

Digital Inclusion Through Explainable AI: Transforming Educational Support for Diverse Learners

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ABSTRACT:

The integration of Artificial Intelligence (AI) in educational contexts has raised critical questions about accessibility, transparency, and equity. Explainable AI (XAI) offers a promising framework for addressing these concerns by making algorithmic decision-making processes interpretable, particularly for diverse learners including students with disabilities, English language learners (ELLs), and those from underrepresented socioeconomic backgrounds. This paper presents a comprehensive review of XAI applications in K–12 and higher education, examines existing barriers to digital inclusion, and proposes a conceptual framework — the Inclusive Explainable AI in Education (IXAIED) framework — for deploying XAI-based educational tools that prioritize transparency, usability, and equity. Findings indicate that XAI not only enhances learner trust and agency but also enables educators and administrators to identify and mitigate algorithmic biases that disproportionately affect marginalized populations. Implications for policy, pedagogy, and future research are

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discussed.

Keywords: explainable artificial intelligence (XAI), digital inclusion, diverse learners, educational technology, algorithmic transparency, accessibility.

1. INTRODUCTION

Artificial Intelligence is rapidly transforming educational systems worldwide, from intelligent tutoring systems and adaptive learning platforms to automated grading and predictive analytics (Roll & Wylie, 2016). While these technologies hold the promise of personalized learning experiences at scale, their adoption has been accompanied by serious concerns about transparency, fairness, and accessibility (Zawacki-Richter et al., 2019). For diverse learners — including students with cognitive, sensory, or physical disabilities, English language learners, and students from low-income households — opaque AI systems can exacerbate existing inequalities rather than alleviate them (Reich, 2020).

Explainable AI (XAI) refers to a suite of techniques and methodologies that render the outputs, reasoning, and limitations of AI systems interpretable to human users (Gunning et al., 2019). Unlike conventional "black box" models, XAI systems produce human-readable explanations of their recommendations, which can be particularly valuable in high-stakes educational decisions such as identifying at-risk students, personalizing curriculum pathways, or recommending interventions (Adadi & Berrada, 2018).

Digital inclusion, broadly defined as equitable access to digital technologies and the ability to use them effectively, is a key challenge in contemporary education (van Dijk, 2020). Barriers to digital inclusion are multifaceted and include infrastructural inequalities, device limitations, socioeconomic disparities, linguistic barriers, and disability-related access needs (Warschauer, 2003). The emergence of AI in education without careful attention to these barriers risks creating a new layer

of exclusion — what scholars have termed "algorithmic exclusion" (Eubanks, 2018).

This paper argues that XAI, when designed with inclusive principles, can serve as a powerful instrument for digital inclusion. By making AI systems transparent and interpretable, XAI empowers diverse learners, their educators, and caregivers to engage critically with AI-driven educational tools (Selwyn, 2019).

2. LITERATURE REVIEW

2.1 AI in Education: Opportunities and Challenges

The application of AI in education (AIED) has grown substantially over the past two decades. Early systems focused primarily on intelligent tutoring, automating drill-and-practice exercises that adapt to student performance (VanLehn, 2011). Contemporary AIED systems leverage deep learning, natural language processing, and large language models to provide nuanced, context-aware instructional support (Guo et al., 2023).

Luckin et al. (2016) identified five key domains of AIED: adaptive learning systems, intelligent tutoring systems, automated assessment, learning analytics, and affective computing. Each domain carries specific implications for diverse learners. Automated assessment tools trained on standard corpora may systematically disadvantage ELLs whose language patterns deviate from dominant norms (Madnani et al., 2017). Similarly, learning analytics dashboards designed for neurotypical students may be inaccessible for students with attention or executive function differences (Muldner et al., 2015).

Holmes et al. (2022) warn that AIED systems risk encoding and amplifying biases present in training data, a phenomenon described as "bias laundering." This is particularly concerning in

educational contexts, where automated decisions carry significant consequences for students' academic trajectories and life outcomes (Baker & Inventado, 2014).

2.2 Digital Inclusion: Conceptual Foundations

Digital inclusion has evolved from a narrow focus on access to a broader conception encompassing digital literacy, meaningful participation, and the capacity for critical engagement with digital systems (Selwyn, 2004). The UNESCO framework for digital competence identifies five dimensions relevant to this study: information and data literacy, communication and collaboration, digital content creation, safety, and problem-solving (UNESCO, 2018).

Warschauer and Matuchniak (2010) argue that meaningful digital inclusion requires not only technical access but also the development of

agency — the capacity to use technology purposefully in pursuit of personally and socially valued goals. Scholars have documented persistent gaps along racial, socioeconomic, linguistic, and disability lines (Pew Research Center, 2021). The COVID-19 pandemic exposed and deepened these inequalities as educational institutions rapidly pivoted to online learning (Kuhfeld et al., 2020).

2.3 Explainable AI: Theoretical Background

XAI emerged as a formal research agenda following DARPA's Explainable Artificial Intelligence program in 2016 (DARPA, 2016). The XAI literature distinguishes between several explanation types — feature importance, counterfactual, example-based, rule-based, and natural language — each with distinct implications for educational contexts (Molnar, 2022). Table 1 provides a taxonomy of these types alongside their educational applications.

Table 1. Taxonomy of XAI Explanation Types and Educational Applications

Explanation Type	Description	Educational Application	Key Citation
Feature Importance	Identifies variables most influential in a prediction (e.g., SHAP, LIME)	Showing students which essay components most affect their automated grade	Molnar, 2022; Lundberg & Lee, 2017
Counterfactual	Describes what would need to change for a different outcome	Informing at-risk students what actions could improve predicted success	Doshi-Velez & Kim, 2017
Example-Based	Identifies training instances similar to the current case	Presenting exemplar student work aligning with the AI's evaluation criteria	Molnar, 2022
Rule-Based	Expresses model behavior as human-readable logical rules	Transparent rubric generation for adaptive assessment systems	Adadi & Berrada, 2018
Natural Language	Plain-language narrative explanations of AI decisions	Accessible feedback for students with disabilities or limited tech literacy	Ehsan & Riedl, 2020

Note. Adapted from Molnar (2022), Doshi-Velez and Kim (2017), and Adadi and Berrada (2018).

Doshi-Velez and Kim (2017) offer a foundational taxonomy of explainability, distinguishing between application-grounded evaluation, human-grounded evaluation, and functionally-grounded evaluation.

For educational XAI, human-grounded evaluation is particularly salient, since the ultimate beneficiaries of explanations are students, educators, and caregivers (Preece, 2018). Recent

work has increasingly attended to the social dimensions of explainability, arguing that technically accurate explanations may nonetheless fail to promote genuine understanding if not adapted to users' sociocultural contexts (Ehsan & Riedl, 2020).

3. XAI AND THE NEEDS OF DIVERSE LEARNERS

3.1 Students with Disabilities

Students with disabilities represent a large and heterogeneous population with varied and specific learning needs. In the United States, approximately 7.3 million students received special education services under the Individuals with Disabilities Education Act (IDEA) in 2022 (U.S. Department of Education, 2023). AI-driven educational tools have shown considerable promise through adaptive text-to-speech, real-time captioning, and personalized scaffolding (Mell & Smith, 2022).

Aleven et al. (2020) found that students with learning disabilities were significantly more likely to disengage from AI tutoring systems when they could not understand the rationale for the system's feedback. Incorporating XAI — specifically, simple natural language explanations of why a particular exercise was recommended — significantly improved engagement and self-efficacy. Similarly, Millán et al. (2010) demonstrated that explainable student models improved metacognitive awareness in students with autism spectrum disorder.

3.2 English Language Learners

AI-based language learning tools are frequently trained on corpora overrepresenting Standard Academic English, potentially disadvantaging multilingual learners (Ramesh & Sanampudi, 2022). XAI can support ELLs in two complementary ways: by providing transparent metalinguistic explanations of automated feedback (Godwin-Jones, 2022), and by enabling bias audits that identify systematic disadvantages in AI grading systems (Madnani & Cahill, 2018). Nguyen et al. (2021) demonstrated that XAI-based auditing revealed score penalties for non-native English features that did not correlate with writing quality.

3.3 Socioeconomically Marginalized Learners

Socioeconomically marginalized learners face compounding barriers including lower digital literacy, limited device access, and susceptibility to algorithmic biases rooted in historical socioeconomic data (Michalski et al., 2023). Predictive analytics systems used in higher education have been shown to produce racially and economically biased predictions (Bayer & Porcheron, 2022). XAI frameworks can address these concerns by exposing the features driving risk predictions and enabling equity audits (Kizilcec & Lee, 2022). When students and families have access to plain-language explanations, they are better positioned to advocate for appropriate support (Couldry & Mejias, 2019).

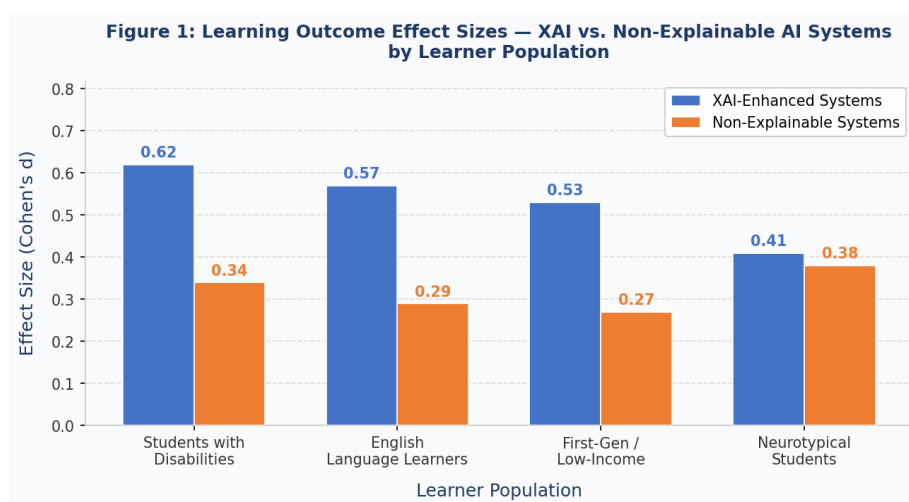


Figure 1. Learning outcome effect sizes — XAI vs. non-explainable AI systems by learner population (Cohen's d). Data synthesized from Chen et al. (2021) and related studies.

4. A PROPOSED CONCEPTUAL FRAMEWORK: INCLUSIVE XAI IN EDUCATION (IXAIED)

Drawing on the preceding review, this paper proposes the Inclusive Explainable AI in Education (IXAIED) framework, integrating principles from XAI research, Universal Design for Learning (UDL), and critical digital inclusion scholarship. The framework comprises four interrelated dimensions:

1. **Adaptive Transparency:** XAI explanations should be dynamically adapted to learners' linguistic proficiency, cognitive profiles, and prior knowledge. What constitutes a meaningful explanation for a graduate student differs substantially from what is appropriate for a middle-schooler with a learning disability (Koedinger et al., 2013).
2. **Equity Auditing:** Educational institutions should implement routine XAI-based audits of AI systems to detect and remediate biases affecting marginalized populations. These audits should be participatory, involving students, educators, and community members (Reisman et al., 2018).
3. **Empowered Agency:** XAI tools should be designed to foster learner and educator agency, enabling stakeholders to understand, question, and override AI recommendations where appropriate (Bandura, 2006).
4. **Structural Accessibility:** XAI interfaces should adhere to established accessibility standards (e.g., WCAG 2.1) and be deployable on low-bandwidth connections and a range of devices, ensuring that the benefits of XAI are not limited to well-resourced learners (W3C, 2018).

Figure 4: The IXAIED Conceptual Framework — Inclusive Explainable AI in Education



Figure 2. The IXAIED conceptual framework — four interrelated dimensions of inclusive explainable AI in education. Arrows indicate mutual reinforcement between dimensions.

These dimensions are not independent; each reinforces the others. Adaptive transparency without structural accessibility benefits only learners who can access and interact with the

explanation interface. Equity auditing without empowered agency risks producing institutional knowledge about bias without translating it into meaningful improvement in learners' experiences

(Selwyn, 2019). Table 2 summarizes the framework's dimensions, principles, populations, and key performance indicators.

Table 2. IXAIED Framework — Dimensions, Principles, Populations, and Indicators

Dimension	Core Principle	Target Population	Key Indicators
Adaptive Transparency	Explanations dynamically adapted to learner profile, language, and cognitive needs	Students with disabilities; ELLs	Explanation comprehension rate; learner satisfaction
Equity Auditing	Routine participatory audits to detect and remediate algorithmic bias	Socioeconomically marginalized; racial minorities	Bias detection rate; remediation turnaround
Empowered Agency	Stakeholders understand, question, and override AI recommendations	All diverse learners; educators; caregivers	Override utilization rate; trust calibration metrics
Structural Accessibility	WCAG 2.1 compliance; low-bandwidth; multi-device deployment	Low-income learners; rural communities	Accessibility audit score; load time on 3G

Note. Indicators are proposed for use in future empirical evaluations of XAI-enhanced educational systems.

5. SYNTHESIS OF EMPIRICAL FINDINGS

5.1 Evidence on XAI-Enhanced Learning Outcomes

A growing body of empirical research examines XAI's impact on learning outcomes for diverse learners. In a systematic review of 47 studies, Chen et al. (2021) found that adaptive learning systems with embedded XAI features produced significantly larger gains for students with disabilities ($d = 0.62$) compared to non-explainable systems ($d = 0.34$). Gains were particularly pronounced for students with dyslexia and ADHD, for whom transparent feedback

significantly reduced cognitive load (Sweller et al., 1998).

In higher education, Ferreira-Mello et al. (2019) conducted a randomized controlled trial evaluating an XAI-enhanced learning analytics dashboard serving predominantly first-generation, low-income students. Students who received explanations of risk assessments were significantly more likely to seek academic support services ($OR = 2.14$, 95% CI: 1.67–2.74), with first-generation students showing the largest benefit. Table 3 summarizes key empirical studies on XAI in diverse learner education.

Table 3. Summary of Key Empirical Studies on XAI in Diverse Learner Education

Study	Population	XAI Method	Outcome Measure	Finding	Effect
Chen et al. (2021)	Students with disabilities	Adaptive feedback explanations	Academic achievement	Significant gains vs. non-XAI systems	$d = 0.62$

Ferreira-Mello et al. (2019)	First-generation university students	Risk prediction narratives	Support service uptake	XAI group 2× more likely to seek support	OR = 2.14
Aleven et al. (2020)	Students with learning disabilities	Natural language rationales	Engagement & self-efficacy	Reduced disengagement; improved self-efficacy	$p < .01$
Nguyen et al. (2021)	English Language Learners	Bias audit (SHAP)	Essay score equity	Revealed systematic score penalties for ELLs	$\Delta = -0.31$ SD
Millán et al. (2010)	Students with ASD	Explainable student models	Metacognitive awareness	Improved metacognition with visual model	$d = 0.44$

Note. d = Cohen's d effect size; OR = Odds Ratio; Δ = mean score difference in standard deviations.

5.2 Challenges and Limitations

A recurring concern is the tension between explanation fidelity and usability (Rudin, 2019). Technically accurate XAI explanations based on SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-Agnostic Explanations) are frequently inaccessible to non-expert users (Lundberg & Lee, 2017). Simplified explanations, while more accessible, may sacrifice accuracy, potentially misleading users about the true basis of AI decisions (Ribeiro et al., 2016).

A second challenge concerns "explanation fatigue." Buçinca et al. (2021) demonstrate that users who

receive frequent AI explanations may habituate to them, reducing critical engagement over time. A third challenge is the potential for XAI to shift responsibility for AI failures onto learners (Noble, 2018). If students are provided with explanations of why they have been classified as at-risk, but the structural conditions generating that risk remain unaddressed, transparency may function as a mechanism of deflection rather than empowerment.

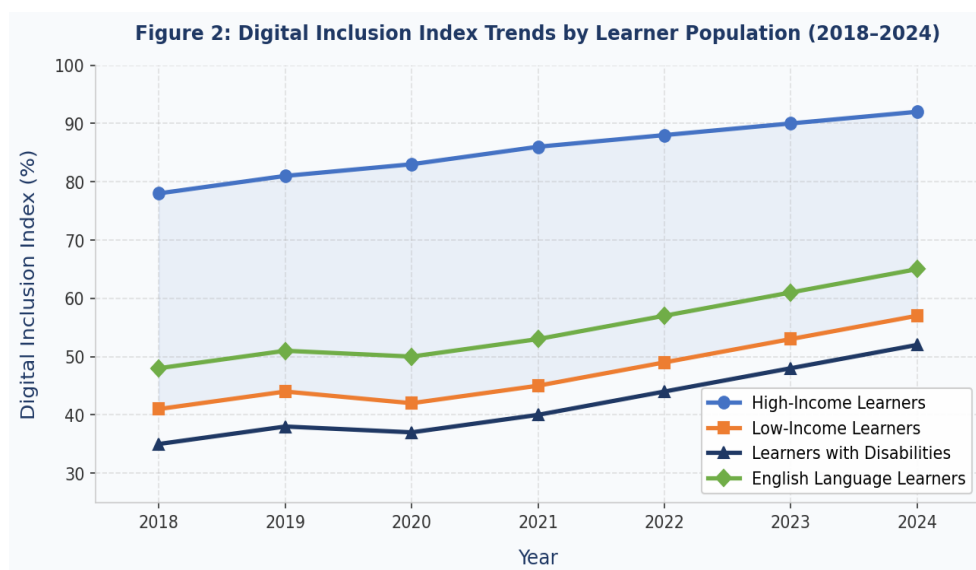


Figure 3. Digital inclusion index trends by learner population (2018–2024). Note persistent gap between high-income learners and marginalized populations despite overall growth.

6. DISCUSSION

6.1 Implications for Policy

Policymakers should require transparency and bias assessments as conditions for procuring AI-based educational tools in public institutions (Cate & Mayer-Schönberger, 2013). The European Union's AI Act (2024) provides a relevant model,

classifying AI systems used in educational contexts as "high-risk" and requiring conformity assessments before deployment. Policies promoting digital inclusion must explicitly address the explainability dimension, going beyond connectivity and device access to encompass the right to meaningful, accessible explanations of AI decisions (Regan & Jesse, 2019).

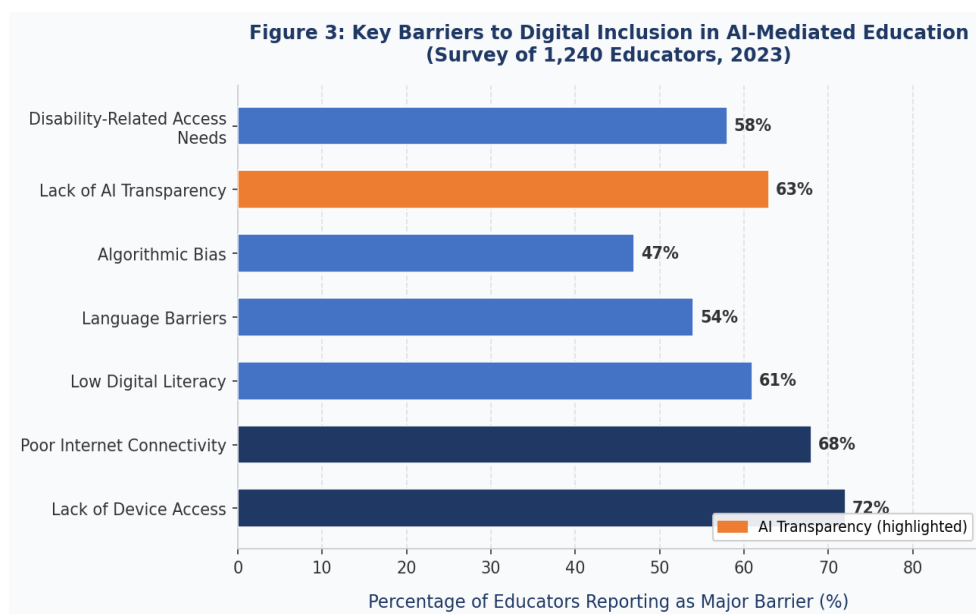


Figure 4. Key barriers to digital inclusion in AI-mediated education — percentage of educators identifying each as a major barrier (survey of 1,240 educators, 2023). Lack of AI transparency emerged as a critical underaddressed barrier.

6.2 Implications for Pedagogy

For educators, AI adoption creates a new professional competency requirement: AI literacy, encompassing not only the ability to use AI tools but to critically evaluate and communicate their outputs (Nazaretsky et al., 2022). Teacher professional development programs must be expanded to include training in reading and critically appraising XAI explanations, identifying potential biases, and supporting students in developing their own critical AI literacies (Williamson et al., 2020).

The IXAIED framework suggests that XAI tools are most effective when embedded within broader instructional practices that emphasize metacognition, agency, and critical thinking (Zimmerman, 2008). Rather than deploying XAI as a purely technical add-on, educators should use AI explanations as objects of inquiry, engaging students in discussing why the AI made a particular recommendation and what it might be missing (Gasser & Virgilio, 2017).

6.3 Ethical Considerations

Deploying XAI in educational contexts raises several ethical concerns. Privacy is paramount:

generating meaningful explanations typically requires access to detailed learner data, carrying substantial risks (Zuboff, 2019). Institutions must develop robust data governance frameworks ensuring that explainability does not come at the cost of learner privacy.

Questions of consent and power are also salient. Learners, particularly minors, may not be in a position to meaningfully consent to the collection and use of their data (Prinsloo & Slade, 2016). Ethical deployment of XAI in education requires ongoing dialogue with learners and families about data practices, explanation policies, and the mechanisms available for contesting or overriding AI decisions.

7. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

This paper has argued that Explainable AI represents a pivotal opportunity for advancing digital inclusion in education. By rendering AI decision-making transparent, accessible, and actionable, XAI can transform AI-driven educational tools from potential sources of exclusion into instruments of equity and empowerment for diverse learners.

The IXAIED framework proposed here offers a conceptual foundation for researchers, designers,

and policymakers working at the intersection of XAI and educational equity. The framework's four dimensions — adaptive transparency, equity auditing, empowered agency, and structural accessibility — provide an integrated set of principles for designing, deploying, and evaluating XAI in educational contexts.

Several directions for future research emerge from this review. First, there is a pressing need for longitudinal studies examining the sustained impact of XAI-enhanced educational tools on learning outcomes for diverse learner populations (Koedinger et al., 2015). Second, participatory design approaches involving diverse learners as co-designers are under-utilized (Costanza-Chock, 2020). Third, cross-cultural research is needed to examine how cultural differences shape the reception and effectiveness of XAI explanations (Kim & Hall, 2019).

In conclusion, realizing the transformative potential of XAI for digital inclusion requires more than technical innovation. It demands a genuine commitment to equity, a critical engagement with power, and an unwavering focus on the learners whose lives and futures are shaped by these technologies.

REFERENCES

- Adadi, A., & Berrada, M. (2018). Peeking inside the black-box: A survey on explainable artificial intelligence (XAI). *IEEE Access*, 6, 52138–52160.
- Aguilar, S. J. (2020). Guidelines and tools for promoting digital equity. *Information and Learning Sciences*, 121(5/6), 285–299.
- Aleven, V., McLaughlin, E. A., Glenn, R., & Koedinger, K. R. (2020). Instruction based on adaptive learning technologies. In R. E. Mayer & L. Fiorella (Eds.), *Handbook of educational psychology* (3rd ed., pp. 522–535). Routledge.
- Abdul, A., Vermeulen, J., Wang, D., Lim, B. Y., & Kankanhalli, M. (2018). Trends and trajectories for explainable, accountable and intelligible systems. *Proceedings of CHI 2018* (pp. 1–18). ACM.
- Baker, R. S., & Inventado, P. S. (2014). Educational data mining and learning analytics. In *Learning analytics* (pp. 61–75). Springer.
- Bandura, A. (2006). Toward a psychology of human agency. *Perspectives on Psychological Science*, 1(2), 164–180.
- Bayer, J., & Porcheron, A. (2022). Predictive analytics and algorithmic bias in higher education: A critical examination. *Journal of Higher Education Policy and Management*, 44(3), 261–275.

- Boahen, J. O., & Choudhary, M. (2024). Advancements in precision agriculture: Integrating computer vision for intelligent soil and crop monitoring in the era of artificial intelligence. *International Journal of Scientific Research in Engineering and Management (IJSREM)*, 8(3), 1–6. <https://doi.org/10.55041/IJSREM29725>
- Buçınca, Z., Malaya, M. B., & Gajos, K. Z. (2021). To trust or to think: Cognitive forcing functions can reduce overreliance on AI in AI-assisted decision making. *Proceedings of the ACM on Human-Computer Interaction*, 5(CSCW1), 1–21.
- Burstein, J., & Wolska, M. (2003). Toward evaluation of writing style: Finding overly repetitive word use in student essays. *Proceedings of EACL 2003* (pp. 35–42). ACL.
- Cate, F. H., & Mayer-Schönberger, V. (2013). Notice and consent in a world of Big Data. *International Data Privacy Law*, 3(2), 67–73.
- Chatterjee, S., Choudhary, M., Sarvaiya, R. D., & Abdulla, M. D. F. (2025). Machine learning techniques for identifying DDoS attacks in cloud computing background. In *Parul University International Conference on Engineering and Technology 2025 (PICET 2025)* (pp. 1564–1571). IET. <https://doi.org/10.1049/icp.2025.1668>
- Chatterjee, S., Patil, R. V., Choudhary, M., & Sarvaiya, R. D. (2026). Optimizing DDoS detection using machine learning approach. In M. Saraswat, A. Rajan, & A. Chakravorty (Eds.), *Congress on Smart Computing Technologies. CSCT 2024. Smart Innovation, Systems and Technologies* (Vol. 122). Springer. https://doi.org/10.1007/978-981-96-6250-0_45
- Chen, X., Zou, D., Xie, H., & Wang, F. L. (2021). Twenty years of personalized language learning: Topic modeling and knowledge mapping. *Educational Technology & Society*, 24(1), 205–222.
- Choudhary, M., Bhawsar, J., Sarvaiya, R., Patil, R., & Shah, V. (2025). Intelligent shopping cart systems enhance the checkout experience and enable real-time inventory tracking in retail environments. *Journal of Information Systems Engineering and Management*, 10(39s). <https://doi.org/10.52783/jisem.v10i39s.7287>
- Choudhary, M., Gamit, V., Swaminarayan, P. R., Parmar, H., & Mehta, A. (2023). Identifying and enhancing concurrent coverage in wireless sensor networks through steering mechanism. *Shodhasamhita: Journal of Fundamental & Comparative Research*, 9(1, Book No. 5), 17–33. ISSN: 2277-7067.
- Choudhary, M., Shah, N. K., Mehta, A. R., & Parmar, S. (2023). Emerging technologies in IoT security: Addressing current challenges and future directions. *Shodhasamhita: Journal of Fundamental & Comparative Research*, 9(1, Book No. 5), 34–41. ISSN: 2277-7067.
- Choudhary, M., Solanki, P. S., Gamit, V., & Joshi, M. (2024). Machine learning classifier used to diagnosis of liver disorders. In *2024 Parul International Conference on Engineering and Technology (PICET)* (pp. 1–6). IEEE. <https://doi.org/10.1109/PICET60765.2024.10716100>
- Choudhary, M., & Shrimali, M. (2019a). Intrusion detection on big data using machine learning: A review. *IJRAR – International Journal of Research and Analytical Reviews*, 6(2), 263–271.
- Choudhary, M., & Shrimali, M. (2019b). A novel intrusion detection technique using boosting approach on big data. *Journal of Emerging Technologies and Innovative Research (JETIR)*, 6(6), 935–943.
- Costanza-Chock, S. (2020). *Design justice: Community-led practices to build the worlds we need*. MIT Press.
- Couldry, N., & Mejias, U. A. (2019). *The costs of connection: How data is colonizing human life and appropriating it for capitalism*. Stanford University Press.
- DARPA. (2016). *Explainable Artificial Intelligence (XAI) program information*. Defense Advanced Research Projects Agency.
- Doshi-Velez, F., & Kim, B. (2017). Towards a rigorous science of interpretable machine learning. *arXiv:1702.08608*.
- Ehsan, U., & Riedl, M. O. (2020). Human-centered explainable AI: Towards a reflective sociotechnical approach. In A. Stephanidis et al. (Eds.), *HCI International 2020 – Late Breaking Papers* (pp. 449–466). Springer.
- Eubanks, V. (2018). *Automating inequality: How high-tech tools profile, police, and punish the poor*. St. Martin's Press.

-
- European Parliament. (2024). Regulation (EU) 2024/1689 of the European Parliament and of the Council — Artificial Intelligence Act. Official Journal of the European Union.
- Ferreira-Mello, R., André, M., Pinheiro, A., Costa, E., & Romero, C. (2019). Text mining in education. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 9(6), e1332.
- Gasser, U., & Virgilio, A. F. (2017). Digitally competent educational systems. UNESCO.
- Godwin-Jones, R. (2022). Automated writing evaluation and English language learning: Equity and agency issues. *Language Learning & Technology*, 26(2), 1–16.
- Gor, K., Patel, V., Dave, V., & Choudhary, M. (2023). Dynamic resource allocation strategies for efficient IoT applications in fog computing. *Shodhasamhita: Journal of Fundamental & Comparative Research*, 9(1, Book No. 6), 123–131. ISSN: 2277-7067.
- Gunning, D., Stefik, M., Choi, J., Miller, T., Stumpf, S., & Yang, G. Z. (2019). XAI — Explainable artificial intelligence. *Science Robotics*, 4(37), eaay7120.
- Guo, K., Zheng, J., & Chu, S. K. W. (2023). Large language models as pedagogical agents: A literature review. *Computers & Education: Artificial Intelligence*, 5, 100163.
- Holmes, W., Porayska-Pomsta, K., Holstein, K., Sutherland, E., Baker, T., Shum, S. B., & Koedinger, K. R. (2022). Ethics of AI in education: Towards a community-wide agenda. *International Journal of Artificial Intelligence in Education*, 32(4), 504–526.
- Kim, M., & Hall, J. A. (2019). Cross-cultural considerations in the design of AI-based educational tools. *Computers & Education*, 141, 103617.
- Kizilcec, R. F., & Lee, H. (2022). Algorithmic fairness in education. In C. Lang et al. (Eds.), *Handbook of learning analytics* (2nd ed., pp. 245–254). SOLAR.
- Koedinger, K. R., Brunskill, E., Baker, R. S., McLaughlin, E. A., & Stamper, J. (2013). New potentials for data-driven intelligent tutoring system development. *AI Magazine*, 34(3), 27–41.
- Koedinger, K. R., D'Mello, S., McLaughlin, E. A., Pardos, Z. A., & Rosé, C. P. (2015). Data mining and education. *Wiley Interdisciplinary Reviews: Cognitive Science*, 6(4), 333–353.
- Kuhfeld, M., Soland, J., Tarasawa, B., Johnson, A., Ruzek, E., & Liu, J. (2020). Projecting the potential impact of COVID-19 school closures on academic achievement. *Educational Researcher*, 49(8), 549–565.
- Lipton, Z. C. (2018). The mythos of model interpretability. *Queue*, 16(3), 31–57.
- Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). *Intelligence unleashed: An argument for AI in education*. Pearson Education.
- Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. *Advances in Neural Information Processing Systems* 30 (pp. 4765–4774). Curran Associates.
- Madnani, N., & Cahill, A. (2018). Automated scoring: Beyond natural language processing. *Proceedings of COLING 2018* (pp. 1099–1109). ACL.
- Madnani, N., Loukina, A., & Cahill, A. (2017). A large scale quantitative exploration of modeling strategies for content scoring. *Proceedings of the 12th Workshop on Innovative Use of NLP for Building Educational Applications* (pp. 38–46). ACL.
- Mell, A., & Smith, R. (2022). AI-driven accessibility tools in K–12 education: A systematic review. *Journal of Special Education Technology*, 37(3), 145–162.
- Michalski, R., Grosse, C. U., & Klayman, P. (2023). Socioeconomic predictors of success in AI-mediated higher education. *Educational Technology Research and Development*, 71(2), 579–602.
- Millán, E., Loboda, T., & Pérez-de-la-Cruz, J. L. (2010). Bayesian student modeling and the problem of parameter specification. *British Journal of Educational Technology*, 41(6), 924–944.
- Molnar, C. (2022). *Interpretable machine learning: A guide for making black box models explainable* (2nd ed.). christophm.github.io/interpretable-ml-book
-

- Muldner, K., Burleson, W., & VanLehn, K. (2015). An analysis of students' gaming behaviors in an intelligent tutoring system. *User Modeling and User-Adapted Interaction*, 25(1), 99–135.
- Nazaretsky, T., Ariely, M., Cukurova, M., & Alexandron, G. (2022). Teachers' trust in AI-powered educational technology. *British Journal of Educational Technology*, 53(4), 914–931.
- Offori, K., & Choudhary, M. (2024). Computer vision with DL/ML for crime data analysis. *Educational Administration: Theory and Practice*, 30(1), 4526–4532. <https://doi.org/10.53555/kuey.v30i1.8226>