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A Review of Artificial Intelligence Integration in Higher Education and Its Implications for Organizational Control and Labour Process in Emerging Economies

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ABSTRACT: The growing use of Artificial Intelligence (AI) in universities is altering how academic work is organized and governed, raising important questions about control and labour in higher education, particularly in emerging economies. Against this background, this paper reviewed artificial intelligence integration in higher education and examined its implications for organizational control and the labour process. The paper specifically examined the patterns and modes of artificial intelligence integration in higher education institutions in emerging economies, analyzed how artificial intelligence adoption shapes organizational control mechanisms within higher education institutions and investigated the effects of artificial intelligence integration on the labour process, The paper was guided by labour process theory, which provides a basis for understanding how technology reshapes managerial control and work relations. A systematic review design was adopted, drawing on recent scholarly publications between 2022 and 2026 sourced from peer-reviewed journals and policy reports. The findings showed that artificial intelligence is increasingly embedded in teaching, assessment, and administrative systems, with emerging economies adopting these tools within resource-constrained and centralized institutional settings. The paper revealed that AI adoption strengthens data-driven oversight, performance monitoring, and standardization of academic tasks, thereby reinforcing managerial control. At the same time, academic labour is being restructured through increased workload demands, digital skill requirements, and reduced autonomy in decision-making processes. While some gains are recorded in efficiency and instructional support, concerns persist regarding surveillance, job insecurity, and uneven capacity for adaptation across institutions. The paper concluded that artificial intelligence integration in higher education is not neutral but reflects existing power relations within institutions. The paper therefore recommended that there should be development of clear regulatory frameworks, inclusive governance structures, and capacity-building initiatives to ensure that AI deployment supports both institutional effectiveness and fair labour practices.

Keywords: *Artificial Intelligence, Higher Education, Organizational Control, Labour Process, Emerging Economies.*

Introduction

Artificial intelligence (AI) has become a central feature of higher education systems across the world, reshaping teaching, research, administration, and governance. Universities in North America, Europe, and parts of Asia have adopted AI-driven tools such as adaptive learning platforms, automated grading systems, predictive analytics, and generative AI applications to improve efficiency and student outcomes. Recent global estimates indicate that the AI in education market is projected to exceed $20 billion by 2027, reflecting growing institutional investment in digital infrastructure and data-driven decision-making (Holmes & Tuomi, 2022; UNESCO, 2023). The emergence of generative AI systems such as large language models has further accelerated this shift, enabling new forms of content production, assessment, and academic support while also raising concerns about academic integrity and epistemic authority (Dwivedi et al., 2023).

Within higher education institutions, AI integration is not limited to pedagogical innovation but extends to organizational processes and labour management. Universities increasingly deploy AI for monitoring staff performance, managing workloads, and optimizing administrative functions. This aligns with broader transformations in the labour process where digital technologies intensify surveillance, standardization, and managerial control (Kellogg et al., 2020; Vallas & Schor, 2020). In academic settings, these developments are evident in algorithmic evaluation of teaching effectiveness, research productivity metrics, and automated decision systems for admissions and funding allocation. While such systems promise efficiency, they also reconfigure professional autonomy and reshape academic labour in ways that reflect managerial priorities.

In emerging economies, the integration of AI into higher education presents both opportunities and structural constraints. Countries such as China, India, Brazil, and South Africa have made notable investments in AI-driven education reforms, often supported by national digital strategies. For instance, China's "Smart Education" initiative has led to large-scale adoption of AI platforms across universities, enhancing access to personalized learning while strengthening centralized oversight of institutional performance (Zawacki-Richter et al., 2022). Similarly, India's National Education Policy (2020) has encouraged the use of AI in curriculum delivery and institutional governance, with measurable expansion in digital learning ecosystems since 2022 (Gupta & Kumari, 2023).

In sub-Saharan Africa, including Nigeria, AI adoption in higher education remains uneven due to infrastructural deficits, limited funding, and gaps in digital literacy. However, there is increasing uptake of AI-enabled tools such as plagiarism detection software, learning management systems with analytics features, and automated administrative platforms (Adeleke & Ebohon, 2023). These developments are occurring alongside broader shifts toward digital governance in universities, where managerial control mechanisms are being strengthened through data-driven oversight. Empirical studies indicate that digital technologies in African universities are often introduced within centralized administrative frameworks, which may reinforce hierarchical control rather than participatory governance (Awosiku et al., 2025).

From a labour process perspective, the integration of AI raises critical questions about the nature of academic work, control, and resistance. Drawing from labour process theory, the use of digital technologies in organizations often leads to the reconfiguration of work through deskilling, intensification, and increased managerial surveillance (Braverman, 1974; revisited in contemporary analyses by Kellogg et al., 2020). In higher education, AI tools can standardize teaching practices, reduce discretion in assessment, and subject academic staff to continuous performance monitoring. At the same time, they may create new forms of digital labour, including the need for academics to adapt to AI systems, curate digital content, and engage with data-driven evaluation frameworks. These transformations are particularly significant in emerging economies where institutional capacity, regulatory frameworks, and labour protections may not adequately address the implications of AI-driven control mechanisms. Therefore, this paper examined the integration of artificial intelligence in higher education and analyze its implications for organizational control and the labour process in emerging economies.

Statement of the Problem

The integration of artificial intelligence in higher education has introduced significant changes in organizational structures and academic labour, yet existing research has not sufficiently examined how these changes affect control mechanisms and the labour process in emerging economies. While studies from advanced economies document the use of AI for enhancing efficiency and decision-making, they also highlight concerns about increased surveillance, reduced professional autonomy, and the commodification of academic work (Dwivedi et al., 2023; Holmes & Tuomi, 2022). However, these findings cannot be directly generalized to emerging economies where institutional conditions, resource constraints, and governance structures differ substantially.

In many emerging economies, including Nigeria, AI adoption in universities is occurring in contexts characterized by limited infrastructure, inconsistent policy frameworks, and existing managerial challenges. Rather than transforming higher education in a balanced manner, AI systems may be deployed primarily as tools for administrative control, reinforcing top-down governance and limiting the agency of academic staff. Evidence suggests that digital technologies in such contexts are often implemented without adequate consultation, training, or regulatory oversight, leading to tensions between institutional management and academic labour (Adeleke & Ebohon, 2023; Awosiku et al., 2025). This raises concerns about the potential for AI to intensify existing inequalities within higher education systems.

Furthermore, there is a lack of systematic understanding of how AI-driven organizational control affects the labour process of academics in emerging economies. Questions remain regarding whether AI leads to deskilling or upskilling, whether it enhances or constrains academic freedom, and how it reshapes power relations within universities. Existing literature has largely focused on technological adoption and student outcomes, with limited attention to the sociological dimensions of work and control. This gap is particularly significant given the central role of academic labour in knowledge production and national development.

The problem is therefore the absence of a critical, evidence-based synthesis of how AI integration in higher education influences organizational control and the labour process in emerging economies. Without such analysis, policymakers and institutional leaders may adopt AI systems without fully understanding their implications for academic work, governance, and equity. Addressing this gap is necessary to ensure that AI integration supports not only efficiency but also fair labour practices, institutional accountability, and sustainable development in higher education systems.

Aim of the Study

The aim of this paper was to critically examine the integration of artificial intelligence in higher education and analyze its implications for organizational control and the labour process in emerging economies.

Specific Objectives

a. To examine the patterns and modes of artificial intelligence integration in higher education institutions in emerging economies.
b. To analyze how artificial intelligence adoption shapes organizational control mechanisms within higher education institutions.

c. To investigate the effects of artificial intelligence integration on the labour process, including work organization, autonomy, and performance management of academic staff in emerging economies.

Methodology

This study adopted a literature review approach to synthesize existing scholarly evidence on artificial intelligence integration in higher education and its implications for organizational control and the labour process in emerging economies. The choice of a review approach is justified by the need to consolidate dispersed empirical and theoretical studies into a coherent analytical framework that allows for critical comparison and interpretation of findings across contexts. Relevant peer-reviewed articles published between 2022 and 2026 were identified through structured searches in major academic databases including Scopus, Web of Science, and Google Scholar using clearly defined keywords such as "artificial intelligence," "higher education," "organizational control," and "labour process."

Inclusion criteria were limited to empirical and theoretical studies focused on higher education, AI applications, and organizational or labour implications within emerging or comparable economies, while non-scholarly sources, duplicates, and studies outside the specified timeframe were excluded. The selected studies were screened based on relevance, methodological rigor, and citation credibility, after which data were extracted and analyzed thematically to identify recurring patterns, divergences, and contextual insights. This approach ensures transparency, replicability, and analytical depth, making it suitable for generating evidence-based conclusions and identifying gaps for further research.

Literature Review

Conceptual Review

Artificial Intelligence

Artificial intelligence has been widely defined in recent scholarly literature as a class of computational systems capable of performing tasks that ordinarily require human cognitive functions such as learning, reasoning, adaptation, and decision-making. In the context of education, Crompton and Burke (2023) describe AI as systems that engage in “human-like processes such as learning, adapting, and self-correction through data use”, while Ifenthaler et al. (2024) emphasize its role as a socio-technical system embedded in pedagogical and institutional practices. More recent work has moved beyond purely technical definitions to frame AI as an infrastructure shaping academic work, governance, and knowledge production (Isaifan, 2026).

Scholars such as Zawacki-Richter et al. (2024) further situate AI within “Artificial Intelligence in Education” (AIEd), highlighting its application through intelligent tutoring systems, learning analytics, and generative models that mediate teaching and research processes. While some authors focus on efficiency and personalization outcomes, others stress its implications for control, surveillance, and academic autonomy. For the purpose of this paper, artificial intelligence is understood as data-driven computational systems embedded in higher education institutions that perform cognitive tasks and restructure teaching, administrative, and decision-making processes.

Higher Education

Higher education is commonly conceptualized as the segment of formal education delivered by universities, polytechnics, and other tertiary institutions responsible for advanced knowledge production, professional training, and research. Recent scholarship situates higher education not only as a teaching and research domain but also as an organizational field shaped by digital transformation and governance reforms. Mosha et al. (2026) describe higher education institutions as systems where teaching, research, and administrative processes are increasingly mediated by digital technologies, including AI. Isaifan (2026) further conceptualizes higher education as a structured institutional environment where AI has become integrated into student learning, faculty workflows, and institutional operations, thereby influencing quality assurance and policy systems.

At the same time, Zawacki-Richter et al. (2024) highlight the expanding functional scope of higher education institutions as sites of technological experimentation and governance innovation. These perspectives suggest that higher education cannot be reduced to instructional functions alone but must be understood as an organizational system with managerial, technological, and labour dimensions. In this paper, higher education is defined as an institutionalized system of advanced teaching, research, and administration in which digital technologies, including AI, increasingly shape organizational practices and academic work.

Organizational Control

Organizational control refers to the mechanisms through which institutions regulate behaviour, coordinate activities, and ensure alignment with organizational goals. Contemporary scholarship has extended classical control theories to include digital and algorithmic forms of control. Kellogg et al. (2020) conceptualize algorithmic control as the use of data-driven systems to monitor, evaluate, and direct worker performance, emphasizing its growing relevance in knowledge-intensive sectors. Building on this, recent studies in educational contexts indicate that AI systems are being used to standardize teaching practices, track performance metrics, and guide decision-making processes within universities (Ifenthaler et al., 2024).

Isaifan (2026) further notes that AI integration in higher education is closely linked to governance and quality assurance mechanisms, often strengthening centralized oversight and institutional accountability . While some authors argue that such systems enhance efficiency and transparency, others caution that they may reduce professional discretion and intensify surveillance. Drawing from these positions, organizational control in this study is defined as the use of managerial, digital, and algorithmic mechanisms within higher education institutions to regulate academic activities, monitor performance, and align institutional operations with strategic objectives.

Labour Process

Labour process refers to the organization, control, and execution of work within institutional settings, particularly how labour is structured, monitored, and transformed by managerial and technological interventions. Contemporary analyses extend labour process theory to digital environments, where technology plays a central role in shaping work relations. Kellogg et al. (2020) argue that algorithmic systems restructure work by embedding control into digital infrastructures, thereby influencing autonomy, task allocation, and performance evaluation. In higher education, recent studies indicate that AI tools are altering academic work by automating administrative tasks, standardizing assessment practices, and introducing data-driven performance metrics (Zawacki-Richter et al., 2024; Ifenthaler et al., 2024).

These developments raise concerns about work intensification, deskilling, and the erosion of professional judgment, while also creating new forms of digital labour that require technological competencies. Mosha et al. (2026) observe that AI applications now support not only teaching but also administrative and research functions, thereby expanding the scope of academic labour . In this paper, the labour process is understood as the organization and regulation of academic work within higher education institutions, shaped by managerial strategies and increasingly mediated by AI-driven technologies.

Emerging Economies

Emerging economies are generally defined as countries experiencing industrialization, economic growth, and structural transformation but still facing developmental constraints such as infrastructural deficits and institutional limitations. Recent literature emphasizes that emerging economies are characterized by rapid technological adoption alongside uneven resource distribution and governance challenges. In the context of AI and higher education, Isaifan (2026) highlights that adoption patterns vary significantly across regions, with countries such as China and India demonstrating large-scale integration, while many African and Latin American countries face constraints related to infrastructure and policy frameworks.

Mosha et al. (2026) further note that institutions in resource-constrained environments often adopt AI selectively, focusing on administrative efficiency and teaching support rather than systemic transformation. Examples of emerging economies include Nigeria, India, Brazil, South Africa, and Indonesia, where higher education systems are expanding but remain shaped by funding limitations and governance challenges. These contexts influence how AI is integrated and how its implications for control and labour are experienced. For this paper, emerging economies are defined as developing national contexts characterized by ongoing economic and institutional transformation, where higher education systems adopt AI within conditions of resource constraints, uneven infrastructure, and evolving governance frameworks.

Patterns and Modes of Artificial Intelligence Integration in Higher Education Institutions in Emerging Economies

The integration of artificial intelligence (AI) in higher education institutions across emerging economies follows identifiable patterns shaped by institutional capacity, national policy direction, and global technological influence. A dominant pattern is the adoption of AI through learning management systems and digital platforms that embed analytics for monitoring student engagement and performance. Studies show that universities in countries such as China, India, and South Africa have incorporated AI-enabled platforms to support adaptive learning, automated feedback, and early-warning systems for at-risk students (Zawacki-Richter et al., 2020; Chen et al., 2022). These systems rely on large datasets generated through student interactions, enabling institutions to personalize instruction while also strengthening centralized oversight of academic processes.

Another pattern is the use of AI for administrative automation and decision-making. Universities increasingly deploy AI tools in admissions, scheduling, and resource allocation. In China, AI-based admission systems have been used to process large volumes of applications efficiently, reducing administrative workload while introducing algorithmic decision-making into institutional governance (Li & Wong, 2021). Similarly, Indian universities have adopted AI-driven chatbots to handle student inquiries and administrative support, improving service delivery but also shifting institutional interactions toward automated systems (Gupta & Kumari, 2023). These developments illustrate a transition from manual administrative processes to data-driven systems that prioritize efficiency and scalability.

A third mode involves the integration of generative AI tools into teaching and research practices. Since the public release of large language models, universities globally have witnessed rapid uptake of AI-assisted writing, coding, and content generation tools. Empirical evidence indicates that a significant proportion of students and academic staff in both advanced and emerging economies have experimented with generative AI for academic tasks, raising concerns about academic integrity and assessment validity (Dwivedi et al., 2023). In emerging economies, where access to educational resources may be uneven, such tools provide new opportunities for academic support, but they also challenge existing pedagogical frameworks.

Public–private partnerships represent another key mode of AI integration. Governments and universities in emerging economies often collaborate with technology firms to implement AI solutions. For example, partnerships between universities and major technology companies in China and India have facilitated the deployment of AI laboratories, research centers, and digital learning infrastructures (Chen et al., 2022). While these collaborations accelerate technological adoption, they also introduce external influence into institutional priorities, particularly in areas related to data governance and curriculum design.

Despite these advancements, AI integration in emerging economies is characterized by uneven distribution and infrastructural limitations. Studies indicate that institutions in urban centers are more likely to adopt AI technologies compared to those in rural areas, reflecting disparities in funding, connectivity, and technical expertise (Czerniewicz et al., 2020). In sub-Saharan Africa, the use of AI remains largely concentrated in pilot projects and externally funded initiatives, with limited large-scale institutionalization. This unevenness contrasts with advanced economies such as the United States and the United Kingdom, where AI integration is more systematically embedded in institutional strategies and supported by robust digital infrastructure (Holmes et al., 2022).

Case studies from advanced countries provide important comparative insights. In the United States, universities have implemented predictive analytics systems to identify students at risk of dropout, leading to measurable improvements in retention rates (Kizilcec & Lee, 2020). Similarly, institutions in the United Kingdom have adopted AI-driven assessment tools that automate grading while maintaining consistency across large student cohorts. These examples highlight the potential of AI to enhance educational outcomes when supported by strong institutional frameworks. However, in emerging economies, similar systems are often adapted to local constraints, resulting in hybrid models that combine manual and automated processes.

In all, the patterns and modes of AI integration in emerging economies reflect a combination of global technological trends and local institutional realities. While there is clear evidence of increasing adoption, the depth and effectiveness of integration vary significantly, with implications for governance, equity, and academic practice.

How Artificial Intelligence Adoption Shapes Organizational Control Mechanisms within Higher Education Institutions

The adoption of AI in higher education has significant implications for organizational control, particularly through the expansion of data-driven governance and algorithmic decision-making. AI systems enable universities to collect, process, and analyze large volumes of data on students and staff, thereby enhancing managerial capacity to monitor performance and enforce institutional objectives. This shift aligns with broader developments in digital management, where control is exercised through continuous data collection and real-time analytics rather than traditional hierarchical supervision (Kellogg et al., 2020).

However, Artificial Intelligence shapes organizational control mechanisms within the higher education institutions in the following ways:

i. ***Performance monitoring***

One of the primary mechanisms through which AI shapes organizational control is performance monitoring. Universities increasingly use AI-driven analytics to evaluate teaching effectiveness, research productivity, and administrative efficiency. For example, learning analytics systems track student engagement metrics such as attendance, participation, and assignment completion, which are then used to assess teaching performance. In China, the integration of AI into classroom environments has enabled real-time monitoring of student attention and behavior, providing administrators with detailed data on instructional effectiveness (Li & Wong, 2021). While such systems enhance accountability, they also introduce new forms of surveillance that may affect academic autonomy.

ii. ***Decision-making processes***

AI also influences decision-making processes within higher education institutions by embedding algorithmic logic into governance structures. Decisions related to admissions, funding allocation, and staff evaluation are increasingly informed by predictive models and data analytics. In advanced economies, universities have adopted algorithmic systems to rank research output and allocate resources accordingly, reinforcing performance-based management frameworks (Beer, 2022). Emerging economies are gradually adopting similar approaches, although often within centralized administrative systems that may amplify existing power asymmetries.

iii. ***Standardization***

Another dimension of organizational control is standardization. AI systems require structured data inputs and predefined parameters, which can lead to the standardization of teaching practices, assessment methods, and administrative procedures. This standardization reduces variability and enhances consistency but may also limit innovation and flexibility. For instance, automated grading systems used in large courses impose uniform criteria for assessment, potentially constraining the discretion of academic staff (Holmes et al., 2022). In emerging economies, where educational systems are already influenced by centralized policies, AI-driven standardization may further consolidate institutional control.

iv. ***Facilitation of remote and centralized oversight***

The integration of AI also facilitates remote and centralized oversight. Digital platforms allow university management to monitor activities across multiple campuses and departments without physical presence. This is particularly relevant in large public university systems in countries such as India and Brazil, where administrative coordination is often challenging. AI-enabled dashboards provide real-time data on institutional performance, enabling centralized decision-making and reducing the autonomy of individual departments (Gupta & Kumari, 2023).

Case studies from advanced countries illustrate the depth of these transformations. In the United States for instance, universities have implemented AI-based systems for faculty evaluation that combine student feedback, publication metrics, and teaching analytics into comprehensive performance profiles. These systems have been shown to influence promotion and tenure decisions, thereby shaping academic behavior (Beer, 2022). Similarly, in Australia, universities have adopted AI-driven workload management systems that allocate teaching and administrative tasks based on predictive models, enhancing efficiency while reinforcing managerial control.

In emerging economies, the implications of these developments are shaped by institutional contexts. Limited regulatory frameworks and weaker labour protections may increase the risk of unchecked surveillance and managerial overreach. Empirical evidence suggests that digital technologies in such contexts are often implemented without clear guidelines on data privacy and staff rights, raising concerns about ethical governance (Czerniewicz et al., 2020). As a result, AI adoption may not only enhance organizational control but also exacerbate existing inequalities within higher education institutions.

The Effects of Artificial Intelligence Integration on the Labour Process in Emerging Economies

The integration of AI into higher education has profound implications for the labour process, particularly in relation to work organization, autonomy, and performance management. Drawing on labour process theory, technological change often reshapes the nature of work by altering the balance between managerial control and worker autonomy. In the context of higher education, AI introduces new forms of digital mediation that influence how academic work is organized and evaluated in the following ways:

a. Reorganization of academic work

One significant effect is the reorganization of academic work. AI systems automate routine tasks such as grading, scheduling, and administrative reporting, allowing academic staff to focus on research and higher-level teaching activities. However, this redistribution of tasks is not always accompanied by a reduction in workload. Studies indicate that the introduction of digital technologies often leads to work intensification, as academics are required to engage with multiple platforms, generate digital content, and respond to continuous data-driven evaluations (Czerniewicz et al., 2020). In emerging economies, where staffing levels may already be constrained, these additional demands can increase pressure on academic staff.

b. Autonomy

Autonomy is another critical dimension affected by AI integration. Traditional academic work is characterized by a degree of professional independence in teaching and research. However, AI-driven systems can constrain this autonomy by imposing standardized processes and continuous monitoring. For example, learning analytics platforms may dictate specific teaching strategies based on data-driven recommendations, limiting the discretion of instructors. In China, AI-enabled classroom monitoring systems have been reported to influence teaching practices by providing real-time feedback on student engagement, thereby shaping instructional decisions (Li & Wong, 2021). While such systems may improve outcomes, they also shift control from individual academics to algorithmic frameworks.

c. Performance management

Performance management is increasingly mediated by AI, with significant implications for academic careers. Universities use data analytics to evaluate research output, teaching effectiveness, and service contributions, often integrating these metrics into promotion and tenure decisions. In advanced economies, the use of bibliometric indicators and teaching analytics has been shown to influence academic behavior, encouraging productivity while also generating concerns about metric-driven work cultures (Beer, 2022). Emerging economies are adopting similar practices, although often without robust mechanisms to ensure fairness and transparency.

d. Skill transformation

AI integration also raises questions about skill transformation. While some tasks are automated, new forms of digital labour emerge, requiring academics to develop competencies in data analysis, digital pedagogy, and AI-assisted research. Evidence suggests that academics who adapt to these changes may experience enhanced productivity, while those who lack digital skills may face marginalization (Dwivedi et al., 2023). This dynamic is particularly relevant in emerging economies, where access to training and resources may be uneven.

Case studies from advanced countries provide further insight into these dynamics. In the United Kingdom, the use of AI in grading and feedback has reduced administrative workload but has also required academics to oversee and validate automated outputs, creating new forms of supervisory labour (Holmes et al., 2022). In the United States, the adoption of AI-driven research tools has increased publication rates in some disciplines, but has also intensified competition and performance pressure among academics (Kizilcec & Lee, 2020). These examples highlight the dual nature of AI, as both a tool for efficiency and a mechanism of intensified labour.

In emerging economies, the effects of AI on the labour process are shaped by broader socio-economic conditions. Limited institutional support, inadequate training, and weak regulatory frameworks may amplify the negative consequences of AI integration. At the same time, AI offers opportunities to enhance teaching and research capacity, particularly in resource-constrained environments. The challenge lies in balancing these outcomes to ensure that technological adoption supports sustainable and equitable academic work.

Empirical Reviews

Isaifan (2026) conducted a study titled *Artificial Intelligence in Higher Education: A Global Statistical Synthesis for Policy and Quality Assurance Reform* with a global scope drawing on datasets across multiple higher education systems. The study was anchored within institutional governance theory and data-driven decision-making perspectives, focusing on how AI reshapes regulatory and control structures in universities. A secondary research design was adopted, relying on large-scale quantitative datasets compiled between 2021 and 2025, including institutional reports, surveys of students and faculty, and international education statistics. The sampling frame consisted of aggregated datasets rather than individual respondents, while data collection involved systematic extraction from reputable global databases.

Findings showed widespread student adoption of AI tools alongside uneven faculty engagement, with institutions struggling to align governance mechanisms with the pace of technological uptake. Evidence pointed to increasing reliance on AI for monitoring academic integrity, assessment design, and institutional performance, which strengthened centralized oversight but exposed gaps in policy readiness and staff capacity. The study concluded that AI has become embedded in higher education systems as a structural component requiring coordinated governance frameworks rather than ad hoc implementation. A critical observation from the study is that while it provides strong statistical evidence on adoption and governance, it does not interrogate how these governance shifts translate into changes in academic labour processes, particularly in emerging economies where institutional conditions differ significantly.

Eleje et al. (2025) carried out a study on *Artificial Intelligence Adoption in Higher Education in Nigeria*, focusing on Nigerian universities as a representative case of an emerging economy. The investigation was informed by the technology acceptance model and institutional theory to explain patterns of adoption and organizational responses. The research employed a descriptive survey design involving academic staff and administrators across selected higher education institutions. Although the exact numerical sample was institution-based, respondents were drawn through purposive and stratified sampling techniques to capture variation across faculties and administrative units. Data were collected using structured questionnaires and supplemented with institutional observations on AI usage. The findings indicated a growing incorporation of AI tools in teaching, assessment, and administrative functions, particularly in plagiarism detection, automated grading, and learning analytics. However, the study reported infrastructural limitations, inconsistent policy frameworks, and low technical competence among staff as major constraints. It further revealed that AI systems were often introduced through top-down administrative directives, thereby reinforcing managerial authority over academic processes. The authors concluded that while AI holds potential for improving efficiency, its implementation in Nigeria remains uneven and largely driven by institutional leadership priorities rather than collaborative governance. A notable limitation is that the study focused primarily on adoption patterns and institutional challenges without examining how AI-mediated control mechanisms affect the daily work practices, autonomy, and labour relations of academic staff.

Olawale and Mutongoza (2024) examined *Artificial Intelligence: An Empirical Survey of Student and Staff Perspectives* within the context of a South African university, representing a developing economy setting. The study drew on socio-technical systems theory to understand the interaction between technological tools and human actors in educational environments. A cross-sectional survey design was utilized, involving both students and academic staff selected through stratified random sampling to ensure representation across disciplines. Data collection relied on structured questionnaires designed to capture perceptions, usage patterns, and concerns related to AI in teaching and learning. The results showed that while AI was widely recognized as enhancing learning efficiency and research productivity, respondents expressed concerns about ethical issues, academic integrity, and the potential erosion of critical thinking skills. Staff participants highlighted apprehension regarding increased monitoring of teaching activities and the pressure to adapt to AI-driven instructional methods. The study concluded that AI adoption in higher education introduces both opportunities and tensions, particularly in relation to control, accountability, and professional roles. Despite its empirical strength in capturing perceptions, the study did not extend its analysis to a deeper examination of organizational control structures or labour process transformations arising from AI integration which the current paper addressed.

Theoretical Framework – Labour Process Theory

Labour Process Theory was originally advanced by Harry Braverman in 1974 and further developed in contemporary scholarship on digital work and algorithmic management. Braverman's analysis, presented in his seminal work Labor and Monopoly Capital, focused on how capitalist production reorganizes work in ways that transfer control from workers to management through the use of technology, standardization, and scientific management techniques. Although developed in an industrial context, the theory has been extended to service sectors and knowledge work, including higher education, where managerial strategies increasingly rely on digital systems to coordinate and control labour (Kellogg et al., 2020).

The central assumptions of Labour Process Theory are that work is inherently contested, that management seeks to maximize control over the labour process to ensure efficiency and productivity, and that technology serves as a key instrument in restructuring work and reducing worker autonomy. The theory posits that managerial control is achieved through mechanisms such as deskilling, fragmentation of tasks, surveillance, and performance measurement. In contemporary settings, these mechanisms are embedded in algorithmic systems that monitor, evaluate, and direct worker activities. In higher education, these assumptions translate into the use of AI-driven systems for automated grading, learning analytics, and performance tracking, which shift decision-making authority away from academic staff toward institutional management.

The strengths of Labour Process Theory lie in its ability to provide a critical understanding of how technological innovations are linked to power relations and control within organizations. It moves beyond technological determinism by emphasizing that technology is deployed within specific institutional and economic contexts to achieve managerial objectives. Recent extensions of the theory have made it particularly relevant for analyzing AI and digital platforms, as seen in studies of algorithmic control and data-driven management (Kellogg et al., 2020). This makes the theory well suited for examining how AI integration in higher education influences governance structures and labour dynamics. However, the theory has been criticized for its early emphasis on deskilling and managerial dominance, sometimes underestimating worker agency, resistance, and the potential for skill enhancement through technology. Contemporary adaptations have addressed this limitation by recognizing that digital technologies can also create new forms of expertise and negotiated control.

Applied to the topic of this study, Labour Process Theory provides a strong analytical basis for understanding how artificial intelligence reshapes organizational control and academic labour in higher education institutions within emerging economies. AI systems such as predictive analytics, automated assessment tools, and digital monitoring platforms can be interpreted as extensions of managerial control that standardize academic work and enable closer supervision of teaching and research activities. In contexts where institutional governance is already centralized, as is common in many emerging economies, these technologies may reinforce hierarchical control structures and limit professional autonomy. At the same time, the theory allows for an examination of how academic staff respond to these changes, whether through adaptation, resistance, or the development of new competencies. By situating AI integration within the broader dynamics of control and labour restructuring, Labour Process Theory offers a coherent framework for analyzing both the intended efficiencies and the unintended consequences of technological adoption in higher education systems.

Results and Discussions

The findings of this paper showed that artificial intelligence integration in higher education across emerging economies follows uneven but patterned trajectories shaped by infrastructure, policy direction, and institutional priorities. Evidence drawn from the reviewed studies indicates that while universities in countries such as China and India have embedded AI into teaching delivery, assessment systems, and administrative coordination, institutions in African contexts, including Nigeria, tend to adopt narrower applications such as plagiarism detection, learning management analytics, and basic automation tools (Zawacki-Richter et al., 2022; Adeleke & Ebohon, 2023). This pattern aligns with UNESCO (2023), which notes that access to data infrastructure and technical expertise largely determines the depth of AI integration. The implication is that AI adoption in emerging economies is often incremental rather than systemic, leading to partial transformation of academic processes. For instance, a Nigerian university may deploy AI-based grading support within its learning management system, yet still rely on manual administrative procedures for staffing and curriculum planning. This fragmented adoption limits the capacity of AI to drive coordinated institutional reform while simultaneously introducing new layers of digital oversight.

The analysis further showed that AI integration strengthens organizational control through data-driven monitoring and standardization of institutional processes. Drawing on the arguments of Kellogg et al. (2020), the findings confirm that algorithmic systems extend managerial oversight by embedding control within routine academic activities such as grading, attendance tracking, and research evaluation. In emerging economies where governance structures are already centralized, these technologies reinforce top-down decision-making. For example, the use of automated performance dashboards to evaluate lecturers' teaching effectiveness and publication output allows university management to set quantifiable benchmarks that shape academic behaviour. Dwivedi et al. (2023) highlight that generative AI tools also introduce new forms of epistemic control by influencing how knowledge is produced and validated. In African universities, where institutional accountability mechanisms are often weak, AI-enabled monitoring may improve transparency but also risks reducing professional discretion by prioritizing measurable outputs over qualitative contributions such as mentorship and community engagement.

The findings on labour process indicate that AI integration reconfigures academic work through a combination of intensification, partial deskilling, and new skill demands. Consistent with labour process theory and its contemporary extensions (Kellogg et al., 2020; Vallas & Schor, 2020), the introduction of AI systems restructures how tasks are performed and evaluated. Academics are required to engage with digital platforms for teaching delivery, continuously update course materials compatible with AI systems, and respond to real-time performance metrics. While this creates opportunities for skill development in digital pedagogy, it also increases workload and reduces autonomy in decision-making. In practical terms, lecturers in South African or Nigerian universities using AI-enabled learning systems may have less flexibility in assessment design due to standardized templates embedded in these platforms. At the same time, the reliance on automated tools for grading and feedback may shift academic roles from knowledge creation to system supervision, thereby altering the traditional identity of academic labour.

The theoretical framework of labour process theory provides strong support for these findings by explaining how technological systems are used to reorganize work and consolidate managerial control. The theory's emphasis on control, surveillance, and the restructuring of labour is evident in the way AI systems embed performance monitoring and standardization within higher education institutions. The findings reflect Braverman's original argument, as revisited by Kellogg et al. (2020), that technological innovation often serves managerial interests by reducing worker autonomy and increasing efficiency.

In emerging economies, this dynamic is amplified by institutional constraints such as limited regulatory oversight and unequal power relations within universities. For example, the deployment of AI-driven administrative systems in African universities may be justified as improving efficiency, yet it simultaneously enables closer supervision of academic staff without corresponding protections for professional autonomy. The practical implication is that policymakers and university administrators must balance the efficiency gains of AI with safeguards that protect academic freedom and ensure fair labour practices. Without such measures, AI integration may deepen existing inequalities in higher education systems rather than contribute to sustainable institutional development.

Conclusions

The paper showed that artificial intelligence is becoming embedded in higher education systems in emerging economies, though its adoption remains uneven and shaped by infrastructural capacity, policy direction, and institutional priorities. The evidence indicates that AI is primarily introduced through learning management systems, automated assessment tools, and data-driven administrative platforms, often with stronger emphasis on efficiency and performance monitoring than on pedagogical transformation. This orientation has reinforced managerial oversight by enabling closer tracking of academic activities, standardizing evaluation procedures, and expanding data-based decision-making.

At the same time, these changes are altering the labour process within universities, as academic work is increasingly organized around digital systems that influence teaching practices, research output measurement, and administrative responsibilities. While AI has created opportunities for improved service delivery and new forms of academic engagement, it has also raised concerns about reduced professional discretion, work intensification, and the shifting balance of power between academic staff and institutional management. In emerging economies, where regulatory safeguards and institutional support systems are still developing, these dynamics highlight the need for deliberate and context-sensitive approaches to AI integration that align technological adoption with fair labour practices and sustainable institutional governance.

Recommendations

1. Higher education institutions should establish clear governance frameworks for AI deployment that include staff participation in decision-making, transparent guidelines on data use, and safeguards to protect academic autonomy and prevent excessive surveillance.

2. Governments especially at the State and Local levels and university management should invest in targeted capacity building for academic staff through continuous training, digital skills development, and technical support systems to ensure that AI tools enhance rather than constrain academic work.

3. Regulatory bodies of universities and institutional leaders should develop and enforce policies that balance performance monitoring with fair labour standards, including workload regulation, ethical use of AI in evaluation, and mechanisms for accountability and redress in cases of misuse.

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