Assessing the Impact of Artificial Intelligence on Job and Task Displacement: Evidence from the Agriculture and Healthcare Sectors

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***Abstract*—The rapid advancement of artificial intelligence has ignited extensive debates regarding its impact on the workforce. A widely held assertion is that artificial intelligence replaces specific tasks within jobs rather than entire occupations. This paper critically examines this assertion by exploring empirical evidence from case studies of artificial intelligence implementations in the agriculture and healthcare sectors. A stratified purposive sampling method was employed to identify 21 use cases from five continents capturing diverse perspectives from all the different economy classifications. Of these 21 cases only 5 of the cases reviewed involved artificial intelligence tools that can fully replace human jobs, and the majority of them are from high income economies. The majority of the analysed 21 cases were not displacing existing jobs but addressing previously unmet needs. In instances were job displacement occurs, there is the opportunity for up-skilling suggesting new career opportunities for the humans. This paper contributes by giving insights from empirical evidence to employment policy makers, employers and educators necessary in preparing the workforce for the future.**

Keywords*-*artificial intelligence; human-AI collaboration; labor market

I. Introduction

Artificial Intelligence (AI) is transforming the modern workplace, driving significant changes in productivity and efficiency in various sectors [1]. A central debate emerges from this transformation and it is on whether AI replaces specific tasks within jobs or entire jobs themselves. The result of this debate is profound in influencing policy making, workforce development, and socioeconomic stability. Despite the extensive literature on AI and job or task automation, significant gaps remain. Previous research lacks a detailed analysis of task displacement within job roles and does not provide comprehensive and sector-specific comparisons. Furthermore, there is a dearth of studies that examine the socioeconomic impacts of AI on different demographic groups and regions.

This research aims to bridge these gaps by critically analyzing the proposition that AI replaces tasks, but not jobs, and further examining the impact of AI on task and job displacement. The analysis is guided by empirical insights from implementations of AI agents in industry. The results are broken down to encompass the impact in various sectors and the resulting socio-economic implications are outlined. The findings are expected to inform policy-makers, business leaders, and workers, guiding them towards strategies that mitigate adverse effects and harness the benefits of AI driven automation.

To carefully address this overall aim, the following research questions are answered:

- To what extent does AI replace tasks within existing jobs compared to entire job roles?
- How do different sectors and industries experience the impact of AI on job displacement and task displacement?
- What are the socio-economic implications of AI-driven tasks and job displacement for the workforce?

The significance of this research lies in its practical and policy-oriented insights regarding the evolving relationship between AI and the workforce. The study provides empirical evidence that challenges the widely held belief that AI primarily leads to job displacement. The research provides a global perspective on how AI affects the workforce, offering valuable insights for both high-income and lower-income economies. Overall, this has important implications for workforce development and educational strategies.

In Section II, we present the theoretical framework underpinning our study, exploring prior research related to investigations of the impact of AI on the workforce. Section III details the research methodology which encompasses the research approach, and strategy. It further details the case selection process, as well as the data collection and analysis procedures. Section IV is a presentation of the results of this research followed by a discussion on results with the analysed prior studies. Finally, Section V details the conclusions and proposed future work.

II. Literature Review

In recent years, various studies have been conducted in a bid to analyse perceptions and impact of AI in the workplace and this section reviews these studies. Firstly, theoretical frameworks that shape this topic are highlighted, followed by analysis of studies grouped into themes guided by the research questions. Gaps identified are put under each theme.

A. Theoretical Framework

This research is guided by two key theories, the Task Based Approach (TBA) and the Job Polarization Theory (JPT). TBA highlights that automation impacts tasks within jobs rather than entire occupations [2]. JPT on the other hand informs that technological advancements including AI, and automation leads to the decline of middle-skill jobs while increasing demand for high-skill and low-skill jobs, thus creating a polarized labor market with a shrinking middle class and fewer middle-class occupations [3].

B. Analysis of Related Studies

1) Job Displacement versus Task Displacement: Task displacement occurs when AI automates specific activities within a job [4] whilst job displacement happens when the automation of tasks leads to the elimination of entire positions [5]. Studies on the impact of AI on job and task displacement present a clear picture of how technology influences the labor market. [6] argued that AI has the potential to perform many tasks more efficiently and inexpensively than humans. This early insight suggested the current debate on AI's role in automating routine tasks. [7] provided a comprehensive view, discussing how automation displaces tasks but also creates new opportunities, such as productivity gains and new task creation, which could potentially increase labor demand. [8] suggested that professionals with substantial skills and education in fields, such as computing, law, and medicine are less at risk, as AI augments rather than replaces their work.

[9] surveyed AI practitioners, finding that a significant portion of human tasks can be automated, with immediate potential to automate 22% of these tasks. However, their study was limited by sample bias, focusing solely on AI practitioners only from Europe, North America, and Asia, and without considering economic impacts. [10] explored the economic implications of generative AI tools like ChatGPT, highlighting the job displacement of routine job workers. [11] supported these findings by showing that while routine jobs are at high risk of automation, non-routine jobs have seen growth, underscoring the complexity of AI's impact on labor markets.

Although these reviewed studies discuss the potential of AI to automate tasks, there is a lack of detailed analysis on the specific skill level within various job roles that are most susceptible to AI. More granular studies are needed to identify which tasks within job roles are being automated. Furthermore, there is a scarcity of longitudinal studies that track the impact of AI on task displacement over time.

2) Sector Specific Impact: The impact of AI varies significantly between different sectors. [12] review that regions with a focus on technology, healthcare and creative industries may benefit from task automation and job transformation. [13] argues AI serves to enhance and optimize the work of medical professionals, highlighting the sector's resistance to full automation due to the complex and interpersonal nature of healthcare tasks.

In the manufacturing industry, the integration of AI and robotics has led to significant productivity gains. Automated systems perform tasks, such as assembly, inspection, and packaging with greater precision and efficiency than human workers. According to [14], each additional robot per thousand workers reduces the employment-to-population ratio by 0.2 percentage points and wages by 0.42%. This suggests that while tasks are automated, the overall number of jobs is also impacted.

The financial sector has embraced AI for tasks, such as data analysis, trading, and customer service. AI-driven algorithms execute trades at speeds and efficiencies beyond human ability, while chatbots handle routine customer inquiries. This has led to a reduction in the need for human traders and customer service representatives, indicating a shift towards job displacement [15].

Although there are studies focused on specific sectors, comprehensive comparative analyses across multiple sectors are limited. More research is needed to systematically compare how different industries are affected by AI in terms of both job and task displacement.

3) Skill Specific Impact: High skill jobs require cognitive and interpersonal skills and are generally less susceptible to automation [16]. These roles often involve complex problem-solving, decision-making, and creativity, areas where AI currently lags human capability. However, AI can augment these jobs, enhancing productivity and enabling workers to focus on more strategic tasks [16].

Middle-skill jobs, particularly those involving routine tasks, face significant risk [17]. The decline in middle-skill jobs contributes to job polarization and a shrinking middle class [3].

Low skill jobs, such as those in personal care and service industries, may see varying impacts. While some routine tasks can be automated, many low-skill jobs require physical presence and human interaction, which are challenging for AI to replicate. Therefore, these jobs may experience less displacement compared to middle skill jobs [17].

4) Socio Economic Impact: [18] provided qualitative insights into employee perceptions on job loss from AI and automation in New Zealand, and the study reveals a mix of no threat, potential threat, and real threat sentiments among workers from various professions. [19] echoed concerns about significant job losses due to AI, despite acknowledging potential productivity boosts and new job opportunities. [20] conducted a literature survey on worker-AI coexistence, proposing that trust issues and the need for continuous skill development are crucial for a symbiotic relationship between workers and AI. They emphasized the importance of human and conceptual skills in complementing technical proficiency, suggesting that ongoing training is essential for effective worker-AI collaboration.

[10] further illustrated the economic impact of AI tools like ChatGPT, predicting significant displacement of routine jobs while also acknowledging the potential for new high-skill job creation and increased productivity. [21] projected that AI could impact a substantial percentage of jobs in both advanced and developing economies, potentially affecting 800 million jobs worldwide by 2025.

Existing studies like those by [20] and [19] discuss broad socio-economic impacts but do not detail how different demographic groups, such as age, gender, and education level are affected. More targeted research is needed to understand the differential impacts of AI on various workforce segments. [21] and other global projections highlight the widespread impact of AI, but there is limited research on regional disparities. Understanding how AI-driven displacement varies across regions, particularly between urban and rural areas, and between developed and developing countries, is crucial.

III. Methodology

This section outlines the research design and procedures employed to investigate the impact of AI on job and task displacement. The methodology is structured to ensure a rigorous and systematic analysis of empirical evidence across diverse sectors and economic contexts.

A. Research Philosophy

The methodology for this research is grounded in a pragmatic research philosophy, which emphasizes practical problem solving. This approach is particularly suitable for exploring the impacts of AI on job and task displacement across various sectors and geographical locations. A qualitative research approach was chosen to provide in-depth insights into the impacts of AI adoption, focusing on context-specific factors rather than broad generalizations.

B. Research Strategy

The content analysis research strategy was used, and this strategy enabled systematic examination and interpretation of textual data on AI use cases across the globe. The analyzed data was from academic publications, industry reports, company websites, as well as reputable news and blog platforms. The strategy further ensured that the findings are rooted in comprehensive and credible evidence, allowing for a detailed understanding of AI's role in transforming jobs and tasks within the agriculture and healthcare sectors.

C. Case Selection

A purposive and stratified sampling technique was adopted to ensure comprehensive coverage of use cases. The purposive sampling encouraged picking the agriculture and healthcare sectors which are identified as the early adopters of AI [22]. Stratification was conducted by continent and economy type to achieve geographical and economic diversity. Continent classification adhered to [23], encompassing Africa, America, Asia, Europe, and Oceania. Economy classifications followed [24], comprising low-income, lower-middle-income, upper-middle-income and high-income economies.

D. Data Collection

Data collection was conducted through desktop research, drawing from academic journals, industry reports, reputable company websites, and blogs. Desktop research was selected due to its broad accessibility to diverse and globally distributed data sources, enabling the study to capture a comprehensive range of implemented AI use cases across sectors and regions. By relying on published academic literature, industry reports, and reputable company websites, we ensured the inclusion of validated and credible data. Peer reviewed articles provide insights on impacts which are verified. Industry reports provide insights into applied observations. Real world deployments from company websites and reputable blogs provide first hand information of AI deployments. Only implemented AI solutions were considered, excluding conceptual studies, as well as research and development efforts. Each continent was represented for healthcare and agriculture sectors, ensuring all four economy classifications were covered without repetition of countries.

To ensure a systematic search; under a particular sector, continent and economy classification, the researchers identified the countries which fall in that continent and economy classification and made a search from the Google search engine to identify AI use cases from countries that satisfy the continent and economy classification. The chosen approach ensured representativeness of AI implementations across diverse geographies and economic classifications, minimizing potential bias. Each continent and economy classification was equally represented, with no country repeated in the dataset. The used keywords included "AI powered agent for *category name* use cases in *country name*", as well as *category name* AI agent AND *country*. For example *Healthcare AI agent AND Angola*. Sticking to a systematic search protocol and following these standards ensured a methodological control allowing for replication of results.

The data assessment in this collection prioritized identifying real-world implementations of AI rather than conceptual or research and development (R&D) efforts. Conceptual studies and R&D efforts were excluded to maintain focus on observable workforce impacts. Implemented cases provided verifiable evidence of displacement. The assessment emphasized role classification, guided by the framework outlined in [25], to evaluate the nature of tasks and jobs influenced by AI technologies. Key areas of analysis included the extent to which AI replaced specific tasks within roles versus entire job roles, as well as the socio-economic implications of these changes. The data was analyzed thematically in alignment with the research questions, enabling a structured exploration of task displacement, sectoral impacts, and workforce impacts.

E. Data Analysis

Several critical factors were considered during the analysis. These included the availability of sufficient data to enable sound deductions, the identification of AI agents or classifications, and the specific roles covered by these implementations. Role classifications were examined to determine whether AI-driven technologies led to task or job displacement. Additionally, the study categorized data by economy classification, continent, and sector, ensuring representation from healthcare and agriculture across diverse geographical and economic contexts. Socio-economic impacts, such as the effect on workforce skills, were also assessed, providing a comprehensive understanding of AI's influence. This approach ensured the analysis addressed the complexities of AI adoption within varying global and sectoral environments. In reporting, findings were presented thematically, guided by the research questions. Themes included job displacement versus task displacement by skill, sector-specific impacts, and socio-economic implications. Analysis considered economy, continent, type of AI, and industry

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classifications to provide a comprehensive understanding of AI's impact on the workforce.

IV. Results and Discussion

This research investigated the impact of AI on job and task displacement focusing on the agriculture and healthcare sectors across the globe. A total of 21 use cases of AI agents implementations were analyzed. Tables I to III all show these analyzed use cases with extra data on the country, economy, role, and skill level. Table I shows use cases where actual job displacements happened. Table II shows use cases where task displacements occured and Table III shows where no displacements are happening. A discussion utilizing the thematic approach guided by the research questions then follows. An attempt was made to obtain both a healthcare and an agriculture use case from each continent and economy classification, but some continents did not have a country falling in a particular economy classification, hence the cases fell short from the expected 40 use cases. Additionally, in some use cases there was no sufficient information online to describe an implemented use case hence these were ignored. Sufficient data in this case encompassed AI agent implemented, and country implemented in. The 21 use cases spanned all 5 continents, with Africa (24%, n=5), Europe (24%, n=5), and the Americas (24%, n=5) equally represented, followed by Asia (19%, n=4) and Oceania (10%, n=2). Economically, cases were distributed across all World Bank classifications: low-income (10%, n=2), lower-middle-income (24%, n=5), upper-middle-income (33%, n=7), and high-income economies (33%, n=7). Sectorally, healthcare cases predominated (57%, n=12) over agriculture (43%, n=9), reflecting AI's earlier adoption in medical applications while still capturing significant agricultural implementations. This stratified distribution ensures our findings account for diverse development contexts and implementation environments.

Table I
SUMMARY OF USE CASES RESULTING IN JOB DISPLACEMENT

Use Case	Role	ISCO Skill Level	Economy
Robotti. Sweden Self-driving robot used for tasks, such as seedbed preparation, sowing, and mechanical weed control in agriculture. [26]	Agriculture Assistant	3	upper-middle-income
John Deere CP770. United States of America Automated cotton harvesting machine that uses AI to optimize harvesting process and improve yield quality. [27]	Agriculture Assistant	2	high-income
Agrist Robot. Japan AI-powered robots to harvest crops like cucumbers and tomatoes autonomously. [28] [29]	Agriculture Assistant	2	high-income
YV01. France Autonomous vineyard spraying robot addressing both labor shortages and environmental compliance. [30]	Agriculture Assistant	2	high-income
Oxin Tractor. New Zealand AI-driven autonomous tractor used for tasks like plowing, seeding, and weeding. [31]	Agriculture Assistant	2	high-income

A. Job Displacement versus Task Displacement

Table I shows where total job displacements are occurring and this is more prevalent in high-income economies and in the agriculture sector. High-income economies accounted for 80% (4 of 5) of full job displacement cases, while low- and lower-middle-income economies exhibited zero instances of complete job replacement. In high-income countries, advanced automation is prevalent, as seen with the John Deere CP770 Cotton Picker in the United States of America, which automates cotton harvesting, and the Robotti in Sweden, which performs sowing and weed control tasks. Such technologies illustrate [6] argument that AI has the potential to execute tasks more efficiently than humans and hence in the end may replace humans.

Table II shows where task displacements are happening and task displacement is more prevalent in the healthcare sector. Upper-middle-income economies led in AI complementation (50%, 7 of 14 cases). Low-income cases focused on unmet needs (90% augmentation). The findings reflect AI technologies automate repetitive and routine tasks, enhancing efficiency and accuracy while preserving the need for human involvement in complex decision-making, empathy, and critical thinking. In healthcare, AI-driven systems like the Automated X-ray Imaging Device in Sudan automate routine processes, such as image interpretation and inquiries. This aligns with [2] argument that automation tends to impact specific tasks within occupations rather than eliminating entire roles. AI technologies automate repetitive and routine tasks, enabling greater efficiency and accuracy, while retaining the need for human involvement in roles requiring complex decision-making, empathy, or critical thinking.

Table III shows where no displacement is happening, but where AI is helping complement human labor. contributing to socio-economic growth and of the analyzed cases these cases where there is no displacement are the majority. Systems, such as Robin the Robot in Armenia augment human capabilities, particularly in tasks requiring professional judgment or emotional intelligence. Whilst high-income countries employ advanced systems like the John Deere CP770 Cotton Picker

Table II
SUMMARY OF USE CASES RESULTING IN TASK DISPLACEMENT

Use Case	Role	ISCO Skill Level	Economy
Automated X-ray Imaging Device. Sudan Portable AI system that screens for tuberculosis (TB) by interpreting X-ray images. [32]	Radiologist	4	low-income
Sophie Bot. Kenya AI powered chatbot offering answers to sexual and reproductive health questions. [33] [34] [35]	Sexual Health Educator	2	lower-middle-income
Tele-health Learning Robot. Cambodia A tele-health robot that enhances health education and tele-consultations in low-resource settings. [36]	Health Educator	3	lower-middle-income
LaLuchy Robotina. Mexico Robot to alleviate loneliness and assist COVID-19 patients by enabling virtual communication. [37] [38] [39]	Healthcare Assistant	2	upper-middle-income
Panafricare Clinic AI Agents. Sychelles AI systems to manage patient records, prescribe medication, and assist in clinical examinations. [40]	Healthcare Assistants	2	high-income
Medicine Delivery Robot. Singapore Voice-activated robot to deliver medications in hospitals. [41]	Assistant Nurse Clinician	2	high-income

in the United States to replace human labor, low- and middle-income countries use these AI systems like MkhulimaGPT in Rwanda and uMudhumeni in Zimbabwe to enhance human productivity. The shortage of this critical staff is addressed by emergence of AI systems. This corroborates with [14] who indicates that AI can create new opportunities, particularly in resource-constrained settings, by augmenting human productivity.

In the healthcare sector, AI-driven systems displace routine and repetitive tasks. For instance, the automated X-ray imaging device in Sudan automate image interpretation and routine inquiries. These examples highlight [2]'s observation that routine tasks are more susceptible to automation. However, high-tech systems like Robin the Robot in Armenia enhance

Table III
SUMMARY OF USE CASES RESULTING IN NO DISPLACEMENT

Use Case	Role	ISCO Skill Level	Economy
Radify AI. South Africa AI system that diagnose medical images. [42] [43] [44]	Radiologist	4	upper-middle-income
Robin the Robot. Armenia Companionship robot providing emotional support to pediatric patients. [45] [46] [47]	Healthcare Assistant	2	upper-middle-income
FoxTac. Ukraine Robotic stretchers for safe medical evacuations in conflict zones. [48] [49]	Healthcare Assistant	2	upper-middle-income
Montreal's Scale AI. Canada AI platforms which optimize hospital operations across Canada. [50] [51]	Hospital Administrator	4	high-income
Mazor X Stealth Platform. Australia Robotic surgery platform that assists spine surgeons. [52] [53] [54])	Surgeon Assistant	4	high-income
MkhulimaGPT. Rwanda Smart chatbot which gives farming advice. [55] [56]	Agriculture Extension Worker	2	low-income
uMudhumeni. Zimbabwe Smart chatbot which poses as an agricultural extension worker. [57] [58]	Agriculture Extension Worker	2	lower-middle-income
Plantix. Bangladesh Mobile application for crop disease diagnosis using photos. [59] [60]	Agriculture Extension Worker	2	lower-middle-income
Anton Tech. Botswana AI platform that uses drones to monitor both plant diseases and soil quality. [61] [62]	Agricultural Assistant	2	upper-middle-income
Jeevn AI. Argentina Expert system which provides personalized farming advice. [63]	Farm Advisory Assistant	2	upper-middle-income

professionals' capabilities, consistent with [2] and [8] assertion that tasks demanding human intelligence and professional skills, such as those involving substantive decision-making or emotional intelligence, are less likely to be affected. In the agriculture sector on the other hand, task displacement varies significantly by economic context.

The extent of displacement also correlates with the economic classification of countries. In low-income countries, AI supports workers by automating routine tasks, allowing them to focus on higher-value activities. In high-income countries, the potential for full automation leads to more significant task displacement in sectors like agriculture. For example, the YV01 autonomous vineyard spraying robot in France and the Agrist Harvesting Robot in Japan replace manual labor in specific agricultural tasks. [3] notes that technological advancements often cause a decline in middle-skill jobs, which rely on routine manual tasks, while increasing the demand for high-skill jobs requiring expertise and creativity. Simultaneously, these advancements can also increase demand for very low-skill jobs that involve tasks difficult to automate, such as caregiving or maintenance.

Overall, the analysis underscores that AI technologies are reshaping tasks within jobs rather than eliminating entire roles. As [2] noted, routine, repetitive, and physically demanding tasks are more prone to automation, while roles requiring human intelligence, creativity, or emotional interaction remain largely unaffected. This distinction is critical for understanding how AI impacts labor markets, as it necessitates targeted upskilling programs to help workers adapt to evolving job requirements. Moreover, [14] highlights the potential for AI to create entirely new opportunities, further mitigating the risk of complete job displacement.

Furthermore, the integration of AI across different economic contexts reflects varied strategies. Low-income countries utilize AI for augmentation, emphasizing human-AI collaboration, while high-income countries adopt AI for efficiency and cost savings, leading to more comprehensive task automation. This is consistent with [3]'s observation that technological advancements can lead to polarization in labor markets, increasing demand for both high-skill and very low-skill jobs while eroding middle-skill roles.

B. Sector Specific Impacts

A notable pattern emerges when comparing sectors; while AI in healthcare often complements human expertise, AI in agriculture leans more towards displacing specific tasks in high-income countries. In healthcare, 67% of cases (8 of 12) involved task displacement without job loss. In the agriculture sector, the research showed higher job displacement rates (44%, 4 of 9 cases) concentrated exclusively in high-income contexts.

The disparity stems from differences in tasks and the economic context of adoption. Healthcare tasks requiring empathy, judgment, or professional skills are less amenable to full automation, aligning with findings by [2], [3] and [8]. In contrast, routine and physically intensive tasks in agriculture are more prone to automation, particularly in wealthier nations with greater access to advanced technologies.

Across both sectors, the economic classification of countries influences AI deployment strategies. In low-income economies, AI technologies are primarily used for augmentation, allowing workers to focus on higher-value activities. For example, advisory chatbots in agriculture and tele-health robots in healthcare supplement human roles without replacing them. In high-income countries, however, AI's potential for full task automation leads to greater task displacement, as seen in autonomous tractors and surgical robots.

C. Skill Specific Impact

In healthcare, expert systems, such as automated X-ray imaging devices reduce dependence on specialized radiologists in remote regions while encouraging healthcare workers to develop skills in AI-assisted diagnostics. Chatbots like Sophie Bot provide healthcare consultation and sexual education support, enhancing digital literacy among healthcare providers and patients. Robotic platforms, such as the Mazor X Stealth Robotic Surgery Platform, augment surgeons' capabilities, requiring professionals to undergo specialized training to operate these advanced systems. Similarly, robots like Robin the Robot and FoxTac, used in pediatric care and healthcare assistance, necessitate that staff learn to integrate robotic technologies into their workflows.

In agriculture, AI applications have reshaped skill requirements for farmers and technicians. Tools like Plantix and Anton Tech use computer vision and machine learning for crop health diagnostics, encouraging farmers to adopt data-driven practices. Robotic systems, such as the Agrist Harvesting Robot and Oxin Autonomous Tractor, reduce the need for manual labor while increasing demand for skilled operators and maintenance technicians. These technologies not only improve productivity but also require workers to develop technical literacy and familiarity with AI-powered systems. For example, initiatives like MkhulimaGPT and uMudhumeni empower agricultural extension workers with improved knowledge in disease management and digital tools.

These examples highlight that AI disproportionately affects low- and middle-skill jobs, leading to job polarization and a shrinking middle class [3]. While AI enhances the efficiency and precision of various tasks, it also creates a pressing need for workforce re-skilling and up-skilling to align with the evolving demands of AI-driven industries. This dual impact underscores the importance of targeted educational initiatives and sector-specific training programs to mitigate the socio-economic disruptions caused by AI automation and ensure equitable access to opportunities in the new labor market.

D. Socio Economic Impacts

The analysed use cases reveal contrasts in AI's impact across economic classifications. Job displacement is heavily concentrated in high-income economies (80%). In contrast, low- and lower-middle-income economies observed zero cases of full job replacement. This reflects AI's role in augmentation. Task displacement dominates lower-middle-income economies (33.3%), where AI automates repetitive tasks. An example is Plantix disease diagnosis in Bangladesh. High-income economies also show significant task displacement (33.3%), but alongside job losses. No displacement is most prevalent in upper-middle-income economies (50%), where AI complements labour. Low-income economies (10%) lag in adoption due to infrastructure gaps.

Furthermore, the socio-economic implications of AI adoption vary widely across sectors and economic classifications. In healthcare, AI improves accessibility and efficiency, particularly in low-income countries where resources are limited. For example, automated X-ray imaging devices in Sudan address critical gaps in healthcare services. However, the integration of AI requires workforce adaptation, as professionals must learn to work with new technologies. In agriculture, AI's economic impact is profound, with advanced automation in high-income countries leading to significant cost savings and productivity gains. However, in low-income countries, AI tools primarily support farmers, fostering productivity without displacing workers.

In healthcare, AI adoption has significantly improved efficiency and accessibility, particularly in low-income economies where resource constraints are severe. For instance, Sudan's automated X-ray imaging devices for Tuberculosis diagnosis demonstrate how AI addresses critical healthcare gaps. However, the integration of AI necessitates workforce adaptation.

Similarly, in agriculture, AI innovations, such as MkhulimaGPT in Rwanda and uMudhumeni in Zimbabwe have empowered smallholder farmers with actionable insights, improving productivity and resilience. However, in high-income economies like the United States and Sweden AI tools, such as John Deere's CP770 Cotton Picker and Robotti automate labor-intensive tasks, displacing low-skill jobs. These examples highlight AI's dual impact: fostering efficiency and innovation while also necessitating workforce realignment to more technical and conceptual roles.

V. Conclusion and Future Work

The research shows that AI reshapes tasks within jobs by automating repetitive processes while preserving human roles in complex decision-making and critical thinking, with deployment strategies differing between high- and low-income countries. In healthcare, AI automates routine tasks but relies on human expertise for roles requiring empathy and judgment, while in agriculture, task displacement is more pronounced in high-income countries due to advanced automation. AI adoption transforms workforce skills, with middle-skill jobs most affected, creating a need for re-skilling and technical literacy, especially in AI-assisted diagnostics and data-driven agricultural practices. Socio-economic impacts vary by sector and economic classification, with AI improving efficiency in low-income countries while driving automation and productivity gains in high-income regions, highlighting the need for strategic adaptation to mitigate disruptions and promote equitable development.

The findings lead to the conclusion that AI is fundamentally transforming the nature of work by displacing tasks rather than entire jobs, with sectoral and economic variations shaping its impact. In both healthcare and agriculture, AI enhances efficiency and productivity by automating repetitive and routine tasks while leaving roles that require human judgment, empathy, and creativity largely intact. The degree of task displacement is influenced by the economic context, with high-income countries leveraging advanced automation technologies to replace labor-intensive tasks, while low- and middle-income countries adopt AI tools to augment human efforts and improve productivity. This underscores the deep relationship between AI deployment and socio-economic contexts, where resource availability and task complexity determine the extent of automation and augmentation. Moreover, the increasing reliance on AI has heightened the need for workforce re-skilling and up-skilling, particularly for middle-skill roles, to address the socio-economic challenges posed by task displacement and job polarization. Overall, while AI offers significant opportunities for innovation, accessibility, and efficiency, particularly in low-income regions, its integration requires strategic adaptation to ensure equitable development and mitigate potential workforce disruptions.

Based on the research findings, several recommendations can be made to address the challenges and maximize the benefits of AI adoption across sectors and economic contexts. First, policymakers and stakeholders should invest in targeted education and training programs to equip workers with the skills necessary to adapt to AI-driven changes. Emphasis should be placed on re-skilling and up-skilling initiatives for middle-skill workers who are most vulnerable to task displacement, with a focus on technical literacy, data-driven decision-making, and AI-assisted processes. Second, governments and organizations in low- and middle-income countries should prioritize the development and deployment of AI tools that augment human efforts rather than replace them, ensuring inclusive growth and minimizing socio-economic disruptions. Partnerships between the private sector, academia, and international organizations can help foster innovation and improve access to AI technologies in undeserved regions.

This research was limited in that it only analyzed case studies from the agriculture and healthcare sectors only. Further research should focus on granular, longitudinal studies for each sector to gain a better understanding of the long-term trends and impacts of AI on job displacement and creation. Furthermore, while the study reveals important socio-economic patterns in AI-driven displacement, the analysis was limited in examining granular demographic impacts, such as gender and age. These factors likely mediate how different workforce segments experience AI adoption. Future research should prioritize these granular demographic impacts and analyzing how AI adoption affects vulnerable subgroups across economic contexts. This enables targeted policy interventions.

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