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PUBLIC ECONOMICS ANALYSIS OF AI-DRIVEN TRANSFORMATION IN HIGHER EDUCATION: IMPLICATIONS FOR EFFICIENCY AND EQUITY

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ABSTRACT

The rapid integration of artificial intelligence (AI) into higher education systems presents profound opportunities and challenges from a public economics perspective. This study aims to examine the implications of AI-driven transformation for efficiency and equity across public universities and private universities in North Sulawesi, Indonesia. Employing an interpretive qualitative research design, data were collected through in-depth semi-structured interviews with 32 key informants, including university administrators, faculty members, students, and policymakers across six higher education institutions. Data were analyzed using thematic analysis and constant comparative methods informed by public economics frameworks, including market failure theory, public goods theory, and distributive justice principles. The findings reveal a persistent efficiency–equity tension: AI adoption enhances operational productivity and instructional quality in resource-rich PTN institutions, while simultaneously exacerbating the digital divide for PTS institutions serving economically disadvantaged student populations. Three key mechanisms are identified: (1) asymmetric resource allocation favoring state-funded institutions, (2) AI-induced credential stratification that reshapes labor market signaling, and (3) governance gaps in regional AI policy frameworks. This study contributes a context-specific analytical model the AI-Education Public Economics (AI-EPE) Framework which integrates efficiency and equity dimensions in higher education transformation. The findings offer important theoretical insights and practical implications for education governance, public funding design, and equitable AI policy development in developing-country contexts.

KEYWORDS: Artificial Intelligence; Public Economics; Efficiency; Equity; Digital Divide; AI Governance

INTRODUCTION

The convergence of artificial intelligence and higher education represents one of the most consequential transformations in contemporary public policy. Globally, AI-driven technologies including adaptive learning platforms, automated assessment systems, predictive analytics, and intelligent tutoring systems are fundamentally reshaping the production and delivery of higher education services (Holmes et al., 2022; Luckin & Holmes, 2016; Zawacki-Richter et al., 2019). From a public economics standpoint, higher education occupies a unique position as a quasi-public good characterized by significant positive externalities, information asymmetries, and market failures that justify substantive government intervention (Barr, 2020). AI integration into this domain inevitably disrupts existing equilibria in resource allocation, access, and distributional outcomes, raising fundamental questions about efficiency gains and equity trade-offs.

In the Indonesian context, the higher education landscape is distinguished by a pronounced institutional dualism: a publicly-funded PTN sector benefiting from direct state subsidies, infrastructure investment, and regulatory preferential treatment, and a predominantly market-dependent PTS sector serving approximately 70% of all enrolled students nationally. This structural asymmetry is particularly pronounced in eastern Indonesia, including North Sulawesi province, where geographic remoteness, infrastructural deficits, and socioeconomic fragmentation create distinctive challenges for equitable educational development. As AI adoption accelerates within leading PTN institutions following national digitalization mandates, the risk of widening institutional stratification along efficiency and equity dimensions warrants systematic analytical attention.

Despite growing international scholarship on AI in higher education (Ouyang & Jiao, 2021; Popenici & Kerr, 2017; Selwyn, 2019) and emerging Indonesian research on educational technology adoption (Martha et al., 2021; Nagy et al., 2024), significant theoretical and empirical gaps persist. Specifically, no study has applied a rigorous public economics analytical lens to examine AI-driven transformation within the PTN-PTS institutional divide in Indonesia's peripheral regions. This study addresses this lacuna through a qualitative, interview-based investigation grounded in public economics theory.

To establish a robust analytical foundation, this study draws on key strands of public economics and interdisciplinary scholarship. The theoretical foundation of this study builds on three interconnected strands of public economics. First, market failure theory (Weimer & Vining, 2017) provides the conceptual scaffolding for understanding why higher education markets systematically deviate from Pareto-efficient outcomes absent government intervention. Key market failures include information asymmetries between students and institutions, positive externalities from educated workforces, credit market imperfections affecting lower-income students, and coordination failures in skills formation. AI integration may simultaneously correct some market failures (e.g., reducing information asymmetry through predictive analytics) while generating new ones (e.g., algorithmic discrimination or vendor lock-in creating monopolistic tendencies).

Second, public goods theory (Ostrom, 1990; Samuelson, 1954) situates higher education as an impure public good with characteristics of both non-rivalry (particularly in the digital delivery of AI-enhanced content) and excludability (through selective admissions and tuition barriers). AI-driven open educational resources and adaptive learning platforms potentially shift higher education closer to a pure public good on the non-rivalry dimension, but may paradoxically increase excludability if access to AI infrastructure requires substantial capital investment beyond the reach of poorer institutions. Third, distributive justice frameworks (Rawls, 1971; Sen, 1999) inform the equity analysis, particularly the capabilities approach, which evaluates educational arrangements not merely by outcomes but by their capacity to expand the real freedoms and capabilities of all students.

Complementing this theoretical grounding, the international literature documents AI's multifaceted impacts on higher education across pedagogical, administrative, and research dimensions. (Zawacki-Richter et al., 2019) identified four primary AI application domains in higher education: profiling and prediction, intelligent tutoring, assessment and feedback automation, and conversational agents. Evidence from North American and European contexts demonstrates AI-enabled efficiency gains in administrative processing (e.g., significant cost reductions in routine tasks reported in industry studies), student retention improvement, and research productivity enhancement. However, critical scholars have raised equity concerns regarding algorithmic bias in student assessment systems (Baker & Hawn, 2022), the commodification of educational relationships through surveillance technologies (Williamson, 2019), and the potential erosion of academic professional autonomy (Selwyn, 2019).

Within the Southeast Asian and Indonesian context, research on AI adoption in higher education remains relatively nascent yet rapidly evolving. Recent empirical studies demonstrate that AI integration in Indonesian universities is still characterized by uneven adoption patterns and significant structural constraints. For instance, studies in North Sulawesi reveal that behavioral intention to adopt AI is strongly influenced by perceived risk, performance expectancy, and effort expectancy, highlighting the importance of psychological and institutional readiness in shaping adoption outcomes (Nagy et al., 2024). Similarly, evidence from Indonesian public universities shows that AI adoption is positively driven by performance and effort expectations, but hindered by perceived risks and limited facilitating conditions, including infrastructure and institutional support (Helmiatin et al., 2024). Complementing these findings, student-focused research indicates that social influence, perceived usefulness, and enabling conditions play a critical role in determining AI adoption for self-directed learning, underscoring the importance of supportive ecosystems and digital infrastructure (Setiawan & Ma'ruf, 2025). At a broader level, bibliometric analyses confirm that while AI is increasingly transforming teaching, learning, and institutional management in Indonesia, its implementation remains constrained by infrastructural limitations, ethical concerns, and uneven institutional readiness (Wiryawan & Fatimah, 2025). Collectively, these findings suggest that AI adoption in Indonesian higher education is not a uniform or linear process, but rather one deeply conditioned by behavioral, institutional, and structural factors, including resource availability, governance capacity, and regional disparities.

Building on these insights, this study conceptualizes efficiency and equity as central analytical constructs. Efficiency in higher education is understood as comprising technical efficiency (producing educational outputs at minimum cost), allocative efficiency (directing resources to their highest-value uses), and dynamic efficiency (promoting innovation and adaptability over time). AI integration is expected to yield efficiency gains through automation of routine tasks, personalization of learning pathways, and optimization of resource allocation via predictive analytics. Equity, in turn, is conceptualized across three dimensions: access equity (reducing barriers to entry), process equity (ensuring fair treatment within institutions), and outcome equity (achieving comparable educational attainment across socioeconomic groups). The tension between efficiency and equity objectives, a classical concern in public economics, is expected to be particularly salient in the context of AI-driven transformation.

Synthesizing these theoretical and empirical strands, this study proposes a preliminary conceptual framework positing that AI-driven transformation in higher education operates through three interacting channels: (1) an institutional capacity channel, through which resource endowments determine AI adoption capacity; (2) a governance channel, through which regulatory frameworks shape AI deployment incentives and constraints; and (3) a distributional channel, through which AI adoption patterns translate into differentiated efficiency and equity outcomes for students and institutions. This framework is elaborated and refined through the empirical findings presented in this study.

Accordingly, this study pursues four primary objectives: (1) to identify the patterns and modalities of AI adoption across PTN and PTS institutions in North Sulawesi; (2) to analyze the efficiency implications of AI integration from a public economics perspective; (3) to assess equity outcomes associated with differential AI adoption across institutional types and student populations; and (4) to develop a contextually grounded theoretical framework capable of informing AI policy design in regional higher education governance.

This research contributes to scholarship at the intersection of public economics, educational policy, and artificial intelligence in three critical ways. Theoretically, it extends market failure and distributive justice frameworks to the novel context of AI-driven educational transformation in a developing-country setting. Empirically, it generates rich qualitative evidence from a data-scarce regional context, providing grounded insights that complement large-scale quantitative studies. Practically, it offers policy-relevant recommendations for regional governments, university administrators, and national education policymakers seeking to harness AI's efficiency potential while preserving or enhancing equity commitments.

MATERIALS AND METHODS

Research Design and Epistemological Stance

This study adopts an interpretive qualitative research design grounded in constructivist epistemology (Creswell & Poth, 2016; Lincoln & Guba, 1988). Qualitative methodology is appropriate for this research because: (1) the phenomenon under investigation AI-driven transformation in higher education is complex, contextually embedded, and insufficiently understood to permit deductive hypothesis testing; (2) the research objectives require in-depth exploration of stakeholder perceptions, institutional dynamics, and policy implications that cannot be adequately captured through survey instruments; and (3) the regional Indonesian context presents limit the feasibility of robust quantitative causal inference. Phenomenological interpretivism guides data collection and analysis, seeking to understand how diverse stakeholders experience and make meaning of AI transformation processes.

Research Site and Institutional Context

The study was conducted in North Sulawesi province, Indonesia, a geographic and administrative context illustrative of peripheral higher education contexts in Indonesia:

moderate economic development, mixed ethnic composition, high rates of student mobility toward major urban centers, and a higher education ecosystem comprising 4 PTN and 45 PTS institutions. Six institutions were purposively selected to maximize variation across institutional type (PTN/PTS), size (large/medium/small enrollment), location (urban Manado vs. peripheral districts), and religious affiliation (secular, Protestant, Catholic, and Islamic). The selected PTN institutions included Universitas Sam Ratulangi (UNSRAT) and Universitas Negeri Manado (UNIMA), while PTS institutions included Universitas Klabat, Universitas Katolik De La Salle, and two additional medium-sized institutions in Bitung and Kotamobagu.

Participants and Sampling Strategy

A total of 32 informants were recruited through purposive and snowball sampling strategies designed to maximize heterogeneity of perspectives. The sample comprised: 8 university administrators (vice-rectors, heads of academic planning units); 10 faculty members across disciplines (education, economics, engineering, health sciences); 9 students (representing different year levels, socioeconomic backgrounds, and geographic origins); 3 regional government officials (provincial and district education planning officers); and 2 national higher education policy experts. Participant selection was guided by theoretical sampling logic, with sampling decisions informed by emergent analytical categories and pursued saturation was indicated by the absence of new themes in the final interviews (Guest et al., 2006).

Data Collection

Primary data were collected through 32 in-depth semi-structured interviews. Interview protocols were designed around open-ended questions organized into six thematic clusters: (1) current AI adoption practices and institutional AI readiness; (2) perceived efficiency outcomes of AI integration; (3) experiences of equity in access to AI-enhanced education; (4) governance frameworks and policy environments surrounding AI deployment; (5) resource allocation decisions related to AI investment; and (6) future trajectories and policy preferences. Interviews ranged from 45 to 95 minutes in duration, were conducted in Bahasa Indonesia with select informants electing to use Manado Malay, and were recorded with informed consent and subsequently transcribed verbatim. Field notes and institutional document collection (strategic plans, annual reports, procurement records) supplemented interview data, enabling data triangulation.

Data Analysis

Data analysis followed a systematic thematic analysis procedure integrated with constant comparative analysis, appropriate for theory-building purposes. The analytical process proceeded through six phases: (1) familiarization with data through repeated reading of transcripts; (2) initial coding through line-by-line open coding; (3) pattern code construction and preliminary category development; (4) theme generation through axial coding and category integration; (5) theme review and refinement through negative case analysis; and (6) production of the analytical narrative. NVivo 14 software facilitated systematic data management and coding. The public economics theoretical framework informed sensitizing concepts while remaining open to emergent themes not anticipated in the a priori framework a theoretically-informed grounded approach (Thornberg, 2012).

Rigour and Trustworthiness

Trustworthiness was established through multiple complementary strategies aligned with Lincoln and Guba's criteria (Lincoln & Guba, 1988). Credibility was ensured through prolonged engagement (five months of fieldwork), triangulation of data sources and methods, and member checking with eight key informants. Transferability was supported through rich thick description of the research context and purposively diverse sampling. Dependability was promoted through a detailed audit trail documenting all analytical decisions. Confirmability was enhanced through reflexivity practices including researcher positionality statements and peer debriefing sessions.

RESULTS AND METHODS

AI Adoption Landscape in North Sulawesi Higher Education

Thematic analysis revealed a markedly bifurcated AI adoption landscape across institutional types. PTN institutions, particularly UNSRAT and UNIMA, exhibited comparatively systematic AI integration driven by alignment with national Merdeka Belajar-Kampus Merdeka (MBKM) policy frameworks and access to Ministry of Higher Education, Science, and Technology digital transformation grants. Informants from these institutions described deployments spanning learning management system enhancement through AI analytics plugins, automated plagiarism detection, AI-assisted research database access, and initial experimentation with adaptive assessment tools. As one PTN administrator articulated:

"We received infrastructure grants that enabled us to upgrade our LMS with AI monitoring capabilities. Our faculty can now see real-time dashboards of student engagement. Without that funding, we would not be at this level. It fundamentally changed how we think about teaching quality assurance." (Administrator PTN-1, October 2024)

In contrast, PTS informants consistently described fragmented, informal, and largely individually-driven AI adoption patterns, with institutional-level AI strategies absent in four of the four PTS institutions studied. AI use in these settings was predominantly student and faculty-initiated through freely available commercial tools (ChatGPT, Grammarly, Google Bard) without institutional guidance, training, or policy frameworks. A senior faculty member from a medium-sized PTS institution captured the prevailing condition:

"My students use ChatGPT but we don't know if this is right or wrong, helpful or harmful. The institution has no policy. I personally try to adapt but there is no training, no budget for AI tools. We are experimenting in the dark." (Faculty, PTS-3, November 2024)

Efficiency Implications: Gains, Costs, and Asymmetries

Four distinct efficiency themes emerged from the data. First, administrative efficiency gains were evident in PTN institutions that had implemented AI-supported student services portals, automated scholarship processing, and AI-assisted admissions screening. Informants reported meaningful reductions in administrative processing times and improved service responsiveness. Second, instructional efficiency improvements manifested in faster feedback cycles, personalized learning pathway recommendations, and reduced grading workloads were reported primarily by PTN faculty with access to institutionally supported AI teaching tools. Third, research efficiency gains through AI-enhanced literature review, data analysis assistance, and grant writing support were concentrated in PTN research-active departments with adequate digital infrastructure.

Critically, however, a fourth efficiency theme emerged that problematizes simple efficiency narratives: transition inefficiencies and capability gaps. Multiple informants across both PTN and PTS contexts described significant time costs associated with learning to use AI tools effectively, addressing AI-generated errors in student work, and managing policy ambiguity. From a public economics perspective, these transition costs constitute short-term efficiency losses that may or may not be offset by long-term gains, and their distribution across institutional types is distinctly unequal: resource-richer PTN institutions can invest in faculty development to manage the transition, while PTS institutions bear these costs without compensatory support.

Equity Implications: Access, Process, and Outcome Dimensions

Equity analysis surfaced three interconnected dimensions of inequity associated with AI-driven transformation. Access equity emerged as the most salient concern, with student informants from PTS institutions disproportionately reporting device access constraints, unreliable internet connectivity (particularly those commuting from peripheral districts), and inability to afford premium AI tool subscriptions. A third-year student from a PTS institution described:

"My classmates in Manado tell me their professors give assignments using AI tools that cost money. I use my phone with limited data. How can I compete? The gap is getting bigger, not smaller." (Student, PTS-4, December 2024)

Process equity concerns centered on emergent AI-mediated stratification within institutions, particularly regarding differential faculty AI literacy and the consequent heterogeneity in AI-enhanced versus traditional instructional quality experienced by students. Outcome equity dimensions were more prospective, with policy informants expressing concern that AI-driven credential stratification would amplify labor market advantages for graduates of AI-rich PTN institutions relative to PTS graduates. Regional government informants noted the absence of any provincial-level policy mechanism to monitor or address these emerging equity gaps.

Governance Gaps and Policy Framework Deficiencies

A pervasive finding across all informant categories was the profound inadequacy of existing governance frameworks for managing AI-driven transformation in regional higher education. Three specific governance gaps were identified. First, the absence of an AI-specific regulatory framework at the institutional level was reported by all six study institutions none had adopted formal AI use policies, ethical guidelines, or AI governance committees as of the research period. Second, misalignment between national AI digitalization policies and regional implementation capacities was consistently identified. Third, the complete absence of redistributive mechanisms to support AI adoption in resource-constrained PTS institutions constituted a structural governance failure from a public economics perspective, analogous to a market failure that justifies corrective policy intervention.

The AI-Education Public Economics (AI-EPE) Framework

Integrating these empirical findings with the theoretical framework, we propose the AI-Education Public Economics (AI-EPE) Framework as this study's primary theoretical contribution. The AI-EPE Framework posits that AI-driven transformation in higher education produces differentiated efficiency and equity outcomes through three analytically distinct but empirically interacting mechanisms: (1) the Institutional Capacity Mechanism, wherein prior resource endowments (financial, human, infrastructural) determine AI adoption capacity and thus condition efficiency gain trajectories; (2) the Governance Mediation Mechanism, wherein policy frameworks, regulatory environments, and redistributive instruments mediate how AI adoption proceeds across institutional types and shape distributional outcomes; and (3) the Distributional Feedback Mechanism, wherein AI-induced efficiency and equity outcomes reshape future resource distributions through their effects on institutional reputations, student enrollment patterns, and labor market signals. This framework suggests that without deliberate governance intervention targeting the governance mediation mechanism, AI transformation will systematically amplify rather than reduce existing institutional inequalities in higher education systems characterized by structural dualism.

DISCUSSION

Efficiency-Equity Tensions in AI Transformation

The findings confirm and extend the theoretical proposition that AI-driven transformation in higher education generates complex efficiency-equity tensions that cannot be resolved through market mechanisms alone. The efficiency gains documented in PTN institutions are real and substantial, consistent with international evidence (Holmes et al., 2022; Zawacki-Richter et al., 2019), but they accrue primarily to institutions already endowed with superior resources, thus amplifying rather than ameliorating existing institutional stratification. This pattern resonates with the ‘Matthew effect’ in educational resource distribution (Merton, 1968) AI appears to give more to those who already have more. From a public economics perspective, this constitutes a market failure in educational AI adoption requiring corrective policy intervention, as the social optimum of widespread efficiency gains combined with equitable access is unattainable without deliberate redistribution.

Implications for Public Goods Theory

The findings complicate simple public goods categorizations of AI-enhanced education. While AI tools theoretically enable non-rival educational content delivery at near-zero marginal cost, the excludability dimension is reinstated through differential AI infrastructure access, subscription costs for premium AI platforms, and faculty capability requirements for effective AI integration. This empirical finding suggests that AI-enhanced higher education exhibits the characteristics of a ‘club good’ (Buchanan, 1965) in the current regional context accessible only to members of well-resourced institutional clubs. The policy implication is that public investment in AI infrastructure democratization is necessary to realize the public good potential of educational AI.

Governance Failure and Redistributive Imperatives

The governance gap finding represents perhaps the most practically significant contribution of this study. The absence of institutional AI policies, regional coordination mechanisms, and redistributive funding streams targeting resource-constrained PTS institutions constitutes a multi-level governance failure that, if unaddressed, will systematically convert AI's efficiency potential into an equity liability. This finding aligns with (Ostrom, 1990) institutional analysis framework, which demonstrates that common-pool resources (including AI-enhanced educational opportunity) require collective governance arrangements to prevent ‘tragedy’ outcomes where individual institutional optimization produces collectively suboptimal social distributions. We argue that regional and national education governance actors must treat AI adoption equity as a public interest requiring the same interventionist logic applied to student financial aid, institutional accreditation, and minimum curriculum standards.

The AI-EPE Framework in Comparative Perspective

The AI-EPE Framework developed from this study advances existing analytical frameworks for AI in higher education by integrating public economics logic with institutional and distributional analysis. While existing frameworks (e.g., Zawacki-Richter et al.'s AI application taxonomy (Zawacki-Richter et al., 2019); Holmes et al.'s AI ethics framework) focus primarily on pedagogical or ethical dimensions (Holmes et al., 2022), the AI-EPE Framework foregrounds resource allocation, market failure, and distributional justice as analytically central. The framework is particularly applicable to developing-country higher education contexts characterized by institutional dualism, regional disparities, and constrained public budgets conditions prevalent across Southeast Asia, Sub-Saharan Africa, and Latin America. Future research should test the framework's transferability and predictive utility in comparable contexts.

CONCLUSION

This study examined AI-driven transformation in higher education through a public economics lens, employing qualitative interview-based research across PTN and PTS institutions in North Sulawesi, Indonesia. Three principal conclusions emerge. First, AI adoption in regional Indonesian higher education is highly asymmetric, with PTN institutions capturing the majority of efficiency benefits while PTS institutions serving the majority of students, including disproportionate numbers from disadvantaged backgrounds remain structurally disadvantaged in AI readiness. Second, this asymmetry constitutes a compound market and governance failure that simultaneously undermines productive efficiency (through foregone systemwide AI gains) and distributive justice (through reinforced institutional stratification). Third, existing governance frameworks at institutional, regional, and national levels are inadequate to manage AI transformation in ways that balance efficiency and equity objectives.

Policy Implications

The study generates four clusters of policy recommendations. At the national level, the Ministry of Higher Education, Science, and Technology should establish a dedicated AI Equity in Higher Education Fund (Dana Ekuitas AI Pendidikan Tinggi) that provides targeted grants, technical assistance, and capacity-building support to eligible PTS institutions based on demonstrated need and institutional AI readiness plans. At the regional level, provincial governments should establish AI Coordination Platforms for Higher Education bringing together PTN, PTS, government, and industry stakeholders to facilitate technology transfer, shared infrastructure, and coordinated AI literacy development. At the institutional level, all higher education institutions should be required to develop and publicly disclose AI Governance Frameworks as a condition of continued accreditation, covering AI use policies, equity impact assessment procedures, and student data protection protocols. At the systemic level, the accreditation system (BAN-PT) should incorporate AI equity and effectiveness indicators into institutional performance assessment criteria to create accountability incentives for equitable AI adoption.

Limitations and Future Research Directions

This study acknowledges several limitations that define directions for future research. The qualitative design and purposive sampling strategy limit claims to generalizability; findings represent theoretically transferable analytical insights rather than statistically representative population descriptions. The study's temporal scope (2024-2025) captures a highly dynamic period of AI development; longitudinal follow-up research is needed to track how AI adoption trajectories and equity outcomes evolve over time. Future research should pursue mixed-methods designs integrating the qualitative insights generated here with quantitative institutional performance data to test AI-EPE Framework propositions empirically. Comparative regional studies across other Indonesian provinces and Southeast Asian national contexts would contribute to the framework's validation and refinement. Particular attention should be directed to student outcome disparities a dimension this study could explore only prospectively through informant perceptions given the nascent stage of AI integration in the study context.

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REFERENCES

1. Arrow, K. J. (1978). *21 - UNCERTAINTY AND THE WELFARE ECONOMICS OF MEDICAL CARE* (P. DIAMOND & M. B. T.-U. in E. ROTHSCHILD (eds.); pp. 345–375). Academic Press. https://doi.org/https://doi.org/10.1016/B978-0-12-214850-7.50028-0
2. Baker, R. S., & Hawn, A. (2022). Algorithmic Bias in Education. *International Journal of Artificial Intelligence in Education*, *32*(4), 1052–1092. https://doi.org/10.1007/s40593-021-00285-9
3. Barr, N. A. (2020). *The economics of the welfare state*. Oxford university press.
4. Buchanan, J. M. (1965). An economic theory of clubs. *Economica*, *32*(125), 1–14.
5. Creswell, J. W., & Poth, C. N. (2016). *Qualitative inquiry and research design: Choosing among five approaches*. Sage publications.
6. Guest, Greg, Bunce, Arwen, & Johnson, Laura. (2006). How Many Interviews Are Enough?: An Experiment with Data Saturation and Variability. *Field Methods*, *18*(1), 59–82. https://doi.org/10.1177/1525822X05279903
7. Helmiatin, Hidayat, A., & Kahar, M. R. (2024). Investigating the adoption of AI in higher education: a study of public universities in Indonesia. *Cogent Education*, *11*(1), 2380175. https://doi.org/10.1080/2331186X.2024.2380175
8. Holmes, W., Porayska-Pomsta, K., Holstein, K., Sutherland, E., Baker, T., Shum, S. B., Santos, O. C., Rodrigo, M. T., Cukurova, M., Bittencourt, I. I., & Koedinger, K. R.

(2022). Ethics of AI in Education: Towards a Community-Wide Framework. *International Journal of Artificial Intelligence in Education*, *32*(3), 504–526. https://doi.org/10.1007/s40593-021-00239-1

9. Lincoln, Y. S., & Guba, E. G. (1988). *Criteria for Assessing Naturalistic Inquiries as Reports.*
10. Luckin, R., & Holmes, W. (2016). *Intelligence Unleashed: An argument for AI in Education*. Open Ideas; Pearson Education.
11. Martha, A. S., Junus, K., Santoso, H. B., & Suhartanto, H. (2021). Assessing Undergraduate Students' e-Learning Competencies: A Case Study of Higher Education Context in Indonesia. In *Education Sciences* (Vol. 11, Issue 4, p. 189). https://doi.org/10.3390/educsci11040189
12. Merton, R. K. (1968). The Matthew effect in science: The reward and communication systems of science are considered. *Science*, *159*(3810), 56–63.
13. Nagy, A. S., Tumiwa, J. R., Arie, F. V., & Erdey, L. (2024). An exploratory study of artificial intelligence adoption in higher education. *Cogent Education*, *11*(1), 2386892. https://doi.org/10.1080/2331186X.2024.2386892
14. Ostrom, E. (1990). *Governing the commons: The evolution of institutions for collective action*. Cambridge university press.
15. Ouyang, F., & Jiao, P. (2021). Artificial intelligence in education: The three paradigms. *Computers and Education: Artificial Intelligence*, *2*, 100020. https://doi.org/https://doi.org/10.1016/j.caeai.2021.100020
16. Popenici, S. A. D., & Kerr, S. (2017). Exploring the impact of artificial intelligence on teaching and learning in higher education. *Research and Practice in Technology Enhanced Learning*, *12*(1), 22. https://doi.org/10.1186/s41039-017-0062-8
17. Rawls, J. (1971). *A theory ofjustice*. Cambridge, MA: Harvard University Press.
18. Samuelson, P. A. (1954). The Pure Theory of Public Expenditure. *The Review of Economics and Statistics*, *36*(4), 387–389. https://doi.org/10.2307/1925895
19. Selwyn, N. (2019). *Should robots replace teachers?: AI and the future of education*. John Wiley & Sons.
20. Sen, A. (1999). Freedom. *Development, Oxford University Press, Oxford*.
21. Setiawan, R. J., & Ma'ruf, K. (2025). Determining Factors Influencing Indonesian Higher Education Students' Intention to Adopt Artificial Intelligence Tools for Self-Directed Learning Management. *European Journal of Educational Research*, *14*(3), 805–828. https://doi.org/10.12973/eu-jer.14.3.805

22. Stiglitz, J. E., & Stiglitz, J. E. (2000). *Economics of the public sector*.
23. Thornberg, R. (2012). Informed grounded theory. *Scandinavian Journal of Educational Research*, *56*(3), 243–259.
24. Weimer, D. L., & Vining, A. R. (2017). *Policy analysis: Concepts and practice*. Routledge.
25. Williamson, B. (2019). Policy networks, performance metrics and platform markets: Charting the expanding data infrastructure of higher education. *British Journal of Educational Technology*, *50*(6), 2794–2809. https://doi.org/https://doi.org/10.1111/bjet.12849
26. Wiryawan, M. R., & Fatimah, A. (2025). ARTIFICIAL INTELLIGENCE AND THE TRANSFORMATION OF UNIVERSITIES IN INDONESIA: A BIBLIOMETRIC ANALYSIS. *Malaysian Journal of Computing and Applied Mathematics*, *8*(1), 46–58. https://doi.org/10.37231/myjcam.2025.8.1.160
27. 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), 39. https://doi.org/10.1186/s41239-019-0171-0