NJMSR

Nepalese Journal of Management Science and Research
2026, Vol. 9, No. 1, pp. 1-33

Original Article

A Theoretical Study of AI-Driven Socio-Economic Challenges for Generation Z from the Perspective of Nepal, and the Global South

Rajendra Ojha

Abstract

Artificial Intelligence (AI) is a transformative yet disruptive force in the 21st century economy, offering innovation while exacerbating socio-economic disparities for Generation Z in developing countries such as Nepal. Using a qualitativedescriptive case study and secondary data (2011–2024), this study examines AI's interaction with infrastructural gaps, digital illiteracy, and policy stagnation. Findings reveal that the algorithmic divide is excessively affecting Nepali youth, causing employment anxieties, unequal educational access, and systemic digital unpreparedness. The study recommends inclusive policies, targeted digital literacy programs, and infrastructure development, while introducing two mid-range theories, the Algorithmic Exclusion Cycle (AEC) and AI-Generation Disparity Theory (AGDT), to examine these context-specific challenges.

Keywords: Algorithmic Divide, Artificial Intelligence, Digital Literacy, Generation Z, Socio-Economic Disparities

---

**Mr. Rajendra Ojha is a PhD candidate at the University of Huddersfield, UK. His research interests encompass Development Economics, Sociology, and Conflict Management. He has also been involved in several scientific research projects co-funded by the Erasmus+ program.*

*Author Email: ojharajendra695@gmail.com

ISSN (Print) :2467-9356, ISSN (Electronic) : 2795 - 1545

https://doi.org/10.53056/njmsr-2026.9.1.001

https://www.nepjol.info/index.php/njmsr

1. Introduction

The rapid development of artificial intelligence (AI) is reshaping global industries while posing significant socio-economic challenges for Generation Z in developing countries. In contexts such as Nepal, where economic opportunities are limited, the integration of AI into daily life requires careful and critical analysis. Academic discourse has moved beyond the traditional concept of the digital divide, which emphasized technological access, to the emerging notion of the algorithmic divide, highlighting accessibility, affordability, and inclusivity within AI systems themselves (Yu, 2020). Despite growing recognition of algorithmic bias, understanding of its generational and context-specific impacts in the Global South remains limited.

AI is not merely a technological innovation; it is a transformative force restructuring socio-economic systems. Generation Z, born between 1995 and 2009 (Salleh et al., 2017), are entering adulthood amid automation, algorithmic governance, and data-driven economies. Yet, opportunities and risks are unevenly distributed due to persistent structural inequalities. Low- and middle-income countries experience AI's effects differently from advanced economies such as North America and Western Europe (Van Dijk, 2020; Eubanks, 2018). Nepal exemplifies this disparity, where digital transformation aspirations confront inadequate infrastructure, underinvestment in education, and a longstanding digital divide, disproportionately affecting marginalized communities and limiting youth opportunities.

For many young Nepalese, particularly in rural areas or historically disadvantaged groups, meaningful engagement with AI remains challenging. Limited internet access, insufficient institutional capacity for digital literacy initiatives, and the absence of inclusive policies constrain participation (UNESCO, 2023). As AI-driven systems increasingly influence labor markets, education, and public services, those lacking digital skills or connectivity risk exclusion from socio-economic opportunities. This dynamic may exacerbate existing inequalities rather than alleviate them (Robinson et al., 2015). The concept of the algorithmic divide captures this multidimensional exclusion, encompassing not only access but also algorithmic literacy, transparency, and governance (Eubanks, 2018; Yu, 2020).

The potential benefits of AI in emerging economies extend beyond technical adoption to issues of social justice, human rights, and equitable development. Investigating how Generation Z in Nepal navigates this digital landscape is therefore a human-centered inquiry into their lived experiences, aspirations, and vulnerabilities. By foregrounding these perspectives, this research contributes to discussions on ethical AI, inclusive innovation, and the right to meaningful digital participation in developing contexts (Yorke-Smith, 2020; UNESCO, 2023).

Problem of the Study

The rapid adoption of artificial intelligence is reshaping global systems, exposing Generation Z in Nepal to conflicting demands for adapting to AI-driven futures amid persistent socio-economic constraints. While AI promises innovation and productivity, its uneven diffusion risks deepening inequalities through job displacement, limited digital access, and uneven technological literacy. The COVID-19 pandemic starkly exposed Nepal's digital divide, particularly affecting educational continuity (Acharya, 2025). Research confirms that disparities in digital infrastructure and literacy significantly influenced remote learning participation, disproportionately disadvantaging public institutions and economically marginalized students.

Empirical evidence reveals persistent digital inequalities in Nepal, where reliable internet access correlates strongly with socioeconomic status, urban residence, and educational attainment (Chand & Maharjan, 2024). While general literacy rates improve, functional digital literacy remains critically low, constraining meaningful participation in digital learning and employment opportunities and thereby reinforcing structural inequalities (K.C., 2025). Despite growing international scholarship on AI's societal impacts, context-specific investigations into generational consequences in developing nations like Nepal remain notably scarce.

This study examines how AI intensifies the socioeconomic vulnerabilities of Generation Z in Nepal and the global south, emphasizing the structural barriers that limit equitable participation within the country's specific socio-educational context.

Research Objectives

Derived from the background and problem statement, this study pursues the following objectives:

1. To analyze the influence of AI on employment patterns among Generation Z in Nepal.
2. To assess the impact of digital literacy on AI adaptability among Nepalese youth.
3. To examine the digital divide and its implications for equitable AI access in Nepal.
4. To identify the socio-economic vulnerabilities that AI exacerbates in the Nepali context.
5. To propose evidence-based policy interventions for the inclusive integration of AI.

Research Questions

The following questions guide this study:

6. How is AI affecting job displacement and creation among young people in Nepal?
7. What socio-economic challenges does Generation Z face in adapting to AI-driven changes?
8. How does the digital divide impact fair access to AI tools and education across different regions of Nepal?
9. How does varying digital literacy affect young people's capacity to participate in an AI-driven economy?
10. What systemic barriers prevent Generation Z from engaging with AI technologies in Nepal?

Rationale of the Study

This research is motivated by the critical need to evaluate AI's impact on Generation Z in developing nations, with a focused lens on Nepal. There exists a significant lacuna in context-specific research that investigates the precise local consequences of AI on younger generations, particularly concerning employment dynamics, inequalities in digital education, and infrastructural limitations. While global AI research proliferates, the lived experiences of youth in countries like Nepal remain underexplored.

The rationale is driven by the observation that AI is catalyzing not just a persistent 'digital divide' but a more complex 'algorithmic divide'. This concept moves beyond mere access to technology to question whether AI systems are accessible, affordable, and genuinely inclusive for all. This division can engender profound socio-political and emotional exclusion, alienating young people from the very future AI is shaping. Therefore, this study aims to provide a human-centric exploration into the real-world experiences of Nepali youth, grounding theoretical discourse in empirical reality.

2. Literature Review

2.1. Potential and Threat of Artificial Intelligence in the Global Development Context

The ascent of Artificial Intelligence (AI) as a defining technology of the Fourth Industrial Revolution presents a complex developmental paradox, particularly for nations in the Global South. Globally, AI is lauded for its capacity to drive economic growth, optimize public service delivery, and accelerate progress toward the Sustainable Development Goals (SDGs) (Nepal, 2024). In the Asia-Pacific region, this has catalyzed a competitive drive to adopt 4IR technologies, positioning AI as a potential catalyst for sustainable development (Mukherjee & Sarma, 2022). However, this narrative of unilinear progress often obscures the deeply stratified nature of technological diffusion. For developing countries like Nepal, the integration of AI is not a simple matter of adoption but a fraught navigation between the promise of enhanced productivity and the peril of exacerbated inequality.

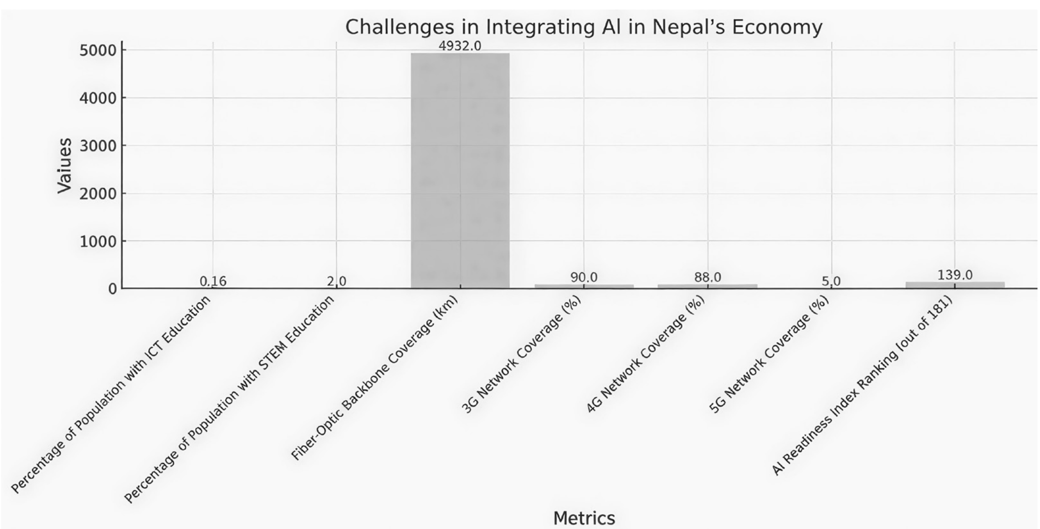
The central challenge lies in the precondition that AI's benefits are dependent

https://doi.org/10.53056/njmsr-2026.9.1.001 https://www.nepjol.info/index.php/njmsr

upon a foundation of robust digital infrastructure, widespread literacy, and proactive governance conditions frequently absent in resource-constrained settings. Consequently, without deliberate intervention, the global AI revolution risks not only leaving countries like Nepal behind but also amplifying internal socio-economic fissures, transforming a technological opportunity into a vector of further disparity (Yu, 2020; Mukherjee & Sarma, 2022).

2.2. Framework for Understanding Socio-Technical Inequalities Through Algorithmic in the Era of AI

To understand AI's impact, one must move beyond the traditional 'digital divide' framework, which primarily addressed gaps in physical access to hardware and connectivity. The emergence of AI necessitates the concept of the 'algorithmic divide' (Yu, 2020; Eder & Sjøvaag, 2024). This advanced form of inequality encompasses not just access to technology but meaningful engagement with algorithmic systems. It includes disparities in algorithmic literacy, which is the ability to understand, question, and interact with AI-driven processes; representational fairness, which involves ensuring AI systems are trained on diverse data that reflects local contexts and does not perpetuate societal biases; and governance and agency, which is the capacity of individuals and communities to influence how AI systems are designed and deployed in their lives. This theoretical shift is critical for analyzing Nepal's situation.



https://doi.org/10.53056/njmsr-2026.9.1.001

Figure 1: Critical Structural Readiness Deficit in Nepal's AI integration landscape

This figure reveals a critical structural readiness deficit in Nepal's AI integration landscape. The co-existence of low ICT/STEM education rates and patchy network coverage alongside targeted investments in fibre-optic backbones reveals a disjointed development strategy. This deficit directly fuels the algorithmic divide (Yu, 2020), wherein even basic connectivity does not guarantee meaningful participation in AI-driven systems. The poor AI readiness ranking further underscores systemic unpreparedness, suggesting that without targeted intervention in education and equitable infrastructure, AI adoption may inadvertently reinforce existing socio-economic hierarchies rather than fostering inclusive growth.

As Figure 1 illustrates, the country faces a foundational readiness deficit, with low levels of ICT/STEM education and uneven network coverage. This creates a population vulnerable to algorithmic deprivation (Yu, 2020), where citizens are not merely offline but are systematically excluded from the benefits and decision-making processes of an increasingly algorithm-mediated society, despite possessing basic connectivity.

2.3. Job Displacement and Creation in the Context of AI Integration

The global proliferation of AI technologies is reshaping labor markets, but the effects are uneven. In Nepal, the entry of Generation Z into the workforce coincides with this technological shift, presenting dual challenges of job displacement and creation. While AI can enhance productivity and generate new roles, it also threatens traditional sectors, especially those reliant on routine tasks (Peiwen, et al., 2025). This dynamic is mediated by the algorithmic divide: unequal access to AI tools and skills exacerbates existing inequities, leaving lower-income youth disproportionately vulnerable to job loss (Yu, 2020). Without proactive training and policy adaptation, this divide may intensify social inequalities, as those already disadvantaged are less able to navigate the changing employment land-

https://doi.org/10.53056/njmsr-2026.9.1.001 https://www.nepjol.info/index.php/njmsr

scape. (Yu, 2020).

The algorithmic divide has a direct impact on labor market outcomes. Digitally privileged young people are better positioned to access new and emerging opportunities, while those who are excluded face heightened risks and fewer pathways into stable employment. This growing divide contributes to increasing polarization within the workforce and threatens to intensify existing socioeconomic inequalities. As a result, it reinforces the conditions described by Standing (2011) as the 'precariat', a generation characterized by job insecurity, unstable income, and diminished long-term prospects.

For Nepal, the employment implications are multifaceted and context-specific:

- **Sectoral Vulnerability:** Traditional pillars of the economy, such as subsistence agriculture and low-skill manufacturing, are susceptible to automation of routine tasks. However, the immediate risk may be less from outright job loss and more from a widening skills mismatch, where the demands of a slowly modernizing economy outpace the skills of the entering workforce (World Bank, 2025).

- **The Quality of Creation:** While vocational training has shown success in increasing non-farm employment (Chakravarty et al., 2019), the question remains whether AI will generate high-quality, stable jobs or contribute to the 'gig market' and informalization of work for Generation Z.

- **Reinforcing Divides:** The algorithmic divide directly translates into labor market outcomes. Those with access to AI tools, digital skills, and quality education (often urban, affluent youth) are positioned to capture new, high-value opportunities. In contrast, those on the wrong side of the divide face compounded vulnerabilities, a phenomenon that Table 2 empirically underscores through Nepal's infrastructural and educational deficits. This can lead to labor market polarization, intensifying socio-economic stratification.

2.4. Intersecting Vulnerabilities and Digital Exclusion among Generation Z of Nepal

Nepal's Generation Z encounters a multilayered configuration of structural vulnerabilities that significantly shape its engagement with digital technologies. Persistent geographic disparities between urban and rural regions, enduring socioeconomic inequalities, and deeply embedded sociocultural norms collectively constrain young people's capacity to access and meaningfully utilize technological resources (UNESCO, 2023). These constraints extend beyond questions of individual agency or personal preference; rather, they are rooted in systemic institutional deficiencies that reproduce unequal conditions of participation within the digital ecosystem.

Within this analytical framework, the concept of 'Algorithmic Deprivation' is introduced to denote a structural condition in which entrenched social, economic, and infrastructural barriers inhibit young people from deriving substantive benefits from advances in artificial intelligence and related digital technologies, even in contexts where basic connectivity is nominally available. This concept emphasizes that mere access to the internet does not guarantee equitable integration into algorithmically mediated systems of opportunity, knowledge production, and economic participation.

Region	Job Displacement	Job Creation
Africa	Up to 40% of tasks in the outsourcing sector could be automated by 2030, with lower-paying Jobs are most at risk. Women are 10% more susceptible to automation than men (Ignatius S., 2025).	AI applications are improving medical diagnostics, aiding farmers in identifying crop diseases, and providing tailored education, potentially creating new job opportunities (Pilling & Murray, 2024).
Latin America and the Caribbean	AI could automate between 2% and 5% of jobs, with women and younger workers in the formal sectors particularly vulnerable (Casas, 2024).	AI advancements could enhance productivity for 8% to 14% of jobs, especially in urban, educational, and formal sectors, benefiting higher-income earners (Casas, 2024).
Developing Countries	AI's impact on jobs is expected to be more gradual, with lower exposure in low-income countries due todifferent labor market structures.(Demombynes, Langbein, & Weber, 2025)	AI is expected to create new job categories, but the extent varies across sectors and economies.(Demombynes, Langbein, & Weber, 2025)

https://doi.org/10.53056/njmsr-2026.9.1.001 https://www.nepjol.info/index.php/njmsr

Nepal	Specific data on AI-induced job displacement in Nepal is limited. (Demombynes, Langbein, & Weber, 2025)	Vocational training programs in Nepal have led to a 10% increase in non-farm employment among youth, with women benefiting significantly (Chakravarty et al., 2019).

***Table 1**: AI's Impact on Job Displacement and Creation in Developing Nations*

This table provides essential empirical data from various developing regions around the world to contextualize the challenges faced by Nepal within the broader framework of the Global South. It offers actual statistical data that supports the claims regarding job creation and displacement caused by AI, thereby adding credibility to this literature review.

Measured Units	Data Point
Population with ICT and STEM Education	Low Percentage
Network Coverage (2G, 3G,4G,5G)	Inadequate
Fibre-Optic Backbone Infrastructure	Significance
AI enthusiasm index position	Significant Challenge

***Table 2**: Major Problems for AI Integration in Nepal*

This table visually reviews serious infrastructural and educational deficits in Nepal. It also delivers a data-driven outline of the initial challenges that unswervingly hamper the adoption of artificial intelligence and worsen the condition of the algorithm and digital divides. It even affords quantitative support for the qualitative findings and problem statements surrounding 'underdeveloped infrastructure', 'low spending on education', 'poor access to quality STEM education', and 'infrastructure neglect'. This adds to the empirical nature of the assertions of this paper. It will provide an empirical, data-grounded rationale for policy recommendations by laying out the readiness state and the deficit. The table illustrates empirically why particular interventions, such as investment in digital literacy programs and equitable infrastructure distribution, are necessary and where they ought to be targeted.

2.5. Digital Literacy in Nepalese Education

The idea that artificial intelligence could transform education is powerful, but it comes with a real dilemma. Many people talk about AI as a way to tailor learning and open up opportunities, yet research suggests that these benefits are not unfolding equally across the globe. According to Bulathwela (2024), while AI tools may support personalized learning, millions of students are still left out because of persistent barriers such as the digital divide. If AI systems are rolled out without careful attention to equity and inclusion, they risk reinforcing existing gaps instead of closing them. Proponents argue that these capabilities can support differentiated learning paths and improve student engagement (Hadheri et al., 2023). On the other hand, AI carries the risk of exacerbating existing educational inequalities, particularly in contexts where access to technology and educational resources is uneven. In Nepal, such risks are especially salient due to persistent infrastructural limitations and gaps in teacher training (Asia-Pacific Centre for Technology in Education (APCTT), 2022). Without addressing these foundational issues, the promise of AI in education may remain largely aspirational rather than transformative.

Educational technologies are effective only within a supportive ecosystem that encompasses reliable internet connectivity, access to devices, and sustained professional development for educators. These structural conditions shape whether technology becomes a tool of empowerment or exclusion. In many marginalized communities in Nepal, the necessary infrastructure and human capacity are often lacking, undermining the potential benefits of AI (APCTT, 2022). When these essential elements are absent, AI risks functioning not as an equalizing force but as a mechanism that reinforces the pre-existing disparities in learning opportunities.

The reality of uneven access underscores the need to move beyond basic digital literacy. It is not sufficient for students to know how to interact with devices; they must also develop critical algorithmic literacy. Algorithmic literacy encompasses the ability to understand how AI systems operate, to recognize potential biases

https://doi.org/10.53056/njmsr-2026.9.1.001 https://www.nepjol.info/index.php/njmsr

embedded in algorithms, and to reflect on the ethical and societal implications of AI-driven decision-making (Gasser & Almeida, 2023). Without such critical awareness, learners risk becoming passive consumers of AI-mediated content rather than informed agents capable of questioning how these systems shape educational trajectories and social outcomes.

Addressing these challenges in Nepal requires developing infrastructure, enhancing teacher capacity, and innovating curricula. Investments must prioritize not only connectivity and hardware but also teacher education that foregrounds pedagogical uses of AI and critical engagement with technology.

Curriculum initiatives should embed algorithmic thinking and ethical reflection into learning objectives across subjects, preparing students to navigate the promises and pitfalls of AI (Selwyn, 2020). AI in education can serve as a tool for empowerment only when technical readiness is paired with critical engagement. This approach allows AI to act as a transformative educational resource while remaining responsive to the diverse social, economic, and cultural contexts of the communities it aims to support.

Conceptual Framework

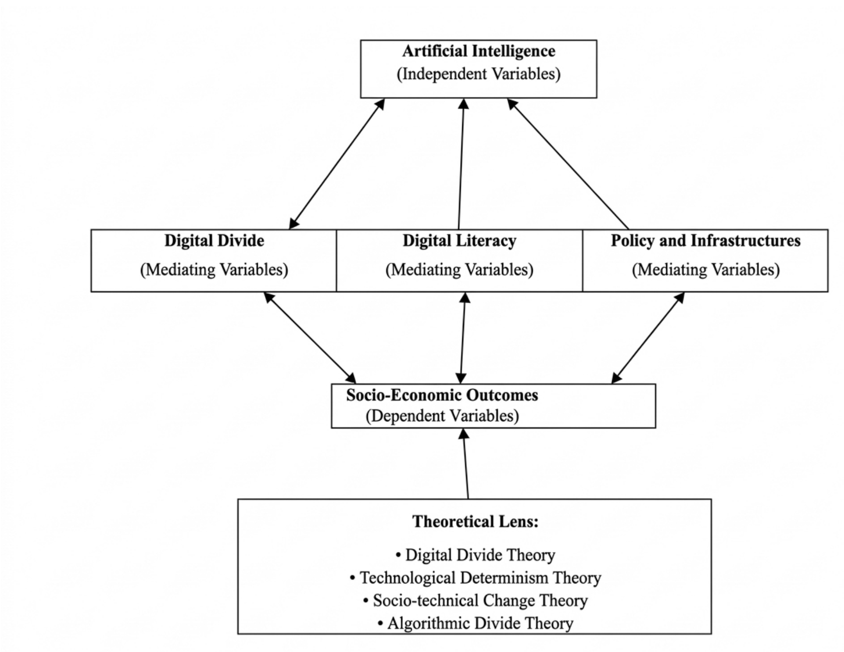


Figure 2: Linear Model Narrative Conceptual Framework of Algorithmic and Digital Disparity

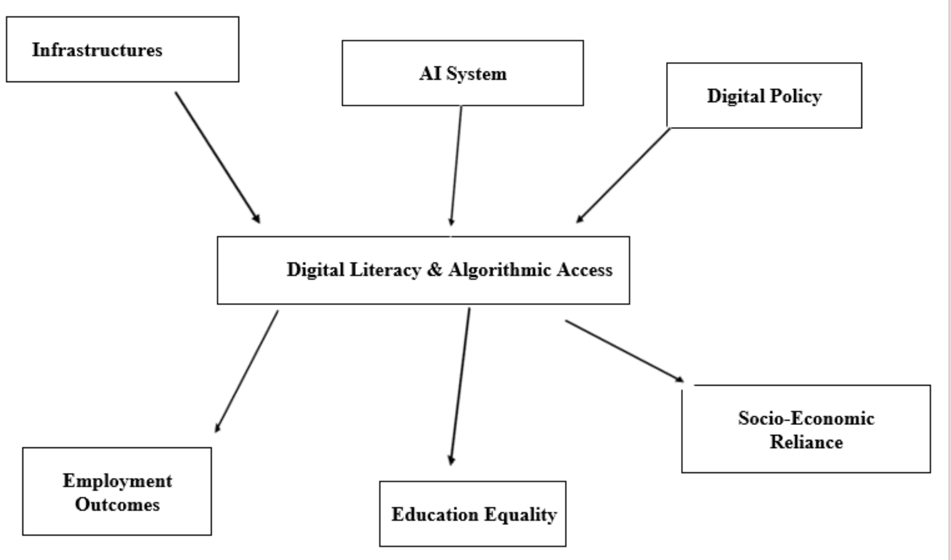


Figure 3: Socio-Technical Framework for Understanding the Algorithmic Division

This study uses Digital Divide, Digital Literacy, and Digital Policy as its mediating variables. Figure 2 (Conceptual Framework), termed the 'Linear Model Narrative Conceptual Framework of Algorithmic and Digital Disparity', illustrates how AI interacts with these variables. Conceptual Framework in Figure 3 highlights digital access inequalities that appear when AI is used and distributed, focusing on algorithmic access and the broader socio-technical system.

2.6. Theoretical Framework

- **Digital Divide Theory**

Digital Divide Theory explains how disparities in access to information and communication technologies produce layered forms of social and economic inequality. Early formulations, particularly those advanced by the OECD (2001), framed the digital divide primarily as a gap in physical access to technological infrastructure. However, later scholarship significantly deepened this understanding. Jan van Dijk (2017) argues that the divide operates through cumulative stages, including

https://doi.org/10.53056/njmsr-2026.9.1.001 https://www.nepjol.info/index.php/njmsr

motivational access, material access, skills access, and usage outcomes. Inequality, therefore, unfolds progressively rather than appearing as a simple distinction between those who are connected and those who are not. This layered conception is particularly relevant in developing contexts where connectivity may expand without corresponding growth in digital competencies or meaningful technological engagement. Likewise, Srinuan & Bohlin (2011) emphasize that the divide encompasses disparities in access, skills, and the socio-economic consequences of digitization. Their perspective reinforces the argument that digital inequality persists even after basic infrastructure has been introduced. This framework illuminates how initial access disparities in Nepal compound through subsequent stages, creating entrenched digital exclusion pathways.

In the context of Nepal, this framework illuminates how initial infrastructural gaps interact with uneven educational capacity to generate entrenched patterns of exclusion. Access alone does not ensure inclusion. Instead, structural disparities compound over time, shaping differential life chances among youth populations. Digital Divide Theory, therefore, provides the structural baseline from which this study proceeds.

- **Socio-technical Change Theory**

The core idea of Socio-technical theory is that the design and performance of any organizational system can only be understood and enhanced if both the 'social' as well as 'technical' parts of the organization are brought together in one place and treated as interdependent parts of a complex system (Leeds University Business School, 2023). In other words, this theory is defined as a method for designing a society or organization that considers human, social, and organizational, as well as technical factors, as top priorities in the strategy of organizational systems (Baxter & Sommerville, 2011). This theory provides analytical tools for examining how Nepal's social structures, educational systems, and policy environments interact with AI technologies to produce specific outcomes.

In Nepal's case, uneven educational quality, limited STEM integration, and inconsistent policy implementation shape the trajectory of AI integration. Technological potential alone does not determine social outcomes. Rather, outcomes are conditioned by the readiness and responsiveness of surrounding institutions. This socio-technical insight supports the transition from descriptive inequality analysis to structured mid-range theorization.

- **Algorithmic Divide Theory**

Building upon the fundamental idea of digital divide theory, Yu (2020) and Eder and Sjøvaag (2024) propose the 'algorithmic divide' as a more sophisticated inequality form encompassing algorithmic literacy, representational fairness, and governance agency. This theoretical shift proves essential for analyzing how AI systems may perpetuate exclusion even among connected populations.

Unlike conventional digital divide frameworks that focus primarily on access to technology, the proposed AEC and AGDT frameworks extend the analytical lens to include algorithmic governance, institutional responsiveness, and generational vulnerability. These frameworks, therefore, contribute to emerging Global South scholarship by demonstrating how AI-driven transformations intersect with structural inequalities in developing contexts. By situating Nepal within the broader comparative dynamics of Africa and Latin America, the study advances mid-range theorization rather than universal generalization.

2.7. Need For Mid-Range Theory in the Global South

Developing contexts undergoing accelerated technological transition face a distinctive structural configuration: externally driven AI diffusion combined with uneven institutional capacity. Traditional digital divide frameworks identify disparities in access and capability, but do not model how such disparities become recursive under AI-mediated economic restructuring. Nor do they adequately account for generational compression effects, whereby younger cohorts must adapt to rapidly transformed opportunity systems during critical educational and labor-market transitions.

To address these analytical limitations, this study proposes two complementary

https://doi.org/10.53056/njmsr-2026.9.1.001

mid-range theoretical frameworks: the Algorithmic Exclusion Cycle (AEC) and the AI–Generation Disparity Theory (AGDT). Together, they explain how structural inequality becomes self-reinforcing in AI-integrated systems and why such dynamics disproportionately affect Generation Z in technologically transitioning societies.

2.8. Core Constructs and Propositions of The Algorithmic Exclusion Cycle (AEC), and AI–Generation Disparity Theory (AGDT) Theory

The Algorithmic Exclusion Cycle (AEC) is a self-reinforcing socio-technical loop where initial structural deficits lead to cumulative disadvantages in the AI economy. It conceptualizes AI-driven inequality as a recursive socio-technical process. It argues that when artificial intelligence diffuses more rapidly than institutional adaptation, pre-existing structural disparities evolve into self-reinforcing mechanisms of exclusion. The framework comprises six constructs: Structural Discrepancy (SD), Digital Literacy Gap (DLG), Algorithmic Disconnection (AD), Economic Vulnerability (EV), Policy Inertia (PI), and Intergenerational Entrenchment (IE).

Proposition 1 (Structural Precondition): The degree of Algorithmic Disconnection (AD) in a developing economy is a function of the 'Readiness Deficit' (RD), where RD is the gap between physical infrastructure (connectivity) and cognitive infrastructure (specialized AI literacy).

Proposition 2 (The Feedback Loop): Socio-economic exclusion (SE) among Generation Z is not a terminal state but a recursive driver that reinforces Structural Discrepancy (SD). As excluded cohorts lack the capital to invest in STEM-based education, the national 'Innovation Capacity' remains stagnant, completing the cycle (SE to SD).

The AI–Generation Disparity Theory (AGDT) complements this model by explaining generational concentration of disadvantage under rapid AI diffusion. The goal of AGD theory is to explain why Generation Z in Nepal faces a unique

'Temporal Crisis'. Hence, it centers five constructs: Externally Driven Diffusion (EDD), AI Uptake Adaptation Gap (AUAG), Generational Technological Burden (GTB), Institutional Support Deficit (ISD), and Socio-Technological Marginalization (STM).

The theory AGDT claims that, unlike previous generations who adapted to technology over decades, Generation Z in the Global South faces 'Compressed Technological Displacement'. They are required to compete in a global AI labor market while their local educational institutions are still transitioning to basic digital platforms.

Together, AEC and AGDT function as mid-range theories linking structural inequality with generational experience, offering a coherent framework for analyzing AI-driven stratification in technologically transitioning societies.

3. Methodology

This study adopts a qualitative case study design grounded in conceptual synthesis and abductive reasoning. The research avoids primary data collection in favor of synthesizing institutional reports, peer-reviewed literature, and national statistics to identify recurring structural patterns of AI integration and generational inequality in Nepal. A systematic document analysis was conducted between January and September 2025, utilizing global databases such as Google Scholar and Scopus alongside national government portals. This work is strictly framed as theoretical research and a conceptual framework paper, intended to provide a robust foundation for future empirical validation.

4. Empirical Applications of the Theories

4.1 Algorithmic Exclusion Cycle (AEC)

The Nepal case aligns closely with the sequential logic of the Algorithmic Exclusion Cycle. Proposition (P1) argues that structural discrepancy increases the digital literacy gap among youth. In Nepal, persistent inequalities in ICT and STEM

https://doi.org/10.53056/njmsr-2026.9.1.001 https://www.nepjol.info/index.php/njmsr

education, uneven urban–rural connectivity, and limited school-level technological infrastructure have produced foundational disparities in digital competency. Although internet access has expanded, meaningful skill acquisition remains stratified along geographic and socio-economic lines. These structural conditions directly contribute to widening digital literacy gaps among Generation Z.

Proposition (P2) suggests that a wider literacy gap increases the probability of algorithmic disconnection, even where nominal connectivity exists. In Nepal, many young people possess smartphones and intermittent mobile internet access, yet lack algorithmic literacy, critical engagement skills for AI-driven systems, and the capacity to navigate digital employment platforms. This produces connected exclusion, where formal access does not translate into effective participation in algorithmically mediated environments. The empirical pattern supports the claim that connectivity without competency generates algorithmic disconnection.

Proposition (P3) links algorithmic disconnection to economic vulnerability. Nepal's labor market reveals concentration of youth in informal and low-skill sectors, limited access to advanced digital opportunities, and a persistent mismatch between educational output and emerging AI-mediated employment demands. Inability to engage effectively with digital recruitment systems and remote work ecosystems reinforces economic precarity among disadvantaged youth. This confirms that algorithmic exclusion carries measurable labor market consequences.

Propositions (P4) and (P5) emphasize institutional lag in reproducing inequality. Despite initiatives such as the Digital Nepal Framework, implementation gaps remain substantial. Budgetary limitations, weak coordination, and insufficient teacher training constrain systemic adaptation. Economic precarity further limits intergenerational skill transmission, reinforcing the original structural discrepancies. Nepal thus exhibits the recursive dynamics predicted by the AEC model.

4.2 AI–Generation Disparity Theory (AGDT)

While AEC explains recursive exclusion, the AI–Generation Disparity Theory clarifies its generational concentration. Proposition (P1) states that a widening AI

Uptake Adaptation Gap increases generational technological burden. In Nepal, ambitious policy discourse around artificial intelligence contrasts with limited curriculum reform, uneven infrastructure, and minimal AI literacy integration. This divergence constitutes an adaptation gap, the burden of which falls primarily on Generation Z as they enter digitally mediated labor markets without adequate preparation. Proposition (P2) argues that institutional support deficits intensify socio-technological marginalization. During the COVID-19 period, disparities between private and public schools and between urban and rural regions exposed infrastructural and pedagogical weaknesses. Youth were required to adapt to digital platforms without sufficient institutional support, reinforcing inequality in skill development.

Proposition (P3) suggests that such marginalization reduces upward mobility. Labor migration trends, youth unemployment, and concentration of high-skill digital opportunities within urban networks indicate a stratified technological landscape. Disadvantaged youth remain excluded from AI-enhanced sectors and digital entrepreneurship. Proposition (P4) highlights external technological pressure. Nepal's digital agenda is shaped by global norms and donor-driven frameworks promoting rapid AI integration. However, domestic absorptive capacity remains constrained, widening the adaptation gap and intensifying generational burden.

Together, AEC and AGDT operate as mid-range theoretical contributions. They specify empirically observable mechanisms rather than universal claims. The Nepal case supports the sequential logic of AEC, where structural deficit produces literacy gaps, literacy gaps generate algorithmic disconnection, disconnection increases economic vulnerability, and vulnerability reproduces inequality. AGDT complements this by explaining how adaptation gaps concentrate these dynamics within a specific generation. Collectively, the two models bridge structural inequality and lived generational experience, offering operationalizable tools for comparative research across technologically transitioning Global South contexts.

5. Data Analysis

https://doi.org/10.53056/njmsr-2026.9.1.001 https://www.nepjol.info/index.php/njmsr

The data for this study were collected through a systematic examination of secondary sources spanning the years 2011 to 2024. This included scholarly articles from peer-reviewed journals and academic databases, relevant policy documents such as the Digital Nepal Framework and the Nepal ICT Policy, and official national statistics from the Central Bureau of Statistics and ICT-related indicators. This research also drew on reports published by international organizations including UNESCO, the World Bank, and UNESCAP, as well as carefully verified media accounts that reflect broader socioeconomic changes and public attitudes.

Source Type	Samples	Analytical Purpose
Educational and Labor Market Report	International Labor Organization, Ministry of Science and Technology, and Vocational Education	Employment Vulnerability and Skill Mismatch
Peer-reviewed Studies	Baxter & Sommerville (2011), Hadheri A et al. (2023), Ignatius S. (2025), and so on.	Theoretical Understanding, and for the research problem justification
National and Sectoral Statistics	CBS Nepal, ICT indicators, and many more.	Structural baseline and Triangulation
National Policy Documents	Digital Nepal Framework, Nepal ICT Policy, etc.	Governance Gap, and Institutional Response
Verified Media Reports	Financial Times (News portal), Reuters (International), Nepal Economic Forum (National), and many more.	Emerging market train, especially in Nepal and other nations, is used as a comparative study in this research.
Reports From International Organisations	World Bank research related to AI & Jobs, UNESCO GEM Report (2023)	Structural willingness, Policy Creating, and Executing capacity.

Table 3: *Data Sources of this Research and Their Analytical Purposes in the Organized Qualitative Secondary Data Analysis*

6. Analytical Discussion

The secondary data reveal systemic, interconnected failures producing technological exclusion for Nepal's Generation Z, rather than isolated challenges. Infrastructure gaps, educational shortcomings, and policy-implementation mismatch-

 https://doi.org/10.53056/njmsr-2026.9.1.001

es reinforce one another. Uneven network coverage (Table 2) and low ICT and STEM participation create vulnerabilities beyond conventional digital divide interpretations. A rural youth with intermittent 3G access but limited digital skills is nominally connected yet effectively excluded from meaningful participation in algorithm-driven social and economic systems. Existing theories, which equate connectivity with inclusion, fail to capture this nuance.

Employment data (Table 1) highlight an adaptation gap: while countries like Rwanda integrate AI into agriculture and healthcare, Nepal emphasizes vocational training for low-skill, non-farm employment. Young people thus confront AI-shaped labor markets with training suited to pre-AI economies. Digital Divide Theory identifies access inequalities but not ongoing exclusion among connected youth; Technological Determinism highlights AI disruption but underestimates socio-cultural constraints; Socio-technical Systems Theory notes social-technical interdependence but lacks generational specificity.

Patterns in the data reveal systematic, not random, processes. First, a self-reinforcing cycle deepens disadvantage: poor infrastructure limits education, limited education restricts economic mobility, and economic vulnerability weakens institutional improvement. Second, generational synchronization imposes compressed temporal demands: Generation Z must navigate global AI-influenced systems while institutions lag in delivering basic digital competencies. Third, algorithmic disconnection emerges: within connected populations, stratification forms between those capable of meaningful engagement and those restricted to passive use, shifting exclusion from connectivity to skills and functional participation.

These findings underpin the frameworks in the Findings section. Nepal's Generation Z faces challenges that are not isolated or temporary but reflect deeper systemic patterns, requiring new theoretical perspectives for understanding and intervention.

7. Limitations and Future Research

https://doi.org/10.53056/njmsr-2026.9.1.001 https://www.nepjol.info/index.php/njmsr

This study employed a qualitative descriptive case study design using only secondary sources, including literature, policy documents, and published reports, enabling a comprehensive review of evidence. A key limitation is the absence of primary data from interviews or focus groups with Nepalese youth. Consequently, the AEC and AGDT frameworks were developed through the interpretation of existing material rather than participants lived experiences. Future research incorporating direct input from Generation Z could deepen understanding, validate these models, and enhance their theoretical and practical relevance.

8. Findings: Theoretical Contributions

1. Proposed Conceptual Models and Mid-Range Theoretical Contribution

Building upon the preceding empirical synthesis, this study advances two mid-range theoretical models designed to explain patterned exclusion under accelerated AI diffusion. Specifically, it introduces the Algorithmic Exclusion Cycle (AEC) and the AI–Generation Disparity Theory (AGDT) to analyze how artificial intelligence restructures inequality in technologically transitioning societies. Rather than positioning AI as an inherent equalizer, these models demonstrate that rapid technological diffusion, when misaligned with institutional capacity, can transform pre-existing structural deficits into self-reinforcing exclusion mechanisms.

The AEC conceptualizes inequality as a sequential socio-technical process. Structural discrepancies in infrastructure, education, and governance generate digital literacy gaps, which in turn produce algorithmic disconnection. This disconnection increases economic vulnerability and exposes policy inertia, ultimately reinforcing the original structural discrepancy. The cycle is cumulative rather than episodic.

The AGDT extends the structural analysis by integrating a generational dimension. It argues that externally driven AI diffusion, coupled with institutional lag, generates generational compression whereby youth must transition into AI-mediated labor markets without sufficient cognitive infrastructure or policy backing. As a result, adaptive pressures become disproportionately concentrated on Generation Z.

Together, the frameworks link macro-level institutional deficits with lived generational experience. Their contribution lies not in universal prediction, but in specifying observable mechanisms through which AI integration may reproduce stratification in resource-constrained contexts.

Moreover, existing theories are also reinterpreted through the unique perspectives of Nepalese youth involvement in this sector, as the rise of AI is slowly integrating into their socio-economic lives. These two new models are presented below.

i. Algorithmic Exclusion Cycle (AEC) Theory

The Algorithmic Exclusion Cycle (AEC) Theory examines how existing disparities in education, infrastructure, and public policy perpetuate a cycle of exclusion, particularly affecting marginalized youth in developing nations undergoing digital transformation. This theory analyses the relationship between structural inequalities and the rapid integration of artificial intelligence (AI) technologies, highlighting how these factors collectively reinforce the socio-economic conditions of young populations. In simple terms, this theory describes a feedback loop where prevailing dissimilarities based on education, infrastructure, and policy have prevented many citizens of developing countries with similar conditions to Nepal from gaining unbiased access to AI. As AI systems become more embedded in society, they further eliminate those who don't have access, strengthening the algorithm and digital divide in a repetitive cycle.

Below are the six sequential and reinforcing phases of this AEC Theory that elucidate the multifaceted impact of artificial intelligence on societies working for their digital advancement. These phases underscore the combined effects of algorithmic disconnection, economic challenges, institutional shortcomings, and socio-cultural dynamics, including the transmission of disadvantage across generations and evolving societal norms. By examining these stages, the model offers a comprehensive insight into how AI unintentionally intensifies the existing inequalities, thus broadening the digital literacy gap and embedding systemic exclusion.

The six-stage AEC model provides a powerful lens to interpret Nepal's stagnation in AI readiness. The secondary data do not merely list problems; they map precisely onto this reinforcing loop.

- **Stage 1 (Structural Discrepancy) & Stage 2 (Digital Literacy Gap): A Foundational Feedback Loop.**

The data in Table 2 and the analysis of Nepal's ICT/STEM education rates are not just indicators but the primary ignition points of the AEC. The co-existence of patchy network coverage and low digital literacy creates a population that is connected but not capable. This directly fuels Stage 3 (Algorithmic Disconnection). For instance, a young person in a rural area may have sporadic 3G access (meeting a basic "digital divide" metric) but, lacking algorithmic literacy, cannot engage with AI-driven job portals, digital governance services, or online skill platforms. Their connectivity is rendered meaningless by the literacy gap, functionally excluding them from the algorithmic layer of society (Yu, 2020). This is the core mechanism of the 'readiness deficit' illustrated in Figure 1.

- **From Disconnection to Vulnerability: Stages 3, 4, and 5.**

The economic implications (Stage 4) are evident in the labor market analysis. The vulnerability of Nepal's youth is less about immediate mass unemployment from AI and more about the 'skills mismatch' and entrenchment in the informal "precariat" (Standing, 2011). The secondary data from the World Bank (Demombynes et al., 2025) and Chakravarty et al. (2019) show that vocational training can increase non-farm employment. However, without concurrent progress in Stages 1-3, this training risks being outdated for an AI-evolving market. This mismatch is a direct outcome of Stage 5 (Policy Idleness), where national AI and digital policies (Prasain, 2025) lack the granularity, budget, and implementation mechanisms to synchronize infrastructure rollout, curriculum reform, and industry needs. The policy, while aspirational, fails to break the cycle.

Stage 5 (Intergenerational Entrenchment): The Looming Outcome. The most critical analytical insight from applying the AEC is its predictive power regarding long-term inequality. The data on digital skill disparities by geography and gender (UNESCO, 2023) are not static snapshots but the inputs for the next cycle. Parents without algorithmic literacy cannot guide their children's digital development; schools without resources cannot build foundational AI competencies. This sets the conditions for the next generation to enter the AEC at an even greater disadvantage, solidifying a caste-like technological class system. The AEC thus transforms descriptive data points (low literacy, poor infrastructure) into a dynamic model of systemic failure.

a. Scope and Conditions of this Theory

The AEC theory applies to developing nations undergoing a positive digital transition, where AI technologies diffuse more rapidly than the expansion of digital infrastructure. It is also applicable in countries with uneven digital literacy rates across socio-economic groups in both rural and urban areas, and where policy-making bodies are slow to adapt to technological disruption.

b. Principal Supposition for this Theory

Artificial intelligence tends to amplify existing social and economic inequalities unless it is guided by inclusive and responsive public policy. For people to meaningfully engage with AI in their daily lives, they need both adequate access to technology and a sufficient level of digital literacy. When individuals or communities are excluded from AI-enabled systems, the disadvantages they face often accumulate over time, creating cycles that become increasingly difficult to break. At the same time, algorithmic systems tend to reward those who are already digitally privileged, allowing them to benefit more quickly and more consistently

https://doi.org/10.53056/njmsr-2026.9.1.001 https://www.nepjol.info/index.php/njmsr

than others.

c. Fundamental Scopes of AEC Theory

The AEC theory is grounded in several core concepts that collectively explain how digital transitions give rise to new forms of inequality. Structural discrepancy refers to the foundational differences in infrastructure, institutional capacity, and economic resources that shape how communities experience technological change. These disparities are reinforced by the digital literacy gap, which reflects the unequal distribution of the skills and competencies needed to navigate emerging digital and AI systems. As a result, many individuals experience algorithmic disconnection, which occurs when people are excluded from meaningful participation in systems such as e-governance platforms, employment-matching algorithms, and automated public services. This exclusion exacerbates economic vulnerability because limited adaptability to AI-driven labor markets and technologies increases the risk of job displacement, downward mobility, and income instability. The situation is further compounded by policy idleness, in which governments respond too slowly or insufficiently to the socio-economic challenges introduced by AI. Over time, these conditions contribute to intergenerational entrenchment, meaning that patterns of digital and economic marginalization are passed down from one generation to the next, thereby solidifying long-term inequality within developing societies.

Thus, AI-driven systems do not merely reflect pre-existing inequalities; they actively reproduce and intensify them. Structural barriers limit digital preparedness, leaving youth increasingly disconnected from algorithmic systems, which in turn amplifies economic vulnerability and exposes the shortcomings of policy interventions. This cycle becomes entrenched across generations unless it is intentionally disrupted through targeted strategies and interventions.

ii. AI-Generation Disparity Theory (AGDT)

The AGDT theory highlights a unique temporal crisis for Nepal's Generation Z. Forced to compete in a global AI-driven labor market while local institutions lag, this cohort faces a "structural disadvantage" defined by five key pillars:

a. Externally Driven Diffusion (EDD): AI is an external imposition rather than an internal evolution, reshaping the job market before domestic systems are ready.
b. AI Uptake Adaptation Gap (AUAG): A widening chasm exists between ambitious national policies (like the Digital Nepal Framework) and the stagnant reality of local curricula and infrastructure.
c. Generational Technological Burden (GTB): Youth must self-fund and self-teach to remain 'AI-ready', leading to significant socio-economic stress.
d. Institutional Support Deficit (ISD): Public institutions fail to provide the cognitive infrastructure or AI literacy, a gap exacerbated by the rural-urban divide seen during COVID-19.
e. Socio-Technological Marginalization (STM): Without access to high-value AI sectors, youth are pushed into unstable, low-skill gig work.

Ultimately, AGDT illustrates how global trends intersect with local limitations to produce generational disadvantage, leaving Generation Z to navigate an uneven digital landscape without sufficient institutional support.

V. The Interplay of AEC and AGDT

The AEC and AGDT frameworks are not statistically tested within this study. Rather, they are abductively constructed mid-range explanatory models derived from patterned secondary evidence. Their empirical validation requires future longitudinal and primary data research.

The Algorithmic Exclusion Cycle (AEC) elucidates the internal and systemic mechanisms of exclusion by demonstrating how structural deficiencies within Nepal generate and perpetuate a self-reinforcing cycle of socio-technical disadvantage. In contrast, the AI-Generation Disparity Theory (AGDT) accounts for external and generational dynamics by explaining why technological transformation is experienced with disproportionate intensity by contemporary youth.

https://doi.org/10.53056/njmsr-2026.9.1.001 https://www.nepjol.info/index.php/njmsr

When considered together, these frameworks suggest that Nepal's Generation Z is positioned at the intersection of structural inequality and accelerated technological transition. The AEC explains how institutional and infrastructural deficits reproduce exclusion, while the AGDT clarifies how externally driven AI diffusion concentrates adaptive pressures on younger cohorts.

Secondary evidence concerning urban–rural disparities, gendered digital skill gaps, and labor market informality can be interpreted as patterns consistent with these theoretical mechanisms. Rather than functioning as isolated findings, these patterns serve as diagnostic indicators of structural breakpoints within both the exclusion cycle and the generational adaptation gap.

Accordingly, the AEC and AGDT are proposed as mid-range theories rather than predictive or universally generalizable theories. Their contribution lies in linking macro-level structural inequality with generational lived experience, offering context-sensitive analytical tools grounded in Nepal's socio-economic realities.

To validate the AEC and AGDT frameworks, future empirical research should employ a Mixed-Methods Longitudinal Design:

Phase	Objective	Suggested Metric/Instrument
I. Quantitative	Measuring the 'Algorithmic Divide'	Correlation between fiber-optic density and AI-tool proficiency scores among Gen Z.
II. Qualitative	Mapping 'Employment Anxiety'	Semi-structured interviews focusing on 'AI-induced career pivoting' in the Kathmandu Valley.
III. Policy	Assessing 'Policy Inertia'	A comparative content analysis of the Digital Nepal Framework vs. actual STEM budget allocations (2019–2024).

Conclusion

The intersection of artificial intelligence (AI) and socio-economic transformation presents both significant risks and opportunities for Generation Z in developing nations such as Nepal. Rather than advancing individual-level causal claims, this study synthesizes institutional reports, policy documents, and secondary empirical evidence to identify recurring structural patterns shaping youth engagement with AI.

The transition into an AI-driven global economy represents a critical juncture for the Global South. This study has demonstrated that for Generation Z in Nepal, the 'Algorithmic Divide' is not merely a technical hurdle but a systemic socio-economic trap. By introducing the Algorithmic Exclusion Cycle (AEC) and the AI-Generation Disparity Theory (AGDT), this research provides a mid-range theoretical lens to understand how structural deficits and institutional inertia converge to create a new class of 'Digital Precariat'.

The findings suggest that the current trajectory of digital development in Nepal is characterized by hardware-centric growth and 'connectivity without competency' is insufficient. Without a fundamental shift toward Socio-Technical Alignment, the rapid diffusion of AI will likely widen existing inequalities rather than bridge them. The proposed strategic model emphasizes that breaking the exclusion cycle requires more than just infrastructure; it demands a radical reimagining of the social contract between technology, education, and governance.

Ultimately, this paper serves as a theoretical foundation for future empirical inquiry. While the 'Methodological Validation Roadmap' provides the tools for testing these models, the urgent call to action remains for policymakers. To ensure that Generation Z in Nepal and similar developing contexts are participants in, rather than victims of, the AI revolution, the state must move from a posture of 'Policy Inertia' to one of 'Adaptive Governance'. The future of national stability in the 21st century may well depend on how effectively these algorithmic barriers are dismantled.

Recommendation

1. **Pre-Infrastructure Algorithmic Literacy Education:** Implement digital literacy programs in schools with minimal connectivity to address foundational

https://doi.org/10.53056/njmsr-2026.9.1.001 https://www.nepjol.info/index.php/njmsr

skill gaps.

2. **Adaptation Bridge Program for IT Vocational Training:** Align vocational training with AI-driven labor market requirements to reduce skills mismatch.
3. Generational Impact Metric: Integrate a 'Generational Inclusion Index' into all digital infrastructure projects to address persistent urban–rural disparities.
4. **Nepali-Language AI Sandbox:** Launch open-source AI initiatives in Nepali, including NLP and agricultural tools, to support context-appropriate, locally relevant innovation.

References

Acharya, T. (2025). Digital inequalities in media education during COVID-19 in Nepalese private and public colleges. *Journal of Vishwa Adarsha College (JOVAC), 2*(1), 17–40. https://www.nepjol.info/index.php/jovac/article/view/83870/64059

Asia Pacific Centre for Technology in Education. (2022). *Educational technology and capacity building in Asia Pacific: Challenges and opportunities.* APCTT Press. https://apctt.org/

Baxter, G., & Sommerville, I. (2011). Socio-technical systems: From design methods to systems engineering. *Interacting with Computers, 23*(1), 4–17. https://doi.org/10.1016/j.intcom.2010.07.003

Bulathwela, S., Pérez Ortiz, M., Holloway, C., Cukurova, M., & Shawe Taylor, J. (2024). Artificial intelligence alone will not democratize education: On educational inequality, techno-solutionism, and inclusive tools. *Educative Digital Transition: New Sustainable Learning Approaches from Other Techno logical Realities, 16*(2), 781. https://doi.org/10.3390/su1602078

Casas, J. (2024, July 31). AI could eliminate up to 5% of jobs in Latin America, study finds. *Reuters.* https://www.reuters.com/technology/artificial-intelligence/ai-could-eliminate-up-5-jobs-latin-america-study-finds-2024-07-31/

Chakravarty, S., Lundberg, M., Nikolov, P., & Zenker, J. (2019). Vocational training programs and youth labor market outcomes: Evidence from Nepal. *Journal of Development Economics, 136*, 71–110. https://doi.org/10.1016/j.jdeve co.2018.09.002

Chand, M. B., K.C., S., & Maharjan, M. (2024). Unveiling disparities: A case of digital divide in Nepal. *The Journal of Economic Concerns, 15*(1), 130–142. https://doi.org/10.3126/tjec.v15i1.70246

Demombynes, G., Langbein, J., & Weber, M. (2025, February 18). AI's impact on jobs may be smaller in developing countries. *World Bank Blogs.* https://blogs.world bank.org/en/investinpeople/AI-impact-on-jobs-may-be-smaller-in-developing-countries

Eder, M., & Sjøvaag, H. (2024). Artificial intelligence and the dawn of an algo rithmic divide. *Frontiers in Communication, 9,* 1453251. https://doi.org/10.3389/fcomm.2024.1453251

Gasser, U., & Almeida, V. A. F. (2023). *Algorithmic literacy in education: Principles and practices.* Springer. https://link.springer.com/book/10.1007/978-3-031-18880-0

Gordon, F. (2019). Review of *Automating inequality: How high-tech tools profile, police, and punish the poor* by V. Eubanks. *Law, Technology and Humans, 1*(1), 162–164. https://doi.org/10.5204/lthj.v1i0.1386

Ignatius, S. (2025, April 3). Study says more women than men in Africa will likely lose outsourcing tasks to AI. *AP News.* https://apnews.com/article/7b6a83e5592f78de9c0d38da97f9fbff

KC, A. (2025). Nepal youth digital skills: Future of work & national prosperity. Gurkha Technology, Nepalese Economic Concern Society (NECS). https://gurkhatech.com/youth-digital-skills-nepal/

Mukherjee, A., & Sarma, A. (2022). Innovation, transfer and diffusion of Fourth Indus trial Revolution (4IR) technologies to catalyze sustainable development in Asia Pacific. United Nations Asian and Pacific Centre for Transfer of Technology. https://repository.unescap.org/server/api/core/bitstreams/7913b309-1e45-4fc8-8d0a-afd3cc79378b/content

Nepal, S. K. (2024). Toward the integration of behavioral sensing and artificial intelligence. *CORE.* https://core.ac.uk/download/617915643.pdf

OECD. (2001). *Understanding the digital divide.* OECD Digital Economy Papers, (49). OECD Publishing. https://doi.org/10.1787/236405667766

Peiwen, C., Sulaiman, N., & Zhenglong, S. (2025). A systematic review of AI's impact on employment and skill demand. *International Journal of Research and Innovation in Social Science (IJRISS), 9*(15), 484–507. https://doi.org/10.47772/IJRISS.2025.90400185

Pilling, D., & Murray, C. (2024, October 17). Can AI help Africa close the development gap? *Financial Times.* https://www.ft.com/content/bdab80fe-e800-4c1c-926d-a6faa750cd57

Prasain, K. (2025, August 16). Nepal rolls out ambitious AI policy. *The Kathmandu Post.* https://kathmandupost.com/money/2025/08/16/nepal-rolls-out-ambitious-ai-policy

Salleh, M., Mahbob, N., & Bahuridin, N. (2017). Overview of "Generation Z" behavioral characteristics and its effect towards hostel facility. *International Journal of Real Estate Studies, 11*(2). https://www.semanticscholar.org/paper/8f05f2efba8c598185826f56678b25b1d58df50b

Srinuan, C., & Bohlin, E. (2011). Understanding the digital divide: A literature survey and ways forward. In *Proceedings of the 22nd European Regional Conference of the International Telecommunications Society (ITS).* International Telecommunications Society. https://www.econstor.eu/bitstream/10419/52191/1/672623358.pdf

Standing, G. (2011). *The precariat: The new dangerous class.* Bloomsbury Academic. https://doi.org/10.5040/9781849664554

UNESCO. (2023). *Global education monitoring report 2023: Technology in education: A tool on whose terms?,* United Nations Educational, Scientific and Cultural Organization. https://www.unesco.org/gem-report/en/publication/technology

Van Dijk, J. A. G. M. (2017). Digital divide: Impact of access. In *The International Encyclopedia of Media Effects, 1*(1), 1–11. https://doi.org/10.1002/9781118783764.wbieme0043

Yorke-Smith, N. (2020). Review: Responsible artificial intelligence: How to develop and use AI in a responsible way (book review). *Prometheus, 36*(3), 299–302. https://starlab.ewi.tudelft.nl/papers/r29.pdf

Yu, P. K. (2020). The algorithmic divide and equality in the age of artificial intelligence. *CORE.* https://core.ac.uk/download/346470889.pdf