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# A New Theoretical Framework for Analyzing the Social and Economic Impacts of Artificial Intelligence Within the Digital Economy

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**Abstract**

*The integration of artificial intelligence (AI) into the digital economy has profoundly transformed business operations and public services. However, this technological advancement has also intensified structural disparities, disproportionately impacting vulnerable groups such as low-skilled workers, micro and small enterprises (MSMEs), and communities with limited access to digital infrastructure. This study aims to construct a new theoretical framework to analyze the social and economic consequences of AI adoption, with a particular focus on digital marginalization. Using a qualitative case study approach, the research employs literature reviews and document analysis, grounded in five sociological theories: Social Stratification, Social Inequality, Social and Cultural Capital, Modern Stratification, and Network Society. The findings reveal that AI implementation predominantly benefits individuals and groups with higher levels of digital literacy and access, while further excluding those lacking technological capital. This leads to the emergence of digital stratification as a new layer of inequality within the AI-driven economy. The proposed conceptual framework provides an interdisciplinary lens to assess the broader social impacts of AI, and serves as a foundation for developing more inclusive and justice-oriented AI policies. By linking classical sociological theory with contemporary digital realities, this study offers a novel analytical model for evaluating technological equity and social inclusion in the era of artificial intelligence.*

**Keywords**: *Artificial Intelligence, Digital Stratification, Inclusive Policy, MSMEs, Technological Exclusion.*

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## I. INTRODUCTION

The rapid evolution of artificial intelligence (AI) has remapped the contours of the digital economy. From finance and manufacturing to retail, AI is celebrated for enhancing productivity, automating routine processes, and accelerating decision-making (Shamsuddoha et al., 2025). The benefits, however, are not evenly distributed, reinforcing prevailing socio-economic disparities. Imbalances in digital infrastructure, skewed technological literacy, and asymmetric institutional support are especially pronounced in the emerging economies (Asongu et al., 2024).

Empirical evidence demonstrates that big companies possess structural advantage in embracing AI, with ample capital, digital infrastructure, and access to skilled human resources. Yet, MSMEs are plagued by poor digital infrastructure, weak access to finance, and absence of regulatory guidelines (Siswanto & Aqdam, 2024; Wibowo et al., 2024). Consequently, economically disadvantaged groups, particularly low-skilled workers and those in the informal sector, are

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systemically excluded from AI-driven transformation (Hidayat et al., 2025; Susatyono et al., 2024). These inequalities raise questions about digital stratification and the propagation of structural inequality in the era of the digital.

Previous research has mainly addressed the economic and technical dimensions of AI, stressing its potential role in business innovation, automation, and efficiency (Malatji & Tolah, 2024; K. H. Wang & Lu, 2025; Zong & Guan, 2024). Dominant paradigms of technological determinism and innovation diffusion have yielded insightful explanations but tend to downplay broader sociological processes (Challoumis, 2025; Moura et al., 2024; C. Wang et al., 2025). More specifically, issues of labor displacement, reduction of worker autonomy, and socio-digital exclusion are under-theorized, despite increasing relevance in policy and academic discussions (Choi & Leigh, 2024; Passalacqua et al., 2025; Zirar et al., 2023). The challenge of integrating these technological advancements into social frameworks remains an area of active research.

To address the said research gaps, this study aims to create a novel interdisciplinary framework that combines both sociological and technological approaches in understanding the socio-economic impacts of AI. It looks specifically at how unequal access to AI technologies exacerbates or mitigates structural inequality among marginalized communities and MSMEs. Furthermore, the study examines manifestations of digital marginalization through qualitative document analysis, and it draws theoretical and practical implications informing inclusive digital policy making and equitable AI adoption strategies (Das, 2025; Djatmiko et al., 2025; Mac Fadden et al., 2024). This approach seeks to provide a foundation for developing policies that reduce the digital divide.

Although nascent literature has started examining the social implications of AI, much research is still conceptually limited and underpinned by empirical realities. Theorizations of inequality are either disjointed or technocratic, not questioning the structural power relations underlying AI adoption. Specifically, there is scant investigation of how digital inequality is realized through class, access, and institutional asymmetry. These lacunae are outlined in the Table 1.

**Table 1. Gap Analysis**

| Analysis Gap | References |
|---|---|
| Limited research explores how unequal access to AI may contribute to increasing social inequality. | (Bulathwela et al., 2024; Robertson & Maccarone, 2023) |
| Few studies investigate how AI adoption might reduce job opportunities and affect income distribution, beyond discussions of efficiency and automation. | (Abrardi et al., 2022; Khogali & Mekid, 2023) |

To address these gaps, this study proposes four research objectives. First, it aims to construct a novel theoretical framework that integrates both technological and sociological perspectives to

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better understand AI's socio-economic impacts. Second, it investigates how unequal access to AI technology may reinforce or mitigate structural inequality, particularly among MSMEs and marginalized populations. Third, it examines real-world manifestations of digital marginalization using qualitative case study methods. Fourth, it gives actionable policy recommendations to support digital inclusion and equitable AI adoption.

The study draws on an interdisciplinary theoretical synthesis of (Castells, 2023; Grusky, 2022; Liu, 2025; Lybeck et al., 2024; Mökander & Schroeder, 2024)' sociological contributions to investigate how AI articulates with labor, institutions, and capital. Unlike previous models that consider technology as a neutral force, the model here draws attention to how the spread of AI is conditioned by power relations and social hierarchies. Based on qualitative document analysis, the study investigates how digital exclusion is experienced and negotiated by vulnerable economic actors. This approach challenges traditional perspectives by emphasizing the role of socio-economic structures in shaping technological adoption.

This research has two main contributions to existing literature. Theoretically, it develops an emergent conceptual framework for making sense of where AI-enabled change intersects with structural inequality in the digital economy. Analytically, it discerns access, agency, and resilience as determining forces shaping the distributional effects of AI. These contributions not only enhance theoretical debate but also inform inclusive policy for equitable digital transformation.

## II. LITERATURE REVIEW

This research departs from the assumption that the adoption of artificial intelligence (AI) in the digital economy does not only influence efficiency and productivity, but also fundamentally influences society with grave social consequences, particularly expanding social and economic inequality. In order to understand the complexity of this influence, this study draws on five main sociological theories: Social Inequality Theory (Liu, 2025), Social Stratification Theory (Mökander & Schroeder, 2024), Social and Cultural Capital (Lybeck et al., 2024), Modern Stratification (Grusky, 2022), and Network Society Theory (Castells, 2023). Each theory provides a different perspective to examine how AI can perpetuate or create new social inequality in the digital era. AI-driven systems are not developed or deployed in neutral contexts but often reflect the interests and values of dominant economic actors.

### A. *Theory of Social Inequality* (Liu, 2025)

Liu theory is premised on the conflict between the owners of the means of production and the laborers. Currently, AI exists as a "new tool of production" in the hands of big corporations and digital elites, while workers and MSMEs might not have equal chances to access this technology. This results in a higher concentration of economic power among a select few, bringing about new structures of domination in the digital age (Liu, 2025). This condition reflects Liu's concern about how technological tools reinforce existing capitalist structures and reproduce class-based inequalities.

B. *Social Stratification Theory* (Mökander & Schroeder, 2024)

Mökander extended the arena of inequality examination to non-economic dimensions such as social standing, power, and access to resources. With respect to AI, education level and occupational position are the most critical variables in gaining access to and utilizing technology. Therefore, people with lower educational levels and lower internet connectivity lag behind in the digital economy (Mökander & Schroeder, 2024). Such disparities indicate that the benefits of AI are often limited to those who already possess social privileges and institutional support.

C. *Social and Cultural Capital* (Lybeck et al., 2024)

Robin Lybeck explained that achievement in a social organization is not merely dependent on economic capital, but social capital (web of relationships), cultural capital (customs and expertise), and symbolic capital (social prestige). MSMEs and people from disadvantaged areas in an AI-based digital world lack this kind of capital, and therefore competing in the digital world is difficult (Lybeck et al., 2024). Limited exposure to digital culture also reduces the ability of these groups to navigate online platforms effectively. Without strong networks or cultural familiarity with digital systems, their participation remains minimal or peripheral.

D. *Modern Stratification Theory* (Grusky, 2022)

Grusky points out the emergence of new forms of labor stratification due to digitalization and automation. Workers with digital or AI skills gain higher ranks and wages, while others who do not obtain these skills risk being replaced by machines and losing their employment. This scenario widens the digital class gap and increases income inequality (Grusky, 2022). This shift has reshaped the structure of the labor market, emphasizing credentialism and technical specialization over traditional work experience.

E. *Network society Theory* (Castells, 2023)

Castells formalized the concept of a network society, in which economic possibility and power are distributed according to one's connection within a global digital network. Without access to the internet, technology or digital competencies, people are more and more excluded from economic participation in the mainstream (Castells, 2023). For AI, digital connectivity is the primary requirement for being able to participate in economic life. Digital disconnection not only

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limits economic opportunity but also reduces individuals' capacity to engage with civic and social life.

## III. METHODOLOGY

To This research applies a qualitative research design with case study methodology in examining the socio-economic impacts of Artificial Intelligence (AI) among vulnerable groups within the digital economy. Case study design permits intensive study of complex social phenomena, particularly inequality, technology access, and the position of MSMEs and low-skilled employees. The study is based on interpretive analysis from secondary sources of data such as academic journals, policy briefs, institution reports, and empirical studies between 2015 and 2024. This methodology allows the researcher to explore in-depth contextual dynamics that influence AI adoption in specific socio-economic settings.

### *A. Data Collection and Document Selection*

Data were collected using purposive sampling of documents that are: on the topic of AI and inequality; published by well-known academic institutions, international organizations (Bank, 2025; IMF, 2024; OECD, 2023; UNDP, 2022), or peer-reviewed journals; and English or Indonesian language availability. The documents collected total 42, which are theoretical articles on digital capitalism, empirical studies on AI adoption in MSMEs, and policy overviews on labor change through automation. The selection criteria ensured that only documents with high credibility and relevance were included in the analysis. These documents represent diverse viewpoints, allowing for comprehensive thematic exploration across different sectors and geographies.

### *B. Thematic Coding and Analytical Process*

Thematic analysis was used to analyze the texts. The coding process involved a series of steps: initial open coding to expose repeated patterns; axial coding to situate themes in wider sociological concepts (e.g., digital stratification, informational capitalism); and selective coding to map relations between themes against the proposed theoretical framework. Analysis was facilitated by NVivo software to ensure maximum consistency and traceability. This structured coding process helped identify not only recurring ideas but also underlying power dynamics present in the texts.

### C. *Validation and Reflexivity*

To ensure analytical strength, themes were validated using source triangulation and iterative comparison against available sociological theory. Theoretical saturation was reached when no new themes were found across sets of documents. Researcher reflexivity was maintained by recording coding choices and an audit trail of interpretive choices. The approach is grounded in constructivist epistemology, acknowledging that the researcher co-constructs meaning through contextual interpretation of texts.

## IV. RESULT AND DISCUSSION

### *A. Result*

This study analyzed qualitative secondary data by thematic coding and sociological analysis to uncover the impact of artificial intelligence (AI) uptake on socio-economic structures in the digital economy. Data were extracted from government publications, global statistics, and inter-disciplinary literature, and analyzed through theory-informed classification. The main variables for study are: (1) access to digital technology and infrastructure, (2) automation and labor transformation through AI, (3) MSME participation in the AI ecosystem, and (4) power dynamics in the digital economy. The selection of these variables reflects the interconnectedness between technological adoption and socio-economic positioning across sectors.

The findings reinforce that integration of AI, in the absence of inclusive frameworks, amplifies existing structural inequalities. Access to AI is especially incredibly uneven between regions and economic agents. Marginalized groups such as rural areas and MSMEs are materially and symbolically excluded, vindicating (Lybeck et al., 2024) social and cultural capital theory. In addition, automation will prefer high-skilled workers and displace lower-skilled workers, a process well in agreement with (Yang et al., 2023) class conflict theory and (Zajko, 2022) digital stratification theory.

In line with (Castells, 2023) network society theory, this research notes that digital infrastructure plays a substantial role in determining who gets included to participate and gain from the AI economy. MSMEs, although economic cornerstones in many local economies, are often excluded on account of limited financial, technical, and human capital. Concurrently, AI innovation and domination increasingly concentrate in the hands of a handful of tech giants, reproducing informational capitalism dynamics (Castells, 2023) and ownership of capital (Liu, 2025). The alignment between the study's key findings and the sociological theories used is summarized in Table 2.

**Table 2. Relationship between Research Findings and Sociological Theories**

| Main Theme | Description of Findings | Applied Theory |
|---|---|---|
| Unequal Access to AI | AI-driven automation benefits high-skilled workers while displacing low-skilled laborers with limited reskilling opportunities | Social and Cultural Capital Theory – (Lybeck et al., 2024) |

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| | | |
|---|---|---|
| Labor Shifts and Class-Based Inequality | AI-driven automation benefits high-skilled workers while displacing low-skilled laborers with limited reskilling opportunities | Class Conflict Theory – (Liu, 2025); Digital Stratification – (Grusky, 2022) |
| MSME Exclusion from the AI Ecosystem | MSMEs face challenges in adopting AI due to financial and technological limitations | Network Society Theory – (Castells, 2023) |
| Centralization of Digital Power | Control of AI technologies is concentrated among digital elites and large corporations, potentially marginalizing social justice concerns | Capital Ownership and Informational Capitalism – (Castells, 2023; Liu, 2025) |
| Development of an Interdisciplinary Framework | A new theoretical model is built by integrating classical and contemporary sociological theories to analyze digital power dynamics | Combined Theories: (Castells, 2023; Grusky, 2022; Liu, 2025; Lybeck et al., 2024) – forming a new interdisciplinary theoretical framework |

Cumulatively, evidence corroborates the hypothesis that AI uptake, in the absence of inclusive policies, reinforces structural inequality and generates novel digital stratification. The theoretical rationale underlying these findings forms the basis for theory formulated in this study an interdisciplinary model combining classical and contemporary sociological theories to investigate processes of digital exclusion, power concentration, and stratification in the digital economy. The integration of multiple theoretical traditions allows for a more comprehensive understanding of how AI systems interact with existing socio-economic hierarchies. This model is illustrated in Figure 1, which presents a thematic map synthesizing these theoretical perspectives and their relationship to the key variables

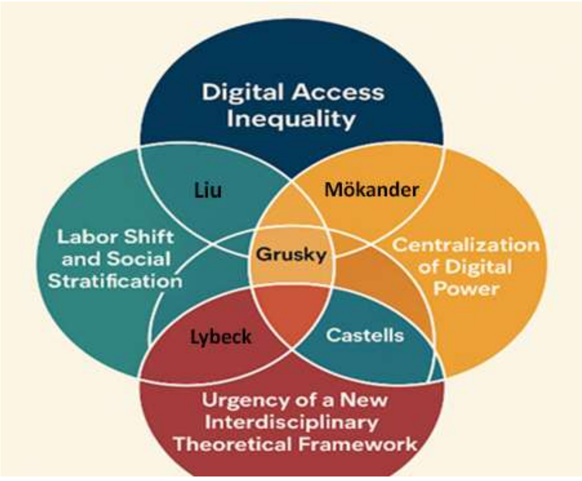


**Figure 1. Thematic Map Of The Relationship Between Ai And Socio Economic Inequality**

Figure 1 illustrates the theoretical framework synthesizing these themes and connecting them to sociological ideas borrowed from (Castells, 2023; Grusky, 2022; Liu, 2025; Lybeck et al., 2024; Mökander & Schroeder, 2024). Rather than running in parallel understandings, the figure demonstrates how these theories intersect to account for AI-induced inequality. (Liu, 2025) class conflict, for example, is supplemented by (Castells, 2023) informational capitalism, and Bourdieu's capital forms condition how digital literacy and infrastructure access are disproportionately distributed. Building on this conceptual foundation, Figure 2 provides a more detailed representation of the interdisciplinary framework, outlining the theoretical lenses, key variables, and measurement indicators used in the study.

| Sociological Theory | Key Variables | Measurement Indicators |
|---|---|---|
| **Lybeck**<br>Social & Cultural Capital | Access to AI & digital literacy<br>Social capital for AI adoption | • Level of digital education<br>• Participation in AI training<br>• Ownership of digital devices |
| **Liu**<br>Class Conflict & Ownership | Ownership of digital means of production<br>Economic disparties from AI | • Ownership of AI pliatiforma. servers or sytems<br>• Ownership of user data<br>• Reskilling access for workers |
| **Castells**<br>Network Society | Connectivity and digital participation<br>Digital exclusion | • Availability of internet infrastructure<br>• Density of active digital users<br>• Participhant in e-commerce |
| **Grusky**<br>Labor Stratification | Changes in job structure<br>Skill stratification | • Skill gap between AI vs. non-AI workers<br>• Participation in training programs |

**Figure 2. Interdisciplinary Framework for AI and Inequality: Theoretical Lenses, Key Variables, and Measurement Indicators.**

In order to illustrate the disparity in access to AI across enterprise size, Table 3 indicates the extent of AI adoption by multinational corporations versus MSMEs in urban and rural settings. The data show that multinational corporations overwhelmingly dominate high-level AI access, while MSMEs, especially in rural areas, lag significantly behind. This discrepancy reflects the structural barriers faced by smaller enterprises such as limited capital investment, low digital infrastructure, and lack of skilled human resources. These figures highlight how enterprise size and location influence technological integration and participation in the digital economy.

**Table 3. Share of AI Access Between Large Enterprises and MSMEs**

| Business Category | High AI Access | Low AI Access |
|---|---|---|
| Multinational corporation | 82% | 18% |
| Urban MSMEs | 36% | 64% |
| Rural MSMEs | 17% | 83% |

This evidence suggests that the greater the gap in access to AI, the more it contributes to widening digital exclusion and entrenching social inequality. Applying (Lybeck et al., 2024) theory of

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cultural capital, those who lack access to digital literacy are likely to be excluded from the digital economy. (Liu, 2025) work regarding the control of the means of production is also relevant, specifically in demonstrating how technological control by major corporations fuels growing class disparity. Access to digital tools and education shapes the ability of individuals and groups to participate effectively in economic and social activities.

(Grusky, 2022) points out the emerging new trends of labor stratification as a result of AI, particularly in terms of displacing low-paid labor. (Castells, 2023) further adds the dimension of network society in which power increasingly relies on connectivity who is in and who is out. These comments point towards the need for inclusive digital policy and the construction of new theoretical thinking that can accommodate today's social realities under the dynamics of AI. The development of digital infrastructure and connectivity determines which communities can engage with emerging technologies and benefit from them.

### *B. Discussion*

The findings of this study show that AI adoption in the digital economy reinforces rather than reduces social inequality. This supports (Liu, 2025) view that technological capital remains concentrated among dominant actors, worsening class divisions. The exclusion of MSMEs and low-skilled workers also aligns with (Lybeck et al., 2024), who stressed the importance of social and cultural capital. These dynamics confirm that AI is not a neutral tool but part of broader systems of social reproduction.

Compared to earlier works, this study extends discussion on the layered effects of AI on digital stratification. (Grusky, 2022) described new forms of labor hierarchy caused by automation, consistent with this study's findings on worker displacement. (Castells, 2023) highlighted the role of network connectivity, which is confirmed here by evidence of exclusion linked to weak infrastructure. Unlike studies focused on efficiency gains (e.g., (Zong & Guan, 2024)), this research offers a sociological critique of unequal technology distribution.

The analysis also reveals that uneven AI adoption is not only linked to digital literacy but also to institutional support and policy. While (Moura et al., 2024) emphasized cultural perceptions, this study shows that financing and governance barriers are more decisive. Digital inequality persists even in communities with basic AI awareness, stressing that systemic issues outweigh individual limitations. This highlights the importance of examining policy-level factors alongside cultural ones.

The implications are both theoretical and practical. Theoretically, the framework bridges classical theories of inequality with current debates on AI and stratification. Practically, the results support inclusive policies such as reskilling programs and subsidized AI for MSMEs, echoing (Djatmiko et al., 2025). Reducing these inequalities is vital not only for social justice but also for sustainable economic participation.

16 Despite its strengths, this study has several limitations. The reliance on secondary qualitative data restricts the generalizability of the findings across industries and regions. In addition, the absence of direct fieldwork or primary validation limits the ability to capture localized experiences of digital exclusion. These constraints should be considered when interpreting the results and the proposed theoretical framework.

## 1 V. CONCLUSION AND RECOMMENDATION

This study shows that the adoption of artificial intelligence (AI) in the digital economy amplifies existing inequalities rather than reducing them. By integrating classical and contemporary sociological theories, it develops an interdisciplinary framework that explains how technological capital, labor stratification, and digital connectivity shape unequal participation. Notably, the findings reveal that AI adoption is not a neutral process but one embedded in structural power relations, leaving MSMEs and low-skilled workers at a disadvantage. As a result, the study
8 reframes AI not simply as a driver of innovation but as a force that reproduces inequality in the digital economy.

In practice, these findings call for inclusive strategies such as reskilling programs for vulnerable workers, subsidies for MSME adoption, and investment in rural digital infrastructure. Governance frameworks must also mitigate algorithmic bias and prevent excessive concentration of digital power. Future research should build on this framework using mixed methods and cross-country
3 evidence, ensuring a more comprehensive understanding of AI's socio-economic impacts. Such efforts will help align AI development with equity, social justice, and sustainable digital participation.

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