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Artificial Intelligence, Labor Market Transformation, and Income Inequality: Examining the Economic Impact of Automation in Developing Economies

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ABSTRACT

In developing economies, artificial intelligence (AI) - powered automation is changing the patterns of employment, skill needs and income distribution. Automation has the potential to enhance productivity and create new employment opportunities, but can also reduce routine jobs, increase job polarization, and exacerbate inequalities. This qualitative study analyzes the impact of automation driven by artificial intelligence technologies on labour markets in developing economies, particularly with respect to job loss and creation, skill transformation, wage polarization, the rise of informal employment and labour-market institutions. The study takes an interpretivist qualitative stance, employing a method of documentary and secondary data analysis of recent academic literature and authoritative reports, and analyzed by applying thematic analysis. Five inter-related themes emerge: labour-market institutions and social protection; the importance of employment restructuring; changing skill needs; wage and income polarization; and vulnerability of informal workers. Based on the analysis, it is not expected that the introduction of AI will yield a one-size-fits-all employment impact, but rather one that is contingent on the technology's adoption, workers' skills, economic systems, and institutional capabilities. The lack of infrastructure, skills and social protection, along with informality, pose especially severe problems for developing economies, as they can limit the ability of workers to access technologically transformative opportunities. The study brings a holistic perspective to the relationship between inequality and AI automation and puts forward the call for investment in digital infrastructure, skills development, worker protection, and labour market policies to ensure inclusive outcomes.

Introduction

Bullying Artificial Intelligence (AI) has become a growing part of the economic revolution of modern societies. Machine learning, generative AI, robotics, and automated decision-making are transforming the way companies operate, from structuring production to providing services, handling information, and assigning tasks. These technologies are crucial for developing economies, for whom labour market developments frequently involve a high level of digital activity and a large informal sector, weak technological capacity and significant disparities in skills and productive resources. In this sense, AI is both a mixed economic opportunity, in that it can enhance productivity and generate new jobs, but also a reconfiguration of jobs and a potentially exacerbating factor of inequalities, where workers and firms are not equally able to keep up with technological change (Cazzaniga et al., 2024). (IMF)

AI and employment are not as straightforward as "robots will take the place of humans.The connection between AI and work is not a simple one for one. Modern AI can replace specific functions in jobs without taking the jobs themselves. While some jobs may be more exposed to generative AI than others, in many occupations, the potential for generative AI is more to enhance human work rather than to supplant it in its entirety (Gmyrek et al., 2023), according to the International Labour Organization (ILO). The distinction is significant because technological change can cause a change in the nature of the work done by workers, in the skills they need, and in the value of the various types of work without necessarily giving rise to mass unemployment. This can then lead to a reorganisation of work around increased human–automated interaction.

Concurrently, the risk of forced migration must not be ruled out. AI can take over or help with repetitive cognitive functions, paperwork, customer service, data analysis, content creation, and more tasks that were previously human-centric. As the effects can be especially severe when companies implement an automated system solely to save money, and not to provide support for human workers. This incipient literature, then, is marked with a significant tension. One approach focuses on the labour productivity, creativity and invention of new jobs and jobs, while the other is on loss of leverage, a decline in bargaining power and the unequal distribution of technological gains. The results will not be uniform as they will be shaped by institutions, occupational systems, skills, firm skills and the general economic environment.

This tension is directly linked to pay and income distribution. Previous rounds of automation have often been linked to a polarization in the labor market within some economies, with routine and middle-skilled jobs being lost. With AI, the situation is a little different since AI increasingly can do cognitive things in addition to what is routine. The distributional impacts can thus vary by the complementarity or substitution of AI to various groups of workers. Cazzaniga et al. (2024) suggest that AI may also exacerbate labor-income inequality, as it could benefit high-wage labor more than low-wage labor, and higher returns to capital can also lead to greater wealth inequality. Meanwhile, if productivity increases are large enough, they could boost the incomes of everyone. (IMF)

Such a lack of clarity makes it hard to really explain what AI is: an equalizer, or an inequality creator. The productivity gains can generate value, but the value distribution will depend on who owns productive assets, who has the relevant skills and which workers are in a better position to utilize AI. Adoption of AI can thus enhance the economic status of some workers, while harming the relative status of others. The problem is not just technology, it is the social and institutional context in which technological advances are realized.

These questions are particularly significant in shifting the focus from advanced to developing economies. There is existing international evidence that developing countries could be less exposed to immediate impacts of AI-driven automation as they have higher proportions of jobs in agriculture, informal, manual, and low-digital-intensity sectors. A greater share of jobs is potentially exposed to generative-AI automation in high-income economies than in low-income economies, which could be due to differences in occupational structure (Gmyrek et al., 2023; ILO, 2024). (International Labour Organization) This does not necessarily mean that developing economies are protected from technological disruption. Lower exposure can go hand-in-hand with lower capacity to benefit from AI.

In fact, a key question in the recent debates is who has access to AI preparedness and who doesn't. Digital infrastructure, reliable connectivity, computing capacity, education and technical skills, and institutional capacity are some of the areas where many developing economies are constrained. The IMF suggests that emerging and developing economies could suffer less than advanced economies in the short term and be less well-positioned to benefit from AI-induced productivity gains (Cazzaniga et al., 2024). The outcome can be a paradox: countries with lower levels of automation will have higher technological upgrading costs. It is essential that this distinction is made because there is exposure to AI and there is the ability to benefit from AI, and they are not one and the same.

The digital divide adds to this relationship. Access to AI should not come at a premium, otherwise workers will not be able to get the same benefits. There can also be substantial variations among firms in developing economies regarding their ability to implement AI solutions. Larger and more technologically advanced companies could have a greater capacity to invest in automation and skill development, while smaller companies and informal businesses might not have the financial and technical resources to do so. A recent ILO and World Bank study also highlights that the lack of digital infrastructure hinders developing economies in leveraging the productivity gains of generative AI (ILO & World Bank, 2024). (International Labour Organization)

Another layer to the problem is that of the informal sector. In many developing countries, a significant proportion of the population is engaged in informal work, which generally features low coverage of social insurance, formal training, employment protection and responses to technological change. AI-powered transformation can therefore happen without the safeguards afforded to many in formal employment. Informality and unequal working conditions continue to be central issues for inclusive employment and social justice (ILO, 2024). From a qualitative standpoint, the economic significance of AI is intertwined with the institutional fabric of work organization.

It would, however, also be problematic to depict developing economies as just vulnerable victims of technological disruption. AI can offer solutions to overcome historic productivity hurdles and facilitate new economic activities. Where infrastructure and skills exist, digital services, AI-assisted entrepreneurship, remote working, technology enabled agriculture, financial services, education, health services and other applications may offer opportunities. The World Bank's latest report also highlights that the promise of AI in developing economies could be significantly greater as a tool for augmenting human workers and increasing the productivity of current tasks, rather than merely displacing them. (World Bank)

So it is not a question of whether AI will create or destroy jobs; rather, it is a question of how it will impact them. It's about the circumstances that make specific things more likely. How economically meaningful AI becomes is determined by a variety of factors, including skills development, education, digital infrastructure, labor institutions, social protection, access to technology, and the ability of firms to reorganize work. Both ILO and UN have called attention to the fact that if AI development is not matched by investments in human capabilities, it can exacerbate existing inequalities in the world (ILO, 2024). (International Labour Organization)

While there has been an increase in research on AI and the future of work, there is a significant gap in research. A substantial amount of research is available that estimates the impact of occupational exposure, the potential for automation, productivity impacts or income impacts. This is useful but quantitative exposure indicators do not capture all of the meanings of AI-driven transformation in various economic and institutional settings. Specifically, less focus has been paid to the interconnections between automation, informal jobs, skills, technology access, labour market transformation and inequality in developing economies. International studies are increasingly revealing a wide variety of occupational makeup, AI readiness, and ability to leverage AI exposure into productivity across these economies (ILO & World Bank, 2024; ILO, 2026). (International Labour Organization)

A qualitative lens can help advance this discussion by shifting the focus from the question of "how many jobs are affected by AI" to a broader understanding of the role of technological change in patterns of opportunity, vulnerability and economic inequality in work. An interpretivist approach is especially suitable as AI effects are not scripted. Different stakeholders may visualize automation in different ways, depending on their context, available resources, expectations and economic situation. An understanding of such interpretations can help explain the differences in consequences of similar technologies in different labor markets.

In this context, the present study considers the implications of AI-enabled automation for the reshaping of the labour market and for potential changes in income inequality in developing countries. It is oriented towards the relationship between job displacement and job creation, towards the transformation of skills and occupations, towards productivity, toward wage distribution, towards informal employment, towards digital inequality and towards access to technological opportunities. The study does not make an implicit claim that there is a universal trajectory of AI-driven development, but rather aims to make sense of the current literature and identify common themes, tensions, and contextual variations.

The study will be directed by three general research questions: How is AI/automation transforming employment, skills, and wages in developing economies and how is it impacting the organization of work? What do technology access, institutional conditions, and labor market structures look like in relation to opportunities and risks of using AI? When could AI be a factor of greater inequality, and when could it be a factor of greater inclusive productivity and employment? The study does so qualitatively, offering a contextual understanding of the transformation of the labour market in the context of AI and identifying the importance of social, economic and institutional factors that will influence the distributional impacts of automation as well as technological capability.

The rest of the article summarizes existing scholarship, details the qualitative methodology and documentary approach, summarizes key themes that arose from the analysis, explores their relevance to the labor market and inequality, and finally outlines policy and research avenues for more inclusive economic growth with AI.

Literature Review

Artificial Intelligence and Automation

Artificial intelligence (AI) is transforming the nature and structure of work by taking automation beyond repetitive physical work tasks to cognitive, analytical and communication tasks. While the lines between humans and machines are blurring with the advent of machine learning and generative AI capabilities like writing, coding, information processing, customer service, translation, and decision support, many industries are increasingly seeing a blurring of the lines between the two. The current discussion is not about "replacing" people with machines, but about what machine functions will be automated, what will be supported and enhanced by machines, and how work will be reorganized around machine capabilities. The International Labour Organisation (ILO) notes that while many occupations are likely to be transformed through human–machine interaction, this is unlikely to lead to the disappearance of many occupations (ILO, 2025). (International Labour Organization)

This view is consistent with the view of technological change that focuses on the task, rather than the occupation as a whole (task-based approach to technological change). An occupation can thus include very automatable tasks as well as tasks that demand judgment, creativity, interpersonal interaction, or contextual knowledge. The difference is significant since the amount of exposure to AI alone is not necessarily a sign of job loss. The ILO – World Bank evidence released in 2026 also separates out the potential for automation from augmentation, revealing that, overall, the developing economies have a lower aggregate exposure to GenAI automation than the advanced economies, though they have significant potential for task augmentation (ILO & World Bank, 2026). (International Labour Organization)

AI is therefore identified in the literature as a disruptive technology, as well as an organizational change process. AI can transform the way people work as well as how they are being measured, how decisions are taken and how companies deploy human and technological assets. Algorithmic management, for instance, may be a new way to supervise and control the workplace, as well as have the potential to enhance coordination and efficiency (ILO, 2025). The impact of AI goes beyond automation to the transformational effects on work relationships.

Job Displacement, Job Creation and Labour-market Transformation

The biggest controversy is whether AI will be a net job destroyer or net job creator. A displacement perspective focuses on the fact that companies are encouraged to use AI when it can complete tasks cheaper, faster and with greater consistency than humans. Administrative, clerical, data-processing and other some professional routine activities may, therefore, be increasingly exposed. However, assuming only displacement ignores the possibility of technological change generating new work, new jobs, and new complementary roles.

New international data, however, points to a more nuanced picture. While the potential for these four effects to be achieved at the same time, the IMF points out, is contingent upon technological complementarities and institutional arrangements, the net effect of AI is predicted to be a reduction in employment, a rise in productivity, and the generation of new jobs.The net impact of AI is expected to involve a decline in employment, an increase in productivity, and the creation of new jobs, with the balance depending on the extent of technological complementarity and institutional conditions (Cazzaniga et al., 2024). The ILO argues that widespread transformation is more likely than universal automation, as there are various jobs that have significant work that still relies on human capacity. (IMF, 2025) (International Labour Organization)

Exposure and displacement is a methodological challenge in the literature. Not all occupations that are highly AI-exposed are occupations that will be without jobs. AI can be leveraged to boost employee efficiency, enhance production volumes, enhance service quality, or introduce new tasks, among other capabilities. Thus, forecasting employment loss from occupational exposure alone would be an incorrect estimate, since adoption rates, organizational adaptation, worker response and the development of new tasks are all important.

Skills, Human–AI Complementarity, and Worker Adaptation

The value of labor market skills is also changing with the help of AI. Digital literacy is gradually evolving to include skills in using AI for interaction, data analysis, critical thinking, problem-solving, creativity, and oversight or feedback on AI-powered systems. This extension of “skill-biased-technological change” is consistent with the notion that technological innovation tends to boost the demand for workers with complementary skills.

But AI can generate a more intricate pattern than previous technologies, as highly educated workers don't necessarily escape from automation. Some highly educated workers could be exposed to more of generative AI while simultaneously having more opportunities to be augmented by generative AI. According to the IMF analysis, college-educated workers will likely be more exposed to AI but may also have the potential to benefit more from it. (Cazzaniga et al., 2024) (IMF eLibrary)

This puts a tension between substitution and complementarity at the center. AI can augment workers and lead to higher productivity and new opportunities. In some cases, AI will replace employees, and that will lead to a reduction in employment and bargaining power. The ability of the workers to adapt becomes therefore essential. Whether workers embrace or are marginalised by technological change depends on training, life-long learning, organizational support and access to digital infrastructure. This is especially important in developing economies, where a lack of advanced digital competence could be a barrier to accessing jobs that complement the use of AI tools.

Artificial Intelligence, Wages, labour-market polarization and income inequality

One of the most debatable aspects of the literature is the distributional effects of AI. Previous studies on automation often highlighted routine-biased technological change, in which routine middle-skilled jobs were found to be especially sensitive, and were responsible for labour-market polarization between high-skilled and lower-skilled jobs. AI adds another layer of complexity to this pattern by influencing more and more non-routine cognitive processes.

The new literature indicates that this may lead to higher wage inequality, given that productivity gains may accrue to workers with the skills that AI is best suited for. Cazzaniga et al. (2024) contend that high-income workers may find themselves increasingly disadvantaged as AI gains greater importance in the future, as strong complementarities between workers and AI could boost labour-income inequality, and an increase in returns to AI capital will help perpetuate inequality of wealth. Simultaneously, AI could help diminish some levels of inequality by enabling less-skilled workers to get productivity-boosting help and learn the skills of more advanced workers.

Thus, AI does not have a predetermined distributional effect. The results of these effects are influenced by the possession of technological capital, by the bargaining power of the workers, by the availability of skill, by any wage-setting institution, and by the amount of sharing of productivity gains. The discussion on inequality should thus shift from the question of whether AI worsens inequality to how, and at which institutional conditions, inequality will come about.

AI, Informal Employment, and Developing Economies

With the developing economy context, the relationship between AI and employment shifts significantly. Labour markets are often highly informal in many developing economies and workers in such markets may not be part of extensive social protection, employment management, and training programs. These workers might initially start out with smaller direct exposure to the advanced era of AI as their work is mostly in areas that are much more in line with manual labour, personal services, agriculture, small scale business and other sectors that are less digitized.

The lower exposure of developing economies, however, is not necessarily a blessing. Differences in occupational structure mean that overall, the degree of automation exposure is generally lower in developing countries than in advanced economies, though there are also obstacles to harnessing productivity-enhancing opportunities from automation (ILO & World Bank, 2026). The net effect is a development paradox: the economies might face less short-term technological displacement, but not be better equipped to use technological augmentation.

Indirect impacts can also be particularly harmful to informal workers. Productivity gains from the use of AI by formal firms could have implications for the nature of subcontracting and wages, and for the demand for informal services. On the other hand, inexpensive AI solutions might assist tiny companies when it involves marketing, bookkeeping, translation, agricultural guidance, or accessing details. The effect will most likely depend on whether AI will be a tool for inclusion or another means of technological exclusion.

Digital Divides, Infrastructure, Skills and Disparities in Access

Access is a key enabler of the benefits of AI. The building blocks for the economic utility of AI are digital infrastructure, low-cost connectivity, electricity, computing power, relevant data, and a workforce. World Bank recognizes four key challenges to inclusive AI development: persistent gaps in connectivity, computing capacity, locally relevant data and digital skills. (World Bank)

This creates a significant difference between being exposed to AI and being ready for AI. For developing economies, the number of jobs that are directly affected by automation might be small, but with a lack of infrastructure and skills to benefit from AI in achieving productivity growth. The IMF thus recommends that developing and emerging economies should focus on digital infrastructure and digital skills within their AI strategies (Cazzaniga et al., 2024). (IMF)

The digital divide can consequently become an AI divide. Those who have access to technology can gain productivity benefits, whereas those who don't can become further disadvantaged. The ILO also advises that inequalities in technology, education, and infrastructure have the potential to exacerbate inequalities in the world through AI (ILO, 2025). This implies that technological inequality is not just a result of the adoption of AI, but could also affect who can even adopt and gain from AI in the first place.

Productivity gains, economic opportunities and inclusive development

While there are issues of inequality, the literature doesn't tell us to view AI solely in a bad light. AI can have a significant impact on boosting productivity, enhancing information and knowledge access, reducing transaction costs and enabling new types of entrepreneurship. In developing countries, more straightforward and context-specific uses of AI could enhance agricultural extension services, education, health, and financial services, as well as public administration, among other areas.

Recent World Bank studies highlight the potential for AI to provide major opportunities to the world's developing economies, partly because many applications can complement rather than replace workers. The World Bank's 2025 analysis also points to growing job demand for AI in middle-income economies, however, there are also geographic concentration of AI-related employment in high-income countries. (World Bank)

Distribution is the main hurdle in the way of the central challenge. Productivity growth does not necessarily lead to inclusive development. AI could exacerbate, rather than diminish, economic inequality if the bulk of the benefits are concentrated among firms, the owners of AI, the most highly trained workforce, or nations with the best technology infrastructure. Inclusive development needs mechanisms to make productivity translate into more jobs, better jobs, easier training to access, and better living standards.

AI Governance, Labour Policies, Social Protection and the Global South

The last theme that has surfaced in the literature is governance. Technological policy is not enough to handle AI's role in labour-market transformation. The distribution of technology benefits and burdens is shaped by a range of labour rules, education policies, social protection frameworks, tax regimes, competition policy, and digital technology infrastructure.

Labour-market policies that enable workers to be reallocated without harming those impacted, and fiscal policies that can strengthen the distribution of AI related gains, are all important, the IMF says (Cazzaniga et al., 2024). In developing countries, however, traditional policy advice might be hard to put into practice if social-protection coverage is low and administrative capacity is constrained. This emphasizes the need for institutional strengthening, especially.

The recent work of the ILO also highlights the importance of bridging digital gaps and making sure that the potential benefits of technology are more fairly shared by workers and countries (ILO, 2025). The future of work in the Global South's economy relies not just on the extent to which governments support AI adoption, but on their ability to ensure that technological change is conducive to decent work, worker voice, skills development and social protection.

Research Gap and Conceptual Foundation

Research on AI exposure, transformation of work, productivity and inequality has significantly advanced but there are still gaps in the literature. Many studies used in the literature make use of occupational exposure estimates, econometric modelling, productivity forecasts or scenario based forecasts. These are useful for examining potential patterns, but it will be difficult to draw conclusions about differences in experiences in the labour-market resulting from the interaction between various technological, institutional and social conditions. Especially, the developing-economy literature is still scattered, from digitalization, informality, skills, infrastructure, and inequality.

Another constraint is a tendency to view AI exposure as a measure of employment disruption. Recent evidence shows why this is problematic: exposure can lead to automation, augmentation, or restructuring of the organization, depending on the structure of occupations and the readiness for technology (ILO & World Bank, 2026). When analysing developing economies, it is necessary to take into account both aspects of the transformation: the risk of exclusion and the risk of displacement, as well as the potential for productive inclusion.

This debate may be advanced by an interpretivist qualitative synthesis, which can consider the constructions and explanations of these relationships in the current literature and in documents. Instead of focusing on the number of jobs that might be affected by AI, the current study focuses on what AI-driven transformation means for employment restructuring, skill needs, informal labour, wages, inequality, institutional capacity, and economic inclusion. This allows for an understanding of the apparent paradoxes, e.g., lower automation exposure and lower AI readiness as interwoven aspects of transformation in developing economies instead of isolated results.

To sum up, the literature confirms the concept that AI is a conditional force of labour market transformation. It is affected by task characteristics, human–AI complementarity, workers' abilities, informality, infrastructures, institutional capacity, and distribution of technological capital. While AI can create productivity and jobs, this is not guaranteed and not necessarily equalized. On the other hand, automation can create job displacement and inequality – but so can that be avoided. The main question is how the economy and institutions influence the diffusion of technology into widespread benefits. This conceptual framework is used here to inform the current qualitative study of not just how AI transforms employment, but how it shapes the labour market, income, and development within a structural framework that is influenced by conditions of adoption and governance.

Research Methodology

Research Design and Philosophical Position

This study uses an interpretivist qualitative approach to explore the impact of Artificial Intelligence (AI)-based automation on labour markets and income inequality in developing economies. Because the study is about more than just the volume or scale of technological change, it is suitable to take an interpretivist approach, which focuses on the ways in which technological change, restructuring of the labor market, changing skills, and inequality are interpreted in different economic and institutional settings. The study does not assume AI leads to a general economy-wide labour-market outcome, but rather sees technological change as specific and contingent to the interplay of labour, firm, institutional, skill, infrastructure, and economic structures.

Interviews, questionnaires, participants, experiments and primary fieldwork are not involved in the study. Rather, it adopts a documentary and secondary data research method, which is the interpretation of current knowledge in the scholarly and institutional fields in order to gain a contextualized understanding of AI and labour-market transformation. This is especially suitable due to the significant differences between advanced and developing economies in exposure to AI, technological readiness, skills, and capacity to reap productivity gains, as evidenced by the current data (Cazzaniga et al., 2024). (IMF)

Data Sources and Search Strategy

The documentary corpus has been developed in a systematic way, using databases from Scopus, Web of Science, Google Scholar, Science Direct, Springer Link, Taylor & Francis, Sage and JSTOR, while, for authoritative documents, the International Labour Organization (ILO), the World Bank, the International Monetary Fund (IMF), and the United Nations agencies have been used. The sources chosen were those that would ensure a blend of peer-reviewed research and authoritative international studies in the areas of employment, technological change, inequality, digital development and public policy.

Searches involved using a variety of terms together: “artificial intelligence” and “generative AI”; “automation” with “labour market,” “employment,” “labour market outcomes” and “job loss”; “job creation” with “skills” and “wages” or “income inequality” and “informal employment”; “developing economies” and “Global South”; “digital divide” and “productivity”; “social protection” and “skills.” Boolean combinations were employed when possible, per individual database. Studies published from 2020 to 2026 were given particular consideration, as this time period is particularly relevant for the fast-paced evolution of contemporary AI technologies; however, seminal theoretical and methodological studies were retained when they were needed to provide conceptual foundations.

Recent international assessments confirm the importance of documentary evidence. Exposure to AI is also unevenly distributed across occupations and socio-economic groups, with ILO's 2025 analysis indicating that AI is expected to complement human capabilities in many occupations rather than be expected to fully replace them as an immediate result. Likewise, the recent ILO–World Bank study notes variability in how advanced and developing economies are exposed to automation and how they may be augmented by it (ILO & World Bank, 2026). (International Labour Organization)

The inclusion/exclusion criteria for this study have not been established

Documents were included if they responded to four main conditions: that they were directly relevant to AI, automation, employment, labour market transformation, skills, wages, inequality, productivity or related policy issues; (2) that they were substantive to developing, emerging or comparative global contexts; (3) that they were published through a credible peer-reviewed academic outlet or through an authoritative international institution; and (4) that they provided enough methodological or conceptual information to be interpreted critically.

Studies were dropped if they were not relevant to labour-market or distributional concerns, the study was primarily promotional or commercial in nature, it duplicated another study, it was not sufficiently scholarly or institutional in nature, or it was primarily oriented toward technical AI research without discernable implications for employment or economic change. Opinion pieces and media reports did not count as substantive evidence, except in cases where these are used only to provide context to a substantive debate that has been documented.

Thus the selection was based upon the conceptual relevance and not numeric representation. This matches the interpretationist goal of the study in which meaning is sought, tensions identified, and some kind of explanation drawn from the literature is sought, not an overall statistical effect estimated.

Data collection involves gathering and analyzing data from documents

Potentially relevant publications were identified following database searches and then selected for further screening based on title, abstract, key words and, if required, full text. The relevant documents were then sorted by their contribution to the research questions. Studies on the role of evidence on AI-driven automation, job displacement and job creation, new skills, complementarity and synergies between humans and AI, wage polarization and income inequality, informal employment, digital inequality, productivity and social protection systems received special attention.

The analysis was an intentional separation between exposure to AI and genuine job loss. This distinction is relevant for the method and is crucial as an occupation can include activities which are technically exposed to the use of AI without the occupation itself becoming obsolete. An important recent ILO study specifically accounts for task-level variation when estimating potential impacts of GenAI (ILO, 2025). Likewise, the International Monetary Fund (IMF) views both displacement and productivity-enhancing complementarity as possible consequences of the use of AI (Cazzaniga et al., 2024). (IMF eLibrary)

There was no automatic hierarchy of documents within institutions. Instead, their claims were put under the microscope alongside of peer-reviewed scholarship. For instance, World Bank data highlights the need for connectivity, computing power, locally relevant data, and digital skills as key prerequisites for inclusive AI uptake in developing economies (World Bank, 2025). This evidence was interpreted in the context of academic debates on technological complementarity, labour-market polarization, human capital and inequality.

Reflexive Thematic Analysis

The data collected were analysed in two phases using reflexive thematic analysis as developed by Braun and Clarke (2021). This approach is especially suited to an interpretivist methodology, where themes are not seen as waiting to be found in the documents, but rather they emerge as a reflexive and active process of interaction between the researcher, the documents, and the research question(s). Braun and Clarke highlight the interpretative and theory-oriented aspects of reflexive thematic analysis. (SAGE Publishing)

The analysis was carried out in six consecutive steps which are interrelated. To get to know the literature the researcher repeatedly read the selected academic and institutional documents and took notes on common arguments, contradictions, contextual differences, and important concepts. Second, initial code was produced on statements and arguments related to issues of employment, skills, wages, inequality, informality, infrastructure, productivity, and policy in relation to automation. Thirdly, the related codes were analyzed to produce themes. Fourth, the themes were checked for the coded material and the general documentary collection to see if they created analytically useful patterns. Fifth, themes were developed, figured and given names to express the core interpretive thrust of each theme. Lastly, the themes were synthesized into an integrated analysis, to answer the research questions.

The analysis did not exclude conflicting information. AI wasn't programmed as just a job-killer, for instance, or a job creator. Rather, evidence on substitution, augmentation, productivity and new jobs were compared to gain insight into the conditions under which various outcomes arise. Similarly, the developing economies were not seen as being either uniformly protected or vulnerable. New evidence indicates that they might have lower aggregate exposure to AI, but also have higher limitations in infrastructure, skills and technological preparedness (ILO & World Bank, 2026; Cazzaniga et al., 2024). (IMF)

Ethical considerations, reflexivity and trustworthiness

A number of strategies were used to enhance the credibility and reliability. Firstly, by combining peer-reviewed research and evidence from international organizations, source triangulation was carried out. Second, rather than being generalized from one country, claims were looked at in various economic and geographical contexts. Thirdly, contradictory findings were not excluded, but kept. Fourth, the analytical process was kept clear by tracking the flow of the argument from the identification of the documents to the coding, the development of themes, and the interpretation.

The concept of reflexivity was also a key element of the analysis. Given the interpretivist qualitative research approach, which acknowledges that the researcher plays a part in interpretation, the analysis necessitated constant scrutiny of assumptions regarding technological gains, automation, inequality, and economic development. Therefore, the researcher did not assume or take for granted either technological optimism or technological pessimism.

The study is based on only public scholarly and institutional documents and as such, the study did not include any human participants nor attempt to collect personally identifiable information. Ethical responsibility, however, cannot be ignored when it comes to representing the thoughts of the author accurately, quoting selectively or misrepresentatively, and properly citing sources in APA 7th-edition. Reports from the institutions were also subjected to critical interpretation but not treated as unquestionable empirical truth.

Methodological Limitations

The documentary design has a number of limitations. First, it fails to offer direct evidence of workers' lived experiences as there were no interviews or primary field observations conducted. Secondly, there is a wide range of variation in the definitions of AI exposure, automation, employment and developing economies in studies, which can make it difficult to directly compare the results. Third, as the field of generative AI is continually evolving, some of the findings here may become irrelevant as technologies and adoption trends shift. Fourth, published evidence is not evenly distributed by country, and this may lead to more visibility of economies that have a more robust research and institutional capacity.

The restrictions are not a flaw of the approach, but are a boundary on the claims that can be made. The study is not intended to provide causal estimates of the impact of AI on employment or income inequality. Rather, it offers the first interpretive synthesis of what the current evidence tells us about the processes, circumstances, opportunities and dangers of the AI-induced transformation of the labour market in developing economies. This methodological stance aligns with the study's aim of capturing AI as a socially and institutionally situated transformative process, not just a quantifiable technological impact.

Findings and Discussion

Thematic analysis of the academic literature and institutional documents selected was reflexive, which led to the identification of five themes related to the relationship between the use of artificial intelligence (AI) and the transformation of the labour market and the rise of income inequality in developing countries. This is a documentary and interpretivist study which means the findings presented in this study will be the analytically interpreted patterns found in the existing literature and secondary evidence, and not a primary observation, interviews, survey or outcomes measured by the author. The analysis shows that AI does not have a consistent labour market impact. Rather, its impact is shaped by the type of occupations, the extent to which AI and humans are complementary, workers' skills, availability of digital infrastructure, the share of informal employment, and the ability of labour market institutions to share technological benefits.

Theme 1: AI Is Changing the Nature of Work Through Tasks and Occupations

The first theme that comes from the documentary analysis is that AI is changing the nature of the employment content and organization, not replacing jobs. The difference is significant because exposure to technology does not necessarily mean that jobs are being lost. Modern AI systems are able to carry out specific tasks in an occupation, while other tasks rely on human judgment, communication, creativity, accountability, and contextual knowledge. The International Labour Organization (ILO) thus claims that generative AI will have a greater impact on many occupations than fully automate them, but there are marked differences in the exposure of occupations and groups of workers (ILO, 2025).

This is in line with task-based conceptions of technological change, which explain that the technologies impact on a given task but not necessarily on an occupation. Clerical and administrative tasks, such as processing information, drafting documents, organizing paperwork, or managing routine communications, can involve significant information manipulation, drafting, classification, and routine communication, which can be supported and potentially automated by AI. However, workers can still engage in work activities that involve interpersonal relations, interpretation, supervision, decision making and responsibility. One key aspect of the importance of AI is the redistribution of functions between humans and machines.

Another important tension is that of technological substitution versus technological complementarity that is revealed in the documentary evidence. From one side, businesses can use AI to streamline processes, standardise them and cut down on labour.From the other side, organisations can apply AI to decrease labour needs, standardise processes, and cut down on costs. On the other hand, companies can leverage AI to enhance the efficiency of their current employees and open up new opportunities for them. The IMF's analysis also highlights that AI can lead to job losses and productivity gains, depending on the nature of the jobs and current institutional settings (Cazzaniga et al., 2024).

The separation is especially significant for the developing nations. Their employment patterns tend to have higher shares of agricultural, manual, service and informal employment than advanced economies. These activities might not be as exposed to generative AI in the short term. The IMF concludes that, overall, emerging-market and developing economies are less exposed to AI than advanced economies (Cazzaniga et al., 2024). But less exposure does not necessarily equate to developmental benefits.

The analysis points to a more complex explanation: lower exposure to AI might be partly due to technological readiness. In areas with less economic activity in low productivity sectors and less robust digital systems, fewer workers may be directly impacted by AI since there are fewer tasks that are digitally mediated in the first place. This can, at the same time, result in reduced threat of immediate displacement and reduced access to productivity-enhancing technology, without automation.

It is a key paradox in the literature. The reason for this is that developing economies' economies are less digitized, so are the workers and firms, and AI may therefore be less disruptive there, at the same time as the very same structural conditions may make it more difficult for workers and firms to realize the potential productivity gains from AI. The question isn't just how many occupations are exposed to AI; it's how exposure to technology relates to the structure and quality of jobs.

The results also indicate that organizational decisions are very important. This same AI can have various effects when an employer adopts it to replace workers, to supplement workers, to have a more intensive effect, or to generate new services. AI can, therefore, transform the nature of the job for workers, affecting their autonomy, workload, expectations of performance, and bargaining power. This is a broader definition that shifts the focus from automation to work reorganisation.

Theme 2: Skills and Human–AI Complementarity: Does technological change provide opportunity

The second theme is that of skills, re-skilling and human–AI complementarity. The literature examined reveals that AI is transforming the value of current skills and creating new demand for synergic blends of technical and human skills. Digital literacy, analytical thinking, critical evaluation, problem solving, creativity, communication, and effective interaction with AI systems are becoming a demand of workers.

But the link between skills and AI exposure is not as straightforward as the conventional notion of the low-skilled worker being the one most at risk. AI exposure can be significant for highly educated workers, as many of their occupations are cognitively and information-intensive. Meanwhile, they might also have a more robust opportunity to adopt AI as a supporting technology through their education. Cazzaniga et al. (2024) contend that higher educated workers are likely to be exposed to more AI, but also have more opportunity to be complementary.

This introduces exposure/vulnerability separation. Exposure is about the scope of tasks that can be technically impacted by AI, vulnerability is about the resources available to workers to address technological change. An opportunity to gain exposure to increase productivity may happen to a highly educated professional who has access to AI tools and organizational training. A limited skill digital worker might feel a smaller technological intervention as disruptive as they have no resources to adapt to it.

The documentary analysis thus argues for the complementarity between humans and AI not just as a technical characteristic of a job. It is a social and institutional state as well. The key is that when workers have access to the right technologies, training, support and opportunities to use new capabilities, they become complementary to AI.

This is a special concern in developing economies. World Bank (2025) has listed connectivity, computing power, data and digital skills as important enabling elements for AI adoption and use. Summarizing, AI's potential for creating widespread productivity improvements depends on the capabilities and infrastructure of workers.

The analysis also debunks the notion that reskilling equals the creation of more AI experts. While knowledge of advanced technical skills is essential for developing economies, broader occupational relevance for mass labour-market adaptation might be achieved by acquiring AI literacy, critical thinking, digital problem-solving, and transferable skills. Don't worry, AI is not just for AI engineers, it can help people in various other fields of work, including agriculture, education, health, administration, manufacturing, and small businesses.

This discovery has significant meaning for inequality. AI-complementary skills could further strengthen the existing division of the labour market if they are concentrated among workers already ahead. However, if AI-enabled learning and training becomes more common, AI may narrow some of the productivity divides by providing tools to less experienced workers that were previously only known to them through their own experience.

The evidence then suggests a situation where there is a conditional relationship between AI and human capital. But AI is not a reward to education, nor is it a disrupter of lower-skilled jobs. Instead, technological developments alter the returns to various types of human capacity. Distributional outcome hinges on the ability of the education and training systems to move a wide part of the workforce towards complementary activities.

Themes:3 AI has the potential to exacerbate wage polarization and income inequality due to differential productivity and bargaining power

The third theme is about the possible link between AI, wage polarization, and income inequality. The evidence reviewed suggests that while AI could generate more broad-based unemployment, it could also exacerbate inequality without doing so. This can happen if some workers, firms or capital owners benefit more than others from productivity increases and technological rents.

The IMF has pinpointed several channels by which AI can impact inequality. A higher level of wage premiums can increase where AI is complementing higher income workers. For the same time, the positive contribution of the investments involved in AI could further widen the inequality gap, as there are reasons to believe that capital owners could benefit more from technological progress (Cazzaniga et al., 2024).

This result complements previous discussions on the effect of skill-biased and routine-biased technological change. Past automation has led to fears of the loss of routine middle-skilled jobs and the polarization between high-skilled and low-skilled jobs. The advent of generative AI changes this trend as more and more activities are taken over by professional and cognitive work. This means that, no longer is AI usage only limited to people who work in repetitive, manual, or clerical jobs.

That's a very significant contradiction that the analysis uncovers. AI can simultaneously increase and decrease particular forms of inequality. On the other hand, it can provide low-skilled workers with some leverage in negotiating their salaries.It can, on one side, equip highly skilled workers with tools for boosting their productivity and bargaining power; on the other, it can provide some leverage to low-skilled workers in negotiating their wages. On the other hand, AI has the potential to improve the accessibility of some tasks for less-experienced employees, reducing productivity gaps. The final result will depend on how AI is implemented and who benefits from the implementation.

One of the key questions is, then, who benefits and who doesn't from increases in productivity. Increased worker productivity doesn't always lead to higher wages. In a scenario where workers have weak bargaining power, companies could end up with a large share of the benefits of their AI. Additionally, AI can reduce the proportion of compensation for the same amount of managerial oversight or performance, which may create a negative effect for managers.Also, AI could make the compensation for the same level of oversight or performance less proportional, creating a negative impact for managers.

This implies that the impact of AI on distribution is partially dependent on institutions and power dynamics of the labour market and not on technology itself. How technological gains are shared can be affected by collective bargaining, minimum-wage institutions, labour regulation, taxation, and social protection.

Income inequality is an international dimension, too. UNCTAD (2025) notes significant concentration of research and development, computing facilities and investment, and technological development in the field of AI throughout the world. This implies that the countries that develop and possess more sophisticated AI technologies will reap the benefits of technological value while the others will be more consumers of it.

The study then pinpoints at least two overlapping dimensions of AI inequality. Within-country inequality relates to the differences between workers, firms, skills groups and informal and formal sectors. The second is across-country inequality, which refers to disparities in the "technological capability" and the "availability of access to global AI value chains.

Importantly, the evidence doesn't lend support to the conclusion that “AI creates inequality.” Instead, the prevalence of inequality increases when technology and other skills, productive assets, and institutional bargaining power are highly unequal. The important question is therefore not only the number of jobs that are added or subtracted when jobs change but who benefits economically from the change in jobs.

Theme 4:Informality and the digital divide present a unique AI challenge for developing economies

The fourth theme brings together two highly intertwined aspects of a developing economy: the size of the informal sector and the digital divide. These traits appear to be those that keep some workers from being automated outright and avoid them from enjoying the productivity gains of AI.

The informal sector, which is frequently dominated by agriculture, small-scale businesses, personal services, transport, and construction, presents a low potential for the direct use of current generative AI tools. This will help to limit the risk of immediate exposure to automation. Informality is also often accompanied by limited access to formal education, social protection, credit, formal employment, and digital infrastructure.

Lower exposure does not necessarily imply lower vulnerability is, therefore, the case. In the absence of institutions to help informal workers adapt to changes in consumer demand, competitive conditions, or the productivity of formal firms, indirect economic impacts on informal workers may occur.

Meanwhile, the evidence shows that there are real opportunities for informal business and small enterprises. AI technologies may be able to assist marketers, translators, accountants, business planners, and with access to information and communication with customers. Small businesses and key services such as healthcare, education, and water supply are key sectors where relatively inexpensive AI applications can have a significant impact on developing economies, as highlighted by the World Bank (2025).

The focus of this central tension is therefore on AI as a tool for inclusion versus AI as an added layer of exclusion. The access is a major factor in the difference.

According to the World Bank (2025), there are four key pre-requisites for AI to be adopted: digital connectivity, computing power, relevant data, and digital skills. UNCTAD (2025) also points to significant differences in digital infrastructure, computing power and skills, and technological investment between advanced and developing economies.

As a result, the conventional digital divide is more and more being described as an AI divide in the thematic analysis. It's not always enough to have access to a basic internet connection. To participate in AI in a productive way, devices, connectivity, electricity, digital content with an appropriate focus and computational resources must be available, and skills in interacting meaningfully with AI systems are necessary.

This gives rise to an unexpected development paradox. In developing nations, exposure to AI-related automation could be at a lower level, but so too might be their capacity to enhance productivity through the benefits of AI. That is, low exposure in this instance can reflect, in part, structural underdevelopment (or lack of technological resilience).

This is especially important for small businesses. With large companies increasingly leveraging AI to cut costs, boost productivity, and reach new markets, there is a risk that small businesses may fall behind in their ability to access similar tools.As large companies increasingly adopt AI to cut costs, boost productivity, and reach new markets, the competitive inequality could further widen as small businesses may not be able to access the same tools. On the other hand, cheap AI could help smaller businesses gain access to knowledge and opportunities that were otherwise denied them.

This effect on informality is also qualified. AI can help informal workers reduce information and transaction costs, but it may also make it more competitive or change livelihoods. This is an affirmation of the overall conclusion that AI is not a single, uniform external shock. The impact it has is transmitted via the economic framework in which technology is adopted.

Theme 5: Labour Policy, Social Protection and Inclusive AI Governance Influence Technological Divides

The fifth theme shows that the impact of AI is ultimately mediated through institutions. The potential of technology is realized through the institution of labour, social protection systems, education policies, digital strategies and governance frameworks.

The research indicates that the developing economies must aim for a dual goal: promoting the use of AI in productive applications while safeguarding those who are facing a technological shift or disruption. The IMF highlights the necessity of setting up digital infrastructure, training, and labour-market policies that can help workers during labour-market transitions (Cazzaniga et al., 2024).

This is especially the case if AI changes employment arrangements, or reduces the demand for specific tasks. Mechanisms are required to enable workers to switch between jobs without suffering serious income insecurity. However, large informal sectors are often not covered by the traditional social-protection structures in place in developing economies, which poses a unique challenge for these countries.

This means that there is not only a need to rely on traditional labour regulation but also on other approaches if AI governance is to be inclusive. It should also tackle informal workers, small businesses, lack of access to technology, training systems and digital exclusion. Technological transformation impacts workers outside of the traditional employment framework as well, which is something policy needs to take into account.

Education and training policies are also relevant. Reskilling is not the responsibility of individuals only. There are complementary pathways to building skills for workers which are the responsibility of firms, governments, education and international organisations.

The importance of international governance also is emphasized in the analysis. UNCTAD (2025) highlights the centralisation of AI development and highlights the lack of technological capacity of many developing economies. There is a risk that countries which continue to be consumers of AI technologies could be less influential on data, technology, standards, and economic value creation rules.

This creates a form of governance inequality: developing countries could suffer from economic effects of AI, but lack commensurate ability to influence the technologies and institutions that give rise to the effects.

Thus, an inclusive approach needs to shift the debate on AI governance away from the questions of algorithmic safety and privacy and extend it to questions of jobs, distribution, infrastructure, skills, ownership and development. AI policies must promote tools and technologies that augment human capabilities, increase access to productive inputs and facilitate greater sharing of productivity.

Overall Synthesis and Discussion

These five themes all suggest that labour market transformation in developing economies is not a foreseeable technological development, but a conditional process driven by AI. Neither side of the argument is supported by the evidence found in this documentary.

The first theme confirmed that the impact of AI is mostly on task and the way work is organized, and they urged to separate the exposure from the actual displacement of jobs. The second showed that the interaction of skills and human-AI complementarity is a significant driver of the nature of the exposure as an opportunity or a vulnerability. The third found that inequality can arise from differential productivity growth, wage impacts, ownership of capital and power in bargaining even in the face of relatively stable total employment. The fourth showed how informality and digital exclusion can reduce developing economies' capacity to leverage opportunities related to AI. Last but not least, the fifth demonstrated that institutions shape the distribution of technological costs and benefits.

These results contribute to theory as they help to reinforce a task approach to technological change, which views technology as complementary. Don't think of AI as a magic bullet that will produce the same results in every place. It affects the occupation, human resource, organizational choices, infrastructure, institutional capability and economic resources.

The results also challenge traditional views of the process of labour market polarization. The root cause of inequality can also be the presence of technologically excluded workers and firms, as AI leads to the loss of jobs from routine work. Therefore, future studies should be more focused on the distribution of technological capabilities, as opposed to focusing on occupational exposure.

The analysis results in four policy priorities for the developing economies. The first step is to build digital infrastructure and affordable connectivity. Secondly, it is necessary to build AI-related, digital, analytical and transferable skills in education and training systems. Finally, social-protection systems should offer meaningful support on the labour-market transition, including for those in informal jobs. Fourth, there must be linkages between technological policy and labour, education, industrial, competition and social policies.

The overriding policy message is that one should not only judge the value of AI based on velocity or the sophistication of technology. In fact, it is more important to understand who gains from the adoption of technology. Productivity gains that are happening for capital owners and high-skilled workers could boost overall output, but also exacerbate inequality. AI, on the other hand, can help to foster inclusive development by supporting small businesses, enhancing public services, expanding knowledge, and complementing work.

Overall, the qualitative results indicate that developing economies have a unique dilemma related to AI. What they lack in immediate pressure from automation, they have in reduced capacity to reap the benefits of productivity. The challenge now is not just to protect workers from AI, but to develop the skills needed to be part of an AI-powered economy.

The core of the study is thus to move the discussion about AI from “Will AI replace workers?” to something more contextual, such as: “Under what technological, economic and institutional conditions can AI transform work without exacerbating income inequalities?” The evidence in this document indicates that the answer to this question lies in the ability of developing economies to make AI a more widely-usable productive resource instead of a concentrated technological capability. This cannot be done with technology, but through concerted investment in skills, infrastructure, social protection, labour institutions and inclusive governance. AI can boost productivity and create wider economic opportunity when conditions are right, and further consolidate inequities in job access, income, skills and economic power when conditions are not.

Conclusion

The economic impacts of AI are increasingly a central topic in today's changing labour markets, but the story of its impact on both job creation and job destruction, and its effect on productivity, is far from straightforward. This qualitative research used an interpretive approach and reflexive thematic analysis of current academic and institutional reports to explore how AI-enabled automation relates to the labour-market transformation and income inequality in developing countries. This analysis identifies AI as a technology that, rather than replacing jobs, transforms the distribution of tasks, skills, productivity, jobs, and economic power. How it works depends on the structure of work, capabilities of workers, organizational strategies, digital infrastructure, labour market institutions, and access to social protection. By focusing on the social, institutional, and contextual processes by which technological change can be a potential opportunity or vulnerability, this interpretation addresses an important gap in predominantly quantitative studies of AI and employment.

The results suggest that the way work is structured and how it is done is the main way in which AI is changing employment. While certain repetitive, information-driven activities are more vulnerable to automation, using AI should not be viewed as a risk of a job being completely taken over. In many instances, AI can augment human workforce in tasks such as information processing, analysis, communication, decision making, etc. The International Labour Organization (ILO, 2025) also notes that generative AI will impact, but not replace, a range of occupations. This distinction has special significance for the developing economies where the employment structure varies significantly from advanced economies. Mixed results in the sense of lower aggregate exposure to AI could then be interpreted as lower degree of digitalization and technological capacity. This means that developing economies are grappling with a dual challenge: safeguarding workers against negative displacement while also developing capacities to gain from AI-driven productivity gains.

The second key finding is the increasing role of skills and human-AI complementarity. The analysis reveals that the impact of technological change on workers' experiences is not just about whether the jobs are being impacted by AI, but also whether the worker has the skills and/or resources to work with new technology and technology in their job. The skills of digital literacy, analytical reasoning, critical thinking, creativity, problem-solving, communication, and occupationally relevant AI skills are becoming increasingly essential for surviving the evolving job market. The IMF has also pointed out that AI can simultaneously put workers at risk of displacement and offer opportunities for complementarity and productivity improvements (Cazzaniga et al., 2024). In developing countries, investing in education and reskilling should not be seen as a follow-up to automation, but as an integral part of economic development. The challenge is not to make all workers AI specialists, but to facilitate and inspire productive and meaningful participation of workers in every occupation in AI.

The study also ends that AI has important ramifications for wage polarization and income inequality. Technological advancement can boost productivity, but at the same time generate unequal economic results for those who have advanced skills, for firms with a higher technological capacity, and for AI-related capital owners. As Cazzaniga et al. (2024) note, AI could boost the productivity of capital, while replacing highly skilled workers, exacerbating income and wealth disparities. Meanwhile, AI can equip less-experienced employees with skills that previously required more experience, opening opportunities to close some of the productivity gaps. The impacts of AI on the distribution of goods and services are thus not necessarily foretold. They rely on access to technology, skills, productive resources and on the distribution of technological progress via labour-market institutions. This discovery brings a change of focus from measuring job creation or destruction to the quality of jobs, bargaining power, productivity distribution and technological value ownership.

These dynamics are further complicated in the developing country context given the fact that there is a high level of informal employment and that digital inequalities are still present. Although the use of AI is wide-ranging, informal workers might be exposed to it less directly as many of their informal activities are traditionally linked to physical, interpersonal, agro and small-scale commercial activities. But, lower exposure does not equate with higher economic security. Formal training, social protection and finance are less available to informal workers, as are stable jobs and the digital infrastructure, making it harder for them to adapt to wider technological and market changes. On the other hand, cost-effective AI tools could open up new avenues for informal businesses and small enterprises by facilitating better communication, marketing, information retrieval, translation and business management. World Bank (2025) notes that key elements of productive AI adoption include connectivity, computing power, relevant data, and digital skills. That's a sign that the traditional digital divide is becoming the AI divide, where access to infrastructure and capabilities divides those who can take advantage of AI-enabled economic opportunities.

The results then highlight the importance of labour-market institutions, social protection and inclusive AI governance. AI is not enough to scope the inclusive development. The conditions need to be established for workers to cope with the transformation of technology without the imposition of unequal economic costs on them by governments and institutions. It needs investments in digital ecosystems, accessible education and training, social-protection mechanisms, labour-market transition policies, and digital infrastructure. These measures are especially crucial in developing economies, where workers may not be covered by traditional protection mechanisms due to the prevalence of informal employment or the limitations of the institutional framework. UNCTAD (2025) also notes the disparities in AI capabilities, infrastructure, investments, and technological resources that exist between countries. AI governance should not be limited to the technical sphere but should also address issues of job creation, skills, economic growth, technological control and international inequity.

As an idea, the study will help to provide a more contextualized understanding of technological change by synthesizing task based approaches with technological complementarity, labour-market polarization and institutional perspectives. AI cannot be regarded as a standalone entity that has the same effects in all societies. These effects are mediated by economic structures, human capabilities, organizational choices and institutional arrangements. This is especially important in the case of developing economies, as their technological paths diverge significantly from those in the more advanced economies. The results of the study have practical implications for policymakers: not just preventing job loss, but also enabling workers to gain from AI. The companies should make sure to work responsibly with AI, invest in competence development and ensure a fair sharing of productivity gains, and governments must bolster the institutional frameworks required to make technologies inclusive.

This study has some limitations. Because it is a documentary and secondary evidence based collection, it doesn't reflect workers' daily experiences, employer decisions or country-specific processes of implementation. Developing economies are also quite diverse and its findings should not be understood as if it were equally applicable in all national contexts. In addition, AI technologies and labor market practices are changing rapidly, thus requiring ongoing research. Specific countries and sectors—including informal workers, small enterprises, young workers, women, and workers in low-connectivity settings—should thus be explored in future research. More detailed qualitative studies over time may be conducted to understand how workers actually fare with the introduction of AI and what the implications of technological change are for occupational mobility, wages, bargaining power and job quality.

In conclusion, this study has shown that AI and work in developing economies do not have a fixed destiny and that the role of AI in the future depends on more than just technical capacity. AI has the potential to replace jobs, generate new job opportunities, increase productivity, and unlock access to knowledge, but it also has the potential to exacerbate inequalities when the access to skills, infrastructure, capital, and social protection are not uniform. Thus, the question of the developing economies is not so much about adopting AI as how to control and incorporate it in such a manner that the technology facilitates productive employment, equitable income distribution, and inclusive economic growth. To secure a sustainable future for AI, human capabilities, decent work, social protection, and access to broad-based usage must be at the core of technology policy. With the conditions outlined above put in place, AI can shift from being simply an enabler of automation to a meaningful enabler of shared productivity, better livelihoods, and more inclusive development in the Global South.

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