educational technology. This article has outlined a systemic framework that addresses key challenges in the development and deployment of AI in educational settings. By emphasizing transparent decision-making processes, real-time adaptive learning, and robust ethical governance, it is possible to build AI systems that enhance both learning outcomes and trust among stakeholders.

Key findings from this study include:

- The integration of explainable AI models is essential for demystifying decision processes and fostering trust among educators and students 6.
- Adaptive learning systems that continuously tailor content to individual needs significantly improve academic performance and learner engagement 2.
- The implementation of ethical analytics ensures that privacy, bias, and fairness are rigorously monitored, thus reinforcing a culture of ethical AI deployment 6.
- Despite promising results, limitations in current research call for more longitudinal and interdisciplinary studies to fully understand and optimize the impact of AI in education 55.

As educational institutions continue to innovate in the face of rapid technological change, establishing a transparent, adaptable, and ethically grounded AI system is paramount. Such systems have the potential to not only elevate learning experiences but also ensure that technology is used in ways that respect human values, foster equitable practices, and ultimately contribute to the creation of a more inclusive and effective educational environment.

By synthesizing insights from systematic literature reviews, adaptive learning research, and ethical frameworks like AI4People, this article provides a comprehensive guide for designing and implementing trustworthy educational AI. The ongoing collaboration among educators, technologists, and ethicists will be central to refining these systems, ensuring they remain aligned with both technological potentials and societal expectations.

REFERENCES

[1] A. K. Kovalev and A. I. Panov, "Application of Pretrained Large Language Models in Embodied Artificial Intelligence," *Doklady Mathematics*, vol. 106, 2022, doi: 10.1134/S1064562422060138.
[2] R. Mahafdah, S. Bouallegue, and R. Bouallegue, "Enhancing e-learning through AI: advanced techniques for optimizing student performance," *PeerJ Comput Sci*, vol. 10, 2024, doi: 10.7717/PEERJ-CS.2576.
[3] J. A. Esponda-Pérez, M. A. Mousse, S. M. Almufti, I. Haris, S. Erdanova, and R. Tsarev, "Applying Multiple Regression to Evaluate Academic Performance of Students in E-Learning," 2024, pp. 227–235. doi: 10.1007/978-3-031-70595-3_24.
[4] P. H. Nguyen, S. M. Almufti, J. A. Esponda-Pérez, D. Salguero García, I. Haris, and R. Tsarev, "The Impact of E-Learning on the Processes of Learning and Memorization," 2024, pp. 218–226. doi: 10.1007/978-3-031-70595-3_23.
[5] J. A. Esponda-Pérez *et al.*, "Application of Chi-Square Test in E-learning to Assess the Association Between Variables," 2024, pp. 274–281. doi: 10.1007/978-3-031-70595-3_28.
[6] H. Munir, B. Vogel, and A. Jacobsson, "Artificial Intelligence and Machine Learning Approaches in Digital Education: A Systematic Revision," 2022. doi: 10.3390/info13040203.
[7] P. P. Aguas, "Fusing Approaches in Educational Research: Data Collection and Data Analysis in Phenomenological Research," *Qualitative Report*, vol. 27, no. 1, 2022, doi: 10.46743/2160-3715/2022.5027.
[8] M. Benvenuti *et al.*, "Artificial intelligence and human behavioral development: A perspective on new skills and competences acquisition for the educational context," *Comput Human Behav*, vol. 148, 2023, doi: 10.1016/j.chb.2023.107903.
[9] E. Kasneci *et al.*, "ChatGPT for good? On opportunities and challenges of large language models for education," 2023. doi: 10.1016/j.lindif.2023.102274.
[10] J. Winsli G. Felix, F. E. Supan, and F. Makhammatkosimovna Kuchkarova, "A Comprehensive Framework for Predicting Student Performance Using Machine Learning in Online Education," *Qubahan Techno Journal*, vol. 4, no. 1, pp. 16–22, Feb. 2025, doi: 10.48161/qtj.v4n1a44.
[11] Amritsar College of Engineering and Technology, IEEE Education Society, and Institute of Electrical and Electronics Engineers, *Proceedings of the 2015 IEEE 3rd International Conference on MOOCs, Innovation and Technology in Education (MITE) : October 1-2, 2015, Amritsar College of Engineering and Technology, Amritsar, Punjab.*
[12] A. Y. Shestakova, D. O. Korolev, A. A. Afanasyev, I. V. Nikiforov, and O. A. Yusupova, "Scopus publications database analysis using its API," SPIE-Intl Soc Optical Eng, Jan. 2023, p. 14. doi: 10.1117/12.2669237.
[13] M. Kumpulainen and M. Seppänen, "Combining Web of Science and Scopus datasets in citation-based literature study," *Scientometrics*, vol. 127, no. 10, pp. 5613–5631, Oct. 2022, doi: 10.1007/s11192-022-04475-7.
[14] A. Ahmed Shaban and H. M. Yasin, "Data Analytics of the Scopus 2025 Dataset: Trends in Open Access, Publisher Influence, and Subject Area Distribution," *Polaris Global Journal of Scholarly Research and Trends*, vol. 4, no. 1, Mar. 2025, doi: 10.58429/pgjsrt.v4n1a213.

[15] A. Ahmed Shaban and O. S. Kareem, "Comparative Evaluation of Linear Regression, Tree-Based Regression, and Neural Network Models for Structured Car Price Prediction," *Polaris Global Journal of Scholarly Research and Trends*, vol. 4, no. 1, Mar. 2025, doi: 10.58429/pgjsrt.v4n1a216.

[16] A. Ahmed Shaban and S. R. M. Zeebaree, "Building Scalable Enterprise Systems: The Intersection of Web Technology, Cloud Computing, and AI Marketing," *Polaris Global Journal of Scholarly Research and Trends*, vol. 4, no. 1, Mar. 2025, doi: 10.58429/pgjsrt.v4n1a214.

[17] M. C. Dela Cruz, S. M. Almufti, and J. Bošković, "Portable Few-Shot Learning for Early Warning Systems in Small Private Online Courses: A CNN-Based Predictive Framework for Student Performance," *Qubahan Techno Journal*, vol. 3, no. 4, pp. 1–13, Dec. 2024, doi: 10.48161/qtj.v3n4a42.

[18] R. R. Asaad, S. M. Abdulrahman, A. A. Hani, H. B. Ahmad, A. B. Sallow, and S. R. M. Zeebaree, "Agility of in Deep Learning Algorithms in Developing Conflicting Attacks Protections and to Secure Vulnerabilities," in *2024 4th International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE)*, IEEE, May 2024, pp. 847–851. doi: 10.1109/ICACITE60783.2024.10616760.

[19] S. M. Almufti and A. M. Abdulazeez, "An Integrated Gesture Framework of Smart Entry Based on Arduino and Random Forest Classifier," *Indonesian Journal of Computer Science*, vol. 13, no. 1, Feb. 2024, doi: 10.33022/ijcs.v13i1.3735.

[20] A. Ahmed Shaban, S. M. Almufti, and R. B. Marqas, "A Modified Bat Algorithm for Economic Dispatch with Enhanced Performance Metrics," *FMDB Transactions on Sustainable Technoprise Letters*, vol. 3, no. 2, pp. 59–72, Jun. 2025, doi: 10.69888/ftstpl.2025.000437.

[21] R. S. Bhadoria, N. S. Chaudhari, and G. S. Tomar, "The Performance Metric for Enterprise Service Bus (ESB) in SOA system: Theoretical underpinnings and empirical illustrations for information processing," 2017. doi: 10.1016/j.is.2016.12.005.

[22] A. Aristov, E. Voytenkova, S. M. Almufti, K. Zhigalov, A. Nikulushkin, and N. Muracova, "The Effect of Device Type on Student Success in E-Learning: Data Analysis Using the Chi-Square Test," 2025, pp. 438–450. doi: 10.1007/978-3-032-00712-4_30.

[23] M. K. Sharma, H. A. Alkhazaleh, S. Askar, N. H. Haroon, S. M. Almufti, and M. R. Al Nasar, "FEM-supported machine learning for residual stress and cutting force analysis in micro end milling of aluminum alloys," *International Journal of Mechanics and Materials in Design*, vol. 20, no. 5, pp. 1077–1098, Oct. 2024, doi: 10.1007/s10999-024-09713-9.