Assessing the Impact of Artificial Intelligence on Job and Task Displacement: A Cross Continental Analysis of Four Economic 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 claim 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 37 use cases from five continents capturing diverse perspectives from all the different economy classifications. Of these 37 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. A significant portion of the analysed 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

In our earlier work [1], we examined the impact of Artificial Intelligence (AI) in the modern workplace, focusing on the debate surrounding whether AI replaces specific tasks within jobs or entire jobs altogether. The study showed that AI is changing the workplace by replacing tasks rather than whole jobs. However, this effect is not the same across all sectors. Differences in economic conditions and levels of technology adoption shape how AI affects work. The findings only provided evidence of task-level automation in agriculture and healthcare. At the same time, they revealed the need for deeper analysis across sectors of varying manual, or cognitive effort. Furthermore, research is required to better understand how AI branches relates to task and job displacement.

Building on this foundation, the present study extends the original analysis by offering a more comprehensive examination encompassing 4 sectors. It adds empirical evidence with refined analytical frameworks to better capture variations in AI adoption and its socio-economic consequences. The findings of this extended investigation are intended to inform policy-makers, educators, and human resource practitioners by providing clearer evidence on the conditions under which AI augments, transforms, or displaces human labor. To achieve this objective, the study addresses the following research questions:

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

The significance of this research lies in its potential to provide practical and policy-relevant insights into the evolving relationship between AI and the workforce. The study proposes an empirical classification model that distinguishes between task displacement, job displacement, and no displacement outcomes. The research further examines how economic and sectoral contexts mediate the impact of AI-driven automation across different industries and income levels. By doing so, the study aims to develop an evidence-informed framework to support education planning, workforce development, and policy formulation in the context of increasing AI adoption.

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 analyze perceptions and impact of AI in the workplace. This section reviews such studies guided by a theoretical framework. The identified gaps 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]. Guided by TBA, this study evaluates AI's impact at the task level across selected industries, rather than assuming wholesale occupational displacement.

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]. In this research, JPT provides a structural lens for interpreting sectoral differences in AI adoption and its implications for skill demand distribution. Together, these frameworks inform the study's analytical design, interpretation of findings, and assessment of whether AI primarily replaces tasks or contributes to broader occupational restructuring.

B. Analysis of Related Studies

1) Job Displacement versus Task Displacement: The distinction between job displacement and task displacement is best understood through the TBA theory. It conceptualizes production as a bundle of tasks rather than indivisible jobs. Task displacement occurs when AI automates specific activities within a job [4], while job displacement occurs when sufficient task automation renders an entire occupation economically redundant [5]. From a TBA perspective, technological change alters the composition of tasks within occupations before it eliminates jobs altogether.

Early insights by [6] suggested that AI could perform many human tasks more efficiently. Extending this reasoning, [7] argued that automation displaces certain tasks but simultaneously generates new ones, potentially increasing productivity and labor demand. This effect aligns with TBA's core assumption that technological change restructures task allocation between humans and machines rather than uniformly destroying employment. Similarly, [8] found that highly skilled professionals in fields such as computing, law, and medicine experience augmentation rather than replacement. [8] further indicates non-routine cognitive tasks remain comparatively resilient to displacement.

Empirical studies further reinforce the task-centered nature of AI's impact. [9] estimated that 22% of human tasks could be immediately automated, though without directly linking this to occupational elimination. [10] demonstrated that routine jobs face higher automation risks, while non-routine occupations have expanded, reflecting patterns consistent with JPT. JPT predicts that technology disproportionately displaces middle-skill routine occupations, leading to employment growth at both high- and low-skill ends of the labor market.

Recent contributions deepen this theoretical linkage. [11] synthesized evidence from 2010–2025 and concluded that AI reshapes labor productivity through both automation and augmentation pathways. Their findings show that routine manufacturing and mid-skill cognitive roles are particularly vulnerable, providing empirical support for JPT's "hollowing out" hypothesis of middle-skill occupations. Similarly, [12] identified clerical, administrative, financial, and customer service roles as highly exposed to generative AI.

However, emerging evidence also complicates traditional theoretical expectations. [13] reported significant exposure among occupations in the 80th earnings percentile, challenging the conventional JPT narrative that high-skilled labor is largely insulated from displacement. Furthermore, the observed decline in entry-level employment within high-exposure occupations suggests that AI may be automating foundational tasks that historically enabled skill accumulation and career progression. This indicates that AI-driven task displacement may have dynamic, long-term effects on occupational structures beyond immediate job elimination.

Focusing specifically on generative AI, [14] found displacement effects in certain occupations, particularly within digital freelance markets, yet noted no statistically significant average effects on aggregate employment or wages. This divergence between micro-level task disruption and macro-level employment stability further supports the TBA view that automation initially manifests as task recomposition before translating into measurable job displacement.

Although these studies collectively affirm that AI primarily operates at the task level, several theoretical and empirical gaps remain. First, there is insufficient granular analysis identifying which task clusters within occupations are most susceptible across different industries. Secondly, there is limited longitudinal evidence tracing how cumulative task displacement evolves into structural job displacement remains scarce. Addressing these gaps is essential to empirically determine whether AI reinforces classical job polarisation dynamics or is reshaping the labour market in unseen ways.

2) Sector Specific Impact: The impact of AI varies significantly across sectors. Rather than producing uniform job displacement, AI reshapes sector-specific task bundles, with varying implications for employment structures. [15] observed that regions specialising in technology, healthcare, and creative industries often experience task transformation rather than outright job destruction. Similarly, [16] argued that in healthcare, AI enhances diagnostic accuracy and decision-making, while the interpersonal and ethical complexity of medical work limits full occupational automation.

Recent work provides stronger empirical grounding for these patterns. [17] identified routine-based sectors such as manufacturing and customer service as facing higher displacement risks, whereas knowledge-intensive professions including healthcare, education, and creative industries tend to experience AI as a complementary tool. These findings align with TBA by demonstrating that sectors dominated by routine cognitive or manual tasks are more susceptible to automation at the task level. They also support the JPT, which predicts the erosion of middle-skill routine occupations.

In manufacturing, AI and robotics have produced measurable employment effects. Automated systems now perform assembly, inspection, and packaging with greater precision and efficiency than human workers. Empirically, [18] found that each additional robot per thousand workers reduces the employment-to-population ratio by 0.2 percentage points and wages by 0.42%. This sector exemplifies JPT's prediction of middle-skill displacement, as routine production roles decline while demand increases for high-skill technical maintenance and low-skill service work surrounding automated systems. Supporting this view,

[19] reported that routine-based occupations in manufacturing face elevated displacement risks, whereas knowledge-intensive roles increasingly adopt AI as a complementary productivity tool.

Healthcare presents a contrasting trajectory. [19] highlighted that AI primarily automates administrative and diagnostic support tasks, while demographic pressures and expanding healthcare demand contribute to net employment growth. This reflects task displacement without proportional job elimination, consistent with TBA. Furthermore, the requirement for empathy, ethical judgment, and contextual reasoning limits full automation, indicating sector-specific resistance to wholesale job displacement.

In finance, AI-driven algorithms increasingly perform data analysis, high-frequency trading, risk modelling, and customer interaction through chatbots. [20] earlier suggested that such automation could reduce demand for routine financial service roles. Sectoral evidence from retail and human resource management further illustrates differentiated impacts. [21] showed that AI accelerates recruitment, personalises training through adaptive learning systems, and enables real-time performance monitoring in the retail sector. While such applications improve efficiency, they also introduce ethical concerns such as algorithmic bias and transparency challenges. These findings demonstrate that in service-oriented sectors, AI often restructures internal task processes rather than directly eliminating occupations.

The public sector similarly exhibits a hybrid pattern of transformation. [22] identified efficiency gains in administrative functions and service delivery, alongside challenges related to trust, ethics, and workforce adaptation. AI automates repetitive administrative tasks while requiring public servants to cultivate higher-order interpersonal and intuitive skills. This pattern again supports the TBA proposition that automation first restructures task composition within occupations.

Collectively, sector-specific evidence suggests that AI adoption does not produce uniform labor market outcomes. Instead, its effects depend on the routine intensity, cognitive complexity, and regulatory environment of each sector. From a JPT perspective, manufacturing and routine service sectors display stronger middle-skill displacement dynamics, whereas healthcare and knowledge-intensive industries show patterns of augmentation and task transformation.

Despite growing sectoral evidence, comprehensive comparative analyses across multiple industries remain limited. Existing studies often focus on single sectors without systematically evaluating task-level exposure across industries. Guided by TBA and JPT, there is a need for empirical research that compares how AI reshapes task structures within occupations across sectors and assesses whether observed task displacement accumulates into broader occupational polarisation. Such comparative analysis is essential to determine whether AI reinforces traditional job polarisation patterns or produces new forms of sectoral restructuring.

3) Socio Economic Impact: [23] provided qualitative insights into employee perceptions on job loss from AI and automation in New Zealand. Their findings revealed sentiments from workers across different professions ranging from perceptions of no threat to potential and real threats to job security. Similarly, [24] highlighted growing concerns regarding the potential for substantial job losses due to AI adoption, despite acknowledging the productivity gains and emergence of new forms of employment that AI technologies may generate.

From the perspective of worker-AI coexistence, [25] conducted a literature survey examining how employees interact with AI systems in the workplace. Their study emphasized the importance of trust in AI systems and the necessity for continuous skill development to enable effective human-AI collaboration.

The economic implications of AI-driven transformation have also been widely explored. For instance, [26] analyzed the economic effects of generative AI tools such as ChatGPT, predicting significant displacement of routine tasks and occupations while also highlighting the potential for increased productivity and the creation of new high-skill job categories. Likewise, [27] estimated that AI technologies could affect a substantial proportion of jobs globally, potentially impacting up to 800 million workers worldwide.

More recent studies provide deeper insights into the mechanisms through which AI reshapes labor markets. For example, [28] investigated the adoption of artificial intelligence in the accounting sector and found that AI-driven automation alters traditional accounting roles by automating repetitive tasks while simultaneously reshaping decision-making processes. The study suggests that while certain clerical and routine accounting tasks may be displaced, the demand for higher-level analytical and strategic roles is likely to increase. These findings align with the TBA, which posits that technologies replace specific tasks rather than entire occupations, leading to a restructuring of job roles rather than complete job elimination.

Similarly, [29] introduced a novel measure termed unemployment risk to quantify technology-driven job loss by analyzing occupation-level unemployment data. Their findings demonstrated that occupations with higher exposure to AI technologies experience greater risks of job separation, reinforcing the importance of understanding how AI affects task composition within occupations rather than employment levels alone.

Supporting this perspective, [30] analyzed global employment trends between 2025 and 2030 and reported that approximately 85 million jobs could be displaced due to AI-driven automation, while around 97 million new roles may emerge, resulting in a net gain of 12 million jobs globally. However, the study also highlighted notable socio-economic disparities, particularly gender disparities in exposure to AI-driven job displacement, with a significantly higher proportion of women occupying occupations susceptible to automation.

While existing studies such as [24] and [25] discuss the broad socio-economic implications of AI adoption, they often overlook how different demographic groups, including age, gender, and education level, are differentially affected by AI-driven transformation. Furthermore, although global projections such as those presented by [27] and [30] provide valuable insights into the overall scale of potential disruption, there remains limited empirical research examining regional disparities in AI-induced labor market changes. In particular, there is a need to investigate how AI adoption affects employment structures in developing economies and rural regions, where labor markets and technological adoption patterns may differ significantly from those in advanced economies.

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. It 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. 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.

A. Case Selection

A purposive and stratified sampling technique was adopted to ensure comprehensive coverage of use cases. Purposive sampling selected four sectors with diverse task structures and varying levels of AI exposure drawing from observations by [31]. The analysed sectors include agriculture, healthcare, finance, and manufacturing. Agriculture and manufacturing represent sectors dominated by routine manual tasks whilst healthcare and finance is characterised by routine cognitive activities. Stratification was conducted by continent and economy type to achieve geographical and economic diversity. Continent classification adhered to [32], encompassing Africa, America, Asia, Europe, and Oceania. Economy classifications followed [33], comprising low-income (LI), lower-middle-income (LIMI), upper-middle-income (UMI) and high-income (HI) economies.

B. 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 each of the four 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. 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. The assessment emphasized role classification, guided by the framework outlined in [34], 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.

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

IV. Results and Discussion

This study investigated the impact of AI on job and task displacement across four key sectors: agriculture, finance, manufacturing, and healthcare. An attempt was made to obtain at least one use case for each sector across all continents and World Bank economy classifications. However, some regions do not contain countries within certain income classifications, which limited the number of available cases. Additionally, several potential cases were excluded because sufficient information was not available online to clearly identify the AI agent used or the country of implementation. Consequently, the final dataset consisted of 37 AI implementation use cases, summarized in Table I.

The analyzed use cases span all five continents, with Africa (24%, n=11) and Asia (24%, n=9) having the highest representation, followed by America (19%, n=7) and Europe (16%, n=6), with Oceania having comparatively fewer cases (11%, n=4). The uses cases distribution by continent is presented in Figure 1.

From an economic perspective, the cases were distributed across all World Bank income classifications, including low-income economies (8%, n=3), lower-middle-income economies (14%, n=5), upper-middle-income economies (35%, n=13), and high-income economies (43%, n=16). The distribution of use cases by economy type is presented in Figure 2.

Sectoral analysis shows that healthcare accounted for the largest share of use cases (43%, n=16), followed by finance (30%, n=11), manufacturing (14%, n=5), and agriculture (14%, n=5). The distribution of use cases by sector is presented in Figure 3.

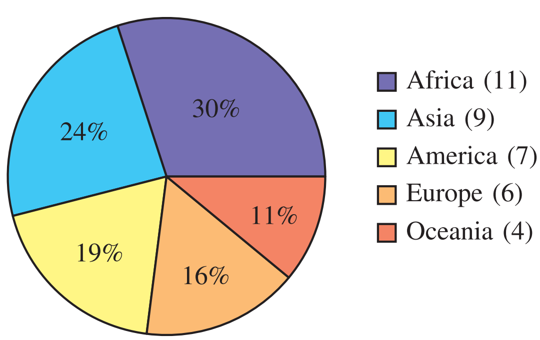

Figure 1. Distribution of AI use cases by continent

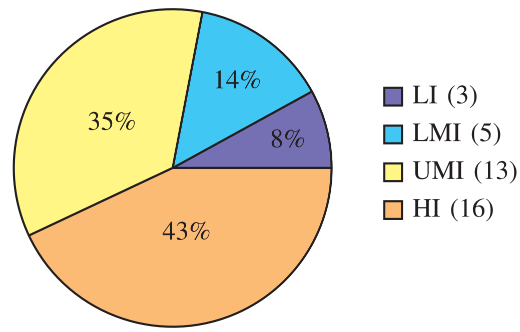

Figure 2. Distribution of AI use cases by economy classification

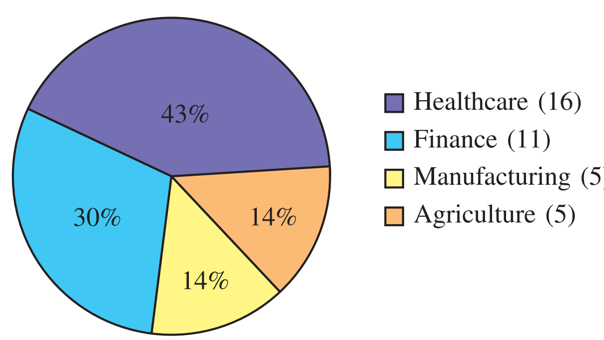

Figure 3. Distribution of AI use cases by sector

TABLE I. SUMMARY OF USE CASES

#	AI Agent	Skill Level	Economy Classification	AI Type	Displacement Type
1	**Radify AI - South Africa**. AI system that diagnose medical images [35][36][37].	4	UMI	Computer Vision	ND
2	**Robin the Robot - Armenia**. Companionship robot providing emotional support to pediatric patients [38][39][40].	2	UMI	Robotics & NLP	ND
3	**FoxTac - Ukraine**. Robotic stretchers for safe medical evacuations in conflict zones [41][42].	2	UMI	Robotics	ND
4	**Montreal's Scale AI - Canada**. AI platforms which optimize hospital operations across Canada [43][44].	4	HI	Expert Systems	ND
5	**Mazor X Stealth Platform - Australia**. Robotic surgery platform that assists spine surgeons [45][46][47].	4	HI	Robotics	ND
6	**MkhulimaGPT - Rwanda**. Smart chatbot which gives farming advice [48][49].	2	LI	NLP	ND
7	**uMudhumeni - Zimbabwe**. Smart chatbot which poses as an agricultural extension worker [50][51].	2	LMI	NLP	ND
8	**Plantix - Bangladesh**. Mobile application for crop disease diagnosis using photos [52][53].	2	LMI	Computer Vision	ND
9	**Anton Tech - Botswana**. AI platform that uses drones to monitor both plant diseases and soil quality [54][55].	2	UMI	Computer Vision	ND
10	**Jeevn AI - Argentina**. Expert system which provides personalized farming advice [56].	2	UMI	Expert Systems	ND
11	**Automated Xray Imaging Device - Sudan**. Screens for tuberculosis (TB) by interpreting X-ray images [57].	4	LI	Robotics	TD
12	**Sophie Bot - Kenya**. AI powered chatbot offering answers to sexual and reproductive health questions [58][59][60].	2	LMI	NLP	TD
13	**Telehealth Learning Robot - Cambodia**. Enhances health education and tele-consultations in low-resource settings [61].	3	LMI	Robotics	TD
14	**LaLuchy Robotina - Mexico**. Alleviate loneliness in patients by enabling virtual communication [62][63][64].	2	UMI	Robotics & NLP	TD
15	**Panafricare Clinic AI Agents - Sychelles**. AI systems to assist in clinical examinations [65].	2	HI	Expert Systems	TD
16	**Medicine Delivery Robot - Singapore**. Voice-activated robot to deliver medications in hospitals [66].	2	HI	Robotics & NLP	TD
17	**NOVISSI AI Targeting System - Togo**. Uses ML to identify poor households to assist in emergencies [67].	4	LI	Machine Learning	TD
18	**Haraka AI Loan App - Zimbabwe**. Uses AI to analyze mobile phone and social media data to assess creditworthiness [68].	4	LMI	Machine Learning	TD
19	**Absa Abby - South Africa**. Virtual assistant that acting as a customer support agent in a bank [69].	3	UMI	NLP	TD
20	**Intelligent Agents for Financial Services - Brazil**. Uses LLMs to automate decision-making in complex digital workflows [70].	4	UMI	NLP	TD
21	**DANA Real-Time Gambling Detection System - Indonesia**. ML system that detects suspicious gambling activity in real time [71].	4	UMI	Machine Learning	TD
22	**Conversational Chatbot for Insurance Operations - Ukraine**. Provides automated insurance support such as claims submission and policy information [72].	3	UMI	NLP	TD
23	**AI-Driven Contact Centre for Tower Insurance - New Zealand**. Provides call transcription, sentiment analysis, and call summarization for the centre [73].	3	HI	NLP	TD
24	**Anaplan Intelligent Role-Based Agents - United States**. Analyses financial data and generate insights for decision-making [74].	4	HI	Generative AI	TD
25	**BlackRock Investment Analysis - United States**. ML models to analyze financial datasets and market signals to support portfolio management [75].	4	HI	Machine Learning	TD
26	**Optasia AI Financial Access Platform - UAE**. AI-driven analytics platform assessing creditworthiness [76].	4	HI	Machine Learning	TD
27	**RPA for Import/Export Operations - UK**. Robotic process automation system to automate contract processing in trade [77].	3	HI	Expert Systems	TD
28	**Yaskawa Robotic Arc Welding System - South Africa**. Automate arc welding by positioning the welding torch and adapting to joint variations [78].	2	UMI	Robotics	TD
29	**Tesla Giga Press - USA**. Produces large single-piece car body components in vehicle manufacturing [79].	2	HI	Robotics	TD
30	**RockyOne Mobile Manipulation Robot - Japan**. Automatically unloads cartons from shipping containers in warehouses [80].	2	HI	Robotics	TD
31	**UR16e Collaborative Robotic Arm - Denmark**. Automates industrial tasks such as packaging, palletizing, and machine tending [81].	2	HI	Robotics	TD
32	**Tesla Grok In-Car AI Assistant - Australia**. Enables drivers to interact with vehicle systems using natural language voice commands [82].	2	HI	NLP	ND
33	**Robotti - Sweden**. Self-driving robot used for various manual farm tasks [83].	3	UMI	Robotics	JD
34	**John Deere CP770 - USA**. Self-driving robot used for various manual tasks in agriculture [84].	2	HI	Robotics	JD
35	**Agrist Robot - Japan**. AI-powered robot that autonomously harvests crops such as cucumbers and tomatoes [85][86].	2	HI	Robotics	JD
36	**YV01 - France**. Autonomous vineyard spraying robot addressing labor shortages and environmental compliance [87].	2	HI	Robotics	JD
37	**Oxin Tractor - New Zealand**. AI-driven autonomous tractor used for plowing, seeding, and weeding tasks [88].	2	HI	Robotics	JD

A. RQ1: To what extent does AI replace tasks within existing jobs compared to entire job roles?

The findings from the analyzed use cases indicate that AI predominantly replaces specific tasks within occupations rather than entire job roles, supporting the theoretical assumptions of the TBA. Among the 37 analyzed cases, the majority demonstrate task displacement, where AI automates particular functions within a job while leaving the broader occupational role intact. Only a smaller subset of cases shows job displacement JD, and several cases illustrate no displacement ND where AI primarily creates a role which was not being served by humans. This distribution aligns with TBA's central premise that production consists of bundles of tasks rather than indivisible jobs, and technological change first reorganizes these tasks before potentially eliminating occupations entirely [4][5].

Many of the examined use cases demonstrate this task-level automation pattern. In the healthcare sector, for example, systems such as Radify AI [35], which diagnoses medical images, and Plantix [52], which identifies crop diseases using computer vision, automate diagnostic or analytical subtasks traditionally performed by professionals. Similarly, AI-driven contact center systems, banking chatbots such as Absa Abby [69], and fraud detection platforms like the DANA system automate customer service interactions [71], transaction monitoring, or information retrieval tasks. In these cases, the underlying occupations such as healthcare professionals, customer service representatives, or financial analysts are not eliminated. Instead, AI systems assume repetitive or data-intensive subtasks, allowing workers to focus on higher-value cognitive or interpersonal activities. These observations support earlier arguments that AI technologies frequently augment rather than replace skilled professionals, particularly in non-routine cognitive occupations [8].

Empirical evidence from the use cases also reflects the broader coexistence of AI agents and humans described earlier in the literature. According to [7], automation can displace specific tasks while simultaneously generating new complementary activities that increase productivity and labor demand. This dynamic is visible in several implementations, particularly in healthcare and financial services, where AI systems support decision-making, diagnostics, or customer engagement rather than fully replacing professionals. The results therefore reinforce the claim that AI-driven technological change often leads to task recomposition within occupations rather than immediate occupational elimination.

However, the results also reveal instances of full job displacement, primarily within routine physical occupations. Autonomous agricultural machinery such as Robotti [83], John Deere CP770 [84], Agrist Robot [85], YV01 [87], and the Oxin Tractor [88] replaces manual agricultural labor traditionally performed by farm assistants or machine operators. These cases illustrate situations where automation can replace a sufficiently large proportion of an occupation's task bundle, making the job economically redundant. Such findings are consistent with empirical research indicating that routine and repetitive tasks are the most susceptible to automation [10]. They also support predictions from JPT, which suggests that routine middle-skill occupations are more vulnerable to technological displacement.

The distribution of displacement types across sectors further reinforces these theoretical insights. Healthcare and financial services cases largely demonstrate augmentation or task displacement, reflecting the persistence of complex decision-making, ethical judgment, and interpersonal interaction in these professions. In contrast, manufacturing and agriculture show stronger evidence of job-level automation, particularly where tasks are standardized and physically repetitive. These sectoral differences illustrate how the nature of tasks within occupations determines susceptibility to automation, a central argument of the TBA framework.

The findings also provide some insight into emerging debates regarding high-skill exposure to AI, particularly in the context of generative AI. While most high-skill roles in the dataset experienced augmentation rather than displacement, several systems such as financial planning agents and automated analytics platforms demonstrate AI's growing ability to perform complex analytical tasks traditionally reserved for highly trained professionals. This observation aligns with recent studies suggesting that generative AI may expose certain high-skilled occupations to automation risks [13], although the evidence from the present cases suggests that these technologies are currently reconfiguring professional tasks rather than eliminating professional roles.

Overall, the results strongly support the TBA perspective that AI primarily operates at the task level, altering the composition of work within occupations before leading to broader structural labor market changes. The predominance of task displacement across the analyzed cases indicates that AI adoption is currently characterized more by work reconfiguration and augmentation than by widespread job elimination. Nevertheless, the observed cases of job displacement in routine sectors suggest that as automation technologies mature and accumulate across multiple tasks, certain occupations may eventually become fully automated.

B. RQ2: How do different sectors and skills experience AI-driven task and job displacement?

The analyzed use cases demonstrate that the impact of AI varies considerably across sectors, supporting the central premise of the TBA that automation reshapes the composition of tasks within occupations rather than uniformly eliminating jobs. Consistent with previous studies, the results indicate that sectoral characteristics particularly the routine intensity of tasks and the level of cognitive complexity involved play a significant role in determining whether AI results in task displacement, job displacement, or augmentation. This aligns with earlier observations that technology-intensive sectors such as healthcare and knowledge-based services often experience task transformation rather than wholesale job destruction [15]. Similarly, research suggests that AI applications in healthcare frequently enhance diagnostic and decision-making capabilities while leaving the interpersonal and ethical dimensions of medical work largely resistant to automation [16].

C. Healthcare

Healthcare accounts for the largest proportion of analyzed cases and shows the strongest evidence of task-level automation rather than full job displacement. Systems such as Radify AI [36], which assists with medical image diagnosis, and automated X-ray screening devices [57], which analyze tuberculosis scans, automate diagnostic tasks traditionally performed by healthcare professionals. Likewise, conversational health assistants such as Sophie Bot [58] and robotic telehealth [61] platforms automate information delivery, patient monitoring, and administrative support tasks. However, these technologies largely complement rather than replace medical professionals, reflecting the continued need for human judgment, empathy, and contextual decision-making. This pattern supports prior findings that AI in healthcare primarily enhances productivity while leaving core clinical roles intact [19]. In this sector, AI adoption therefore manifests mainly as task displacement and augmentation, consistent with TBA's prediction that complex professional occupations are less susceptible to full automation.

D. Finance

The finance sector also largely exhibits task-level automation. AI-driven systems in banking and financial services perform functions such as credit assessment, fraud detection, customer service automation, and financial data analysis. For instance, Haraka AI Loan App [68] uses machine learning to assess creditworthiness using mobile data, while DANA's real-time detection system identifies suspicious financial transactions [71]. Similarly, conversational agents such as Absa Abby and automated insurance chatbots perform customer service interactions that were previously handled by human agents. These implementations reduce the need for routine clerical and customer-facing tasks but do not fully eliminate the associated occupations. Financial analysts, compliance officers, and customer service representatives continue to play roles in oversight, decision-making, and complex problem resolution. This pattern mirrors earlier predictions that AI would primarily reduce demand for routine financial service activities while transforming rather than eliminating professional roles [20]. The results therefore reinforce the view that in service-oriented sectors, AI typically restructures internal task processes rather than displacing entire occupations.

E. Manufacturing

In contrast, the manufacturing sector demonstrates stronger evidence of automation at the job level, particularly for routine manual roles. Several use cases illustrate the deployment of robotics systems capable of performing highly repetitive industrial tasks with minimal human intervention. Examples include the Yaskawa robotic arc welding system [78], which automates welding operations, the Tesla Giga Press [79], which replaces multiple manual assembly processes with a single automated casting system, and the UR16e collaborative robotic arm [81], which performs packaging and machine-tending tasks. These technologies directly substitute manual labor traditionally performed by assembly workers and machine operators. This pattern aligns with empirical findings that industrial robotics can reduce employment in routine production roles while increasing demand for high-skill technical roles responsible for system maintenance and management [18]. The sector therefore provides strong evidence supporting the JPT, which predicts the displacement of middle-skill routine occupations.

F. Agriculture

The agriculture sector similarly exhibits examples of full job displacement driven by autonomous machinery. Autonomous farming systems such as Robotti [83], John Deere CP770 [84], Agrist Robot [85], YV01 vineyard robots [87], and the Oxin autonomous tractor [88] which automate tasks including planting, harvesting, spraying, and field monitoring. These technologies replace a large proportion of manual agricultural labor tasks traditionally performed by farm assistants and machine operators. Unlike healthcare and finance applications, where AI tends to support professional decision-making, agricultural automation directly replaces physical labor tasks that are repetitive and easily standardized. These findings align with research indicating that sectors dominated by routine manual tasks face higher automation risks [10]. As a result, agriculture demonstrates clearer examples of complete job displacement compared to knowledge-intensive sectors.

G. RQ3: What are the socio-economic implications of AI-driven task and job displacement for the workforce?

The findings from the analyzed use cases suggest that the socio-economic implications of AI-driven task and job displacement are multifaceted, affecting workforce structures, skill requirements, and perceptions of job security. While AI adoption can enhance productivity and efficiency, it also introduces concerns regarding employment stability and the evolving nature of work. These outcomes align with earlier qualitative research indicating that workers exhibit mixed perceptions regarding the risks posed by AI technologies. For instance, [23] reported that employees across various professions perceive AI either as a complementary tool or as a potential threat to job security, depending largely on the nature of their roles and exposure to automation. Similarly, [24] highlighted growing anxieties about the possibility of large-scale job displacement, despite recognizing that AI adoption may also generate new forms of employment.

The analyzed cases provide practical examples of how these socio-economic dynamics unfold across sectors. In many instances, AI systems automate repetitive tasks rather than replacing entire occupations, leading to job transformation rather than immediate job elimination. For example, financial systems such as Absa Abby [69], Haraka AI Loan App [68], and AI-driven financial analytics platforms automate routine tasks including credit scoring, customer support, and financial data analysis. Similarly, healthcare technologies such as Radify AI [35] and automated diagnostic tools assist medical professionals by performing data-intensive diagnostic functions. These cases illustrate how AI reshapes occupational roles by shifting workers away from repetitive activities toward tasks requiring judgment, oversight, and interpersonal interaction. Such patterns are consistent with the TBA, which suggests that technological change restructures the composition of tasks within jobs rather than eliminating occupations entirely.

At the same time, the emergence of fully automated systems in certain sectors highlights the potential for direct job displacement, particularly in occupations dominated by routine manual tasks. Autonomous agricultural machinery such as Robotti [83], Agrist Robot [85], and the Oxin Tractor [88], along with industrial robotics such as the Yaskawa arc welding system [78] and Tesla Giga Press [79], illustrate cases where automation replaces a large portion of human labor in specific roles. These examples reinforce arguments that routine manual occupations are particularly vulnerable to technological displacement. As suggested by [89], such patterns may contribute to labor market polarization, where middle-skill routine jobs decline while demand increases for both high-skill technical roles and low-skill service positions that remain difficult to automate.

Beyond direct employment effects, AI-driven transformation has broader implications for skills development and workforce adaptation. As AI systems assume routine tasks, workers increasingly need to develop competencies that complement automated technologies. Research by [25] emphasizes that successful human–AI collaboration requires workers to cultivate human-centric capabilities such as critical thinking, problem solving, communication, and creativity. The analyzed cases support this observation, as many AI systems function as decision-support tools that require human oversight and interpretation. Consequently, workforce resilience in an AI-driven economy depends heavily on the ability of workers to continuously update their skills and adapt to changing task requirements.

The economic implications of AI adoption further extend to productivity and labor market restructuring. Studies examining generative AI technologies suggest that these tools may significantly increase productivity while simultaneously transforming occupational structures. For instance, [26] predicted that AI could automate a substantial share of routine tasks while also creating new high-skill job categories related to AI development, deployment, and oversight. Similarly, global projections indicate that although AI may displace a large number of jobs, it may also generate new opportunities in emerging technological fields. Estimates presented by [30] suggest that while approximately 85 million jobs may be displaced globally, up to 97 million new roles could emerge, resulting in a net increase in employment.

However, the socio-economic consequences of AI adoption are unlikely to be evenly distributed. Several studies highlight the potential for inequality and demographic disparities in AI-driven displacement. According to [89], automation may disproportionately affect workers in routine occupations, many of which are concentrated among lower-income groups. Furthermore, [30] identified gender disparities in exposure to automation, noting that women are often overrepresented in occupations susceptible to AI-driven task automation. Such disparities suggest that the benefits and costs of AI adoption may be unevenly distributed across different demographic groups.

The present findings also highlight the importance of considering regional differences in AI adoption and labor market impacts. Many of the analyzed cases originate from high-income economies where technological infrastructure and investment in AI development are more advanced. In contrast, developing economies often adopt AI technologies in targeted sectors such as agriculture and financial inclusion, as illustrated by cases like MkhulimaGPT [49], Plantix [52], and the NOVISSI AI targeting system [67]. These applications often aim to improve productivity and service accessibility rather than replace large numbers of workers. Nevertheless, the long-term implications of AI adoption in developing economies remain uncertain, particularly in rural labor markets where employment opportunities may already be limited.

Overall, the socio-economic implications of AI-driven task and job displacement extend beyond immediate employment effects. AI technologies are reshaping workforce structures by transforming occupational tasks, altering skill requirements, and influencing the distribution of economic opportunities. While the analyzed cases suggest that AI adoption currently leads more frequently to task transformation and workforce augmentation than to widespread job elimination, the long-term effects may include structural changes in labor markets, shifts in skill demand, and potential increases in economic inequality. Addressing these challenges requires policies that support workforce reskilling, promote equitable access to technological opportunities, and ensure that the benefits of AI-driven productivity gains are broadly shared across society.

H. RQ4: How do different classes of AI systems relate to patterns of task and job displacement?

The analyzed use cases indicate that the relationship between AI technologies and displacement outcomes varies according to the class of AI system deployed. Different AI technologies automate different types of tasks, and therefore produce distinct patterns of task displacement, job displacement, or augmentation. These findings are consistent with the TBA, which emphasizes that the effects of automation depend on the nature of the tasks being automated rather than the occupation itself. In practice, this means that AI systems designed for analytical reasoning, perception, or physical automation influence the workforce in different ways depending on the task characteristics they target.

I. Robotics

Among the analyzed cases, robotics-based systems are most strongly associated with job displacement, particularly in sectors involving routine physical tasks. Autonomous machinery such as Robotti [83], Agrist Robot [85], John Deere CP770 [84], YV01 vineyard robots [87], and the Oxin autonomous tractor [88] automate agricultural activities including planting, harvesting, spraying, and field monitoring.

Similarly, robotics systems in manufacturing such as the Yaskawa robotic arc welding system [78], Tesla Giga Press [79], and the UR16e collaborative robotic arm [81] perform repetitive industrial operations that were traditionally carried out by human workers. These technologies replace a substantial proportion of the task bundles associated with manual labor occupations, making entire job roles economically redundant. This pattern supports previous research indicating that robotics and industrial automation primarily affect routine manual tasks, which are easier to standardize and automate.

J. Conversational Chatbots

In contrast, natural language processing (NLP) and conversational AI systems tend to produce task displacement rather than full job displacement. Systems such as Absa Abby [69], Sophie Bot [58], MkhulimaGPT [48], and the conversational insurance chatbot automate customer interaction, information retrieval, and advisory functions. These systems reduce the need for human agents to perform routine communication tasks but still require human oversight, escalation handling, and decision-making in complex situations. Consequently, customer service representatives, financial advisors, and extension workers continue to play active roles in service delivery. This pattern aligns with earlier research suggesting that AI technologies in service sectors typically restructure internal workflows rather than fully eliminating occupations.

K. Machine Learning Based Systems

Machine learning systems used for analytics and prediction demonstrate a similar pattern of task-level automation. Financial analytics platforms such as BlackRock's investment analysis tools, Haraka AI Loan App [68], and the Optasia financial access platform automate data analysis [76], credit scoring, and fraud detection. These technologies replace time-consuming analytical tasks previously performed by financial professionals but do not eliminate the broader occupational roles that involve strategic decision-making and regulatory oversight. This observation reinforces the argument that data-driven AI systems augment professional work by improving efficiency and decision accuracy, rather than fully replacing expert labor.

L. Computer Vision

Another important category observed in the dataset is computer vision systems, particularly in healthcare and agriculture. Applications such as Radify AI [36], Plantix [52] , and automated X-ray diagnostic devices perform image-based analysis tasks that previously required specialized human expertise. These systems demonstrate high accuracy in pattern recognition tasks, enabling them to automate diagnostic subtasks within professional workflows. However, the broader occupations of medical professionals and agricultural specialists remain necessary for contextual interpretation, treatment decisions, and field-level interventions. Consequently, computer vision technologies primarily contribute to task augmentation rather than occupational elimination.

M. Expert Systems

The findings also highlight the role of expert systems and generative AI technologies, which automate knowledge-intensive tasks such as financial planning, decision support, and operational optimization. Systems such as Anaplan's intelligent agents [74] and Scale AI healthcare platforms [44] assist professionals by generating recommendations and insights from large datasets. These systems typically function as decision-support tools, requiring human interpretation and oversight. As a result, they primarily lead to task displacement rather than direct job loss, reflecting the continued importance of human judgment in complex decision-making environments.

V. Conclusion and Future Work

This study examined the impact of artificial intelligence on task and job displacement across agriculture, finance, manufacturing, and healthcare sectors using 37 global use cases. RQ1 findings show that, consistent with the TBA, AI most commonly replaces specific tasks within existing jobs rather than entire occupations, with task displacement occurring predominantly in knowledge-intensive sectors such as healthcare and finance. Sectoral differences were also evident in answering RQ2, as manufacturing and agriculture exhibited stronger patterns of job-level automation due to routine physical tasks, whereas healthcare and financial services largely experienced task augmentation and workflow restructuring. The socio-economic implications assessed through RQ3 suggest that AI adoption is likely to reshape skill requirements and labor market structures, increasing demand for higher-order cognitive and interpersonal skills while raising concerns about job polarization and inequality among workers in routine occupations. Finally, the analysis of AI technology classes assessed through RQ4 indicates that robotics systems are more closely associated with job displacement, particularly in manual labor sectors, whereas machine learning, computer vision, NLP, and expert systems primarily lead to task-level automation and human–AI collaboration. Overall, the results highlight that AI-driven labor market transformation is primarily characterized by task recomposition and occupational restructuring rather than widespread job elimination, although certain routine occupations remain vulnerable to full automation as AI technologies continue to evolve.

Based on the findings of this study, several recommendations can be proposed to support policy-makers, educators, and human resource practitioners in responding effectively to AI-driven changes in the labor market. These recommendations are informed by the observed patterns of task displacement, sectoral variation, and the relationship between AI technologies and workforce transformation.

First, policy-makers should prioritize workforce reskilling and lifelong learning initiatives to support workers whose tasks are increasingly automated. Since the findings indicate that AI most commonly replaces specific tasks rather than entire jobs, policies should focus on enabling workers to transition into complementary roles that require human judgment, creativity, and interpersonal skills. Governments should therefore invest in continuous training programs, digital literacy initiatives, and vocational education systems that prepare workers to collaborate with AI technologies rather than compete against them.

Second, education systems should adapt curricula to reflect the evolving skill demands of an AI-driven economy. The results demonstrate that routine tasks both cognitive and manual are more susceptible to automation, while non-routine analytical, creative, and interpersonal tasks remain more resilient. Educational institutions should therefore emphasize interdisciplinary learning that combines technical knowledge with human-centered competencies such as critical thinking, problem solving, ethical reasoning, and communication. In addition, integrating AI literacy into school and university curricula will help prepare future workers to effectively interact with AI systems across different industries.

Third, human resource practitioners should redesign job roles to leverage human–AI collaboration. Rather than viewing AI solely as a tool for labor substitution, organizations should adopt strategies that integrate AI systems into existing workflows in ways that augment employee capabilities. This may involve redefining job roles so that AI handles routine data processing tasks while employees focus on strategic decision-making, innovation, and customer engagement. HR departments should also implement structured reskilling programs to ensure that employees can transition into new roles created by AI-enabled transformation.

Fourth, sector-specific workforce strategies should be developed, particularly for sectors where job displacement risks are higher. The findings indicate that sectors such as manufacturing and agriculture, where tasks are highly routine and standardized, are more likely to experience full job displacement through robotics and automation. In these sectors, targeted labor transition programs such as retraining for technical maintenance roles, digital agriculture management, or advanced manufacturing operations can help mitigate the negative employment effects of automation.

Fifth, inclusive AI adoption policies should be implemented to reduce socio-economic inequalities that may arise from automation. Since routine occupations are often concentrated among lower-income workers, AI-driven displacement could exacerbate existing labor market inequalities if adequate support mechanisms are not established. Governments and organizations should therefore implement policies that support equitable access to training, promote fair AI deployment practices, and ensure that productivity gains from AI adoption are shared across the workforce.

Finally, future labor market monitoring and research should be strengthened. As AI technologies continue to evolve, it will be essential for policy-makers and organizations to track emerging patterns of task and job displacement across sectors and regions. Establishing labor market observatories, collecting task-level employment data, and supporting interdisciplinary research on AI and employment will help ensure that workforce policies remain responsive to technological developments.

Despite providing valuable insights into the relationship between artificial intelligence and labor displacement, this study has several limitations that should be acknowledged. Addressing these limitations presents important opportunities for future research.

First, the number of analyzed use cases was limited. Although the study initially aimed to collect approximately 80 use cases across sectors, continents, and income classifications, only 37 cases met the inclusion criteria due to limited publicly available information about implemented AI systems and their deployment contexts. In many instances, online sources did not provide sufficient details regarding the specific AI technology used or the country of implementation. Consequently, while the dataset spans all continents and income classifications, the relatively small sample size may limit the generalizability of the findings.

Second, the study relies primarily on secondary data obtained from publicly available case studies and online reports. Such sources may emphasize successful implementations of AI technologies and may not fully capture unsuccessful deployments or negative employment outcomes. This may introduce publication bias, where visible implementations receive greater attention than cases where AI adoption did not achieve expected results or led to unintended consequences. Future research could address this limitation by incorporating primary data sources, such as surveys, interviews with organizations adopting AI, or labor market datasets that track occupational changes over time.

Third, the analysis focused primarily on qualitative classification of displacement types namely task displacement, job displacement, or no displacement. While this approach provides valuable conceptual insights, it does not quantify the magnitude of displacement effects. For example, it does not measure the proportion of tasks within a job that have been automated or the number of workers affected by each AI implementation. Future studies could integrate quantitative approaches, such as task-level automation metrics, employment statistics, or econometric analyses to estimate the scale of AI-driven displacement across industries.

In light of these limitations, several avenues for future research emerge. Future studies should aim to expand the dataset of AI use cases, incorporate quantitative labor market data, and conduct comparative analyses across sectors and regions. Additionally, research focusing on longitudinal labor market changes and demographic impacts of AI adoption would provide deeper insights into the evolving relationship between artificial intelligence and employment. Such efforts would contribute to a more comprehensive understanding of how AI reshapes the global workforce and inform policies aimed at promoting equitable and sustainable technological transformation.

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