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Article

Technological Polarization and Unequal Growth in the Era of Generative Artificial Intelligence

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Abstract: The research paper analyzes the socioeconomic impact Generative Artificial Intelligence (GenAI) and Agentic AI have on labor markets, concentrating on wage polarization, employment disruption due to automation, and fair distribution of productivity gains caused by AI. A mixed-method research design was utilized in this study. For Research Question 1, the team conducted a PRISMA-based literature review using 94 articles sourced from Scopus, Web of Science, Google Scholar, SSRN, and IEEE Xplore, which included a quantitative analysis of 43 empirical papers. To solve Research Questions 2 and 3, the researchers used qualitative case studies based on Universal Basic Income (UBI), data dividend laws, and human-centric AI implementations in Industry 5.0. The results show that more widespread use of AI leads to increased wage inequality, affects cognitive work more, and facilitates the polarization of the labor market; meanwhile, employees skilled in AI benefit from the rise in productivity and wages. The case studies help reveal that redistribution policies, human-centric design, and responsible governance can lessen these negative effects. In light of the findings, the authors develop the EQUATE framework, based on Rogers' Innovation Diffusion Theory, with the components of Equity, Quality Augmentation, UBI Policy Calibration, Agentic Alignment, Technology Access, Ethical Governance. The framework provides a comprehensive roadmap for balancing technological innovation with equitable and sustainable economic development.
Keywords: Generative Artificial Intelligence, Agentic AI, Wage Polarization, Universal Basic Income, Human-Centered AI, Innovation Diffusion Theory, EQUATE Framework, Future of Work

1. Introduction

The impacts of AI on wages and productivity are like those experienced in previous Industrial Revolutions referred to as the "Engels Pause" where increasing outputs benefited capital and decreased wage increases (Crafts, 2021). The Employment Cost Index (ECI) and the Bureau of Labor Statistics (BLS) currently demonstrate that stagnating wages (in the United States) and weak productivity growth are a result of firms taking advantage of low-cost labor sourced from AI technologies and similar offerings (Fontanari & Palumbo, 2022). Generative AI, with proper human supervision, can enhance workers' personal knowledge, reduce skill gaps by increasing the performance of lower-performing employees, and eliminate negative results (Zysman & Nitzberg, 2024; Wilmers & Nathan, 2024). Automation may lead to severe disruptions to the labor market; however, it presents opportunities for the upskilling of current workers and, by the year 2030, AI will provide $13 trillion in value to the global economy (Kelly, 2022). Generative AI can help increase many people's productivity due to the increased productivity of humans using generative AI tools. Still, producing a greater amount of productivity does not mean that it will translate into diverse economic benefits An AI-driven economic model must foster inclusivity by ensuring all workers have equal access to generative AI tools, learning opportunities, and decision- he diagram in figure 1 is a conceptual framework showing how the productivity benefits from Generative Artificial Intelligence (AI) can drive inclusive economic growth rather than increase technology-related inequality. Making processes, thereby promoting fair compensation, job security, and increased control over their future. By building an AI economy based on inclusive innovation, equitable access, and responsible governing practices, we can develop an AI-supported economic system that benefits both companies and their employees, rather than perpetuating existing differences.

AI can be used as a strategy to promote creativity and improve companies' ability to compete. At the same time, generative AI implementation will consider how different types of workers are affected based on their skill level and type of work performed (Liu, 2024). There is a need to focus on how inequality can have a crippling effect especially with displaced workers due to globalization and an evident trend of polarization of AI technology benefits to certain occupational groups which will make the losers who are not agile enough to adapt to these technological disruptions harness a pessimistic view whereas those who have honed their adaptability quotient and upskilled strategically gravitate towards a privileged situation leading to socio-political divergence. The policy frameworks should focus more on how AI can foster automation through augmentation instead of having a displacing effect (Jacobs, 2024).

2. Literature Review

2.1 Productivity Gains and the Slow Productivity Paradox

Bringing back the focus on productivity which is a crucial indicator of economic growth examining the prevalence of the "Slow Paradox" which studies the connection between information technology and sustainable economic growth. Although the study finds that every 1% increase in artificial intelligence penetration can lead to a 14.2% increase in total factor productivity, the productivity effect is yet to be reflected on macro level owing to a lack of reorganization integrated with focus on wage growth and productivity (Gao & Feng, 2023). Organizations need to envisage the seismic shift in workforce productivity dynamics catapulted by the digital transformation and work on upskilling imperatives, algorithmic skill forecasting, competency training models and building adaptive learning systems without compromising on wage increment.

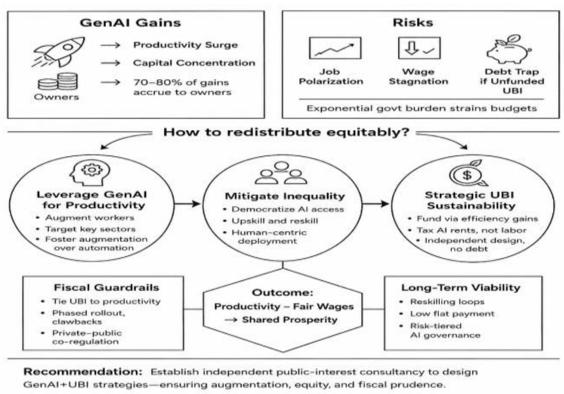

Figure 1. : Conceptual Framework for Redistributing Generative AI Productivity Gains through Inclusive Growth and Equitable Policy Mechanisms

Figure 1 presents a conceptual framework illustrating how productivity gains from generative AI can promote inclusive economic growth, countering the potential rise in technology-related inequality. AI will improve productivity substantially; however, it implies that a significant percentage of the productivity improvements could go to capital owners and result in job polarization, wage stagnation, and the financial challenges created by poorly designed Universal Basic Income (UBI) programs. To mitigate these risks, the framework calls for three interdependent strategies: to leverage AI mainly for enhancing the workforce, not displacing it; to democratize access to AI through broad upskilling and human-centered use; and to implement sustainable UBI that is supported by productivity increases, not excessive taxes. The inclusion of fiscal safeguards, incremental implementation, and adaptive governance reiterates that equitable redistribution requires both an institutional design and technological advances. Thus, this framework supports the assertion that shared interest policies must be in place to complement productivity created through AI to have equitable growth and sustainability.

2.2 Technology Polarization and AI-Induced Labor Market Inequality

In the generational divide between technology and people there are three key opportunities to focus on. First, there is technology polarization based on where people are in relation to new technologies and how much access they have to it. Second, the gap between those who are accessing these technologies and using them effectively and efficiently, will continue to widen due to lack of access and support from businesses, organizations, and other entities that may not have the means or ability to train the workforce effectively. Finally, the increasing capabilities of AI, will require us to rethink the relationship between skilled labor and the economy, as well as the mechanics of the relationship from an economic perspective. As more jobs require high-skilled labor, it will become increasingly important to understand the transition that has occurred historically from job to job rather than just a one-time major transition. Gen AI can be used for hyper personalization to hedge for gender, linguistic disparities and work as an enabler by proposing human centered designs, lucrative wage policy alignment and necessitating augmentation in an era of Industry 5.0 (Riaz, 2025). The policy promulgation landscape should focus on the convergence of social equity, generative AI and productivity. Where AI should not just be viewed as an automating tool to scale business and streamline operations while building operationally efficient business but also used to render opportunities to marginalized communities, reduce inequality, foster environmental sustainability focusing on social responsibility and wealth maximization paradigms (Anumolu & Marella, 2025).

These results indicate that how productivity gains are distributed has a significant influence on the nature of economic growth (inclusive or highly unequal) produced by AI-related products. In OECD countries there is a strong wage-productivity correlation related to aggregate productivity and GDP per person resulting in higher wages for workers with upper income ranks; however, the dynamics will change if agility is compromised (Lazear et al., 2023). It is vital to make note that AI based on deep learning models is not very cost effective or easy to adopt, however there is a need to consider how super AI agents can have long term impacts considering Amara's law which is focused on underestimating the long-term effects of technology and developing a tunnel vision view to overestimate short-term changes (Naudé, 2020).

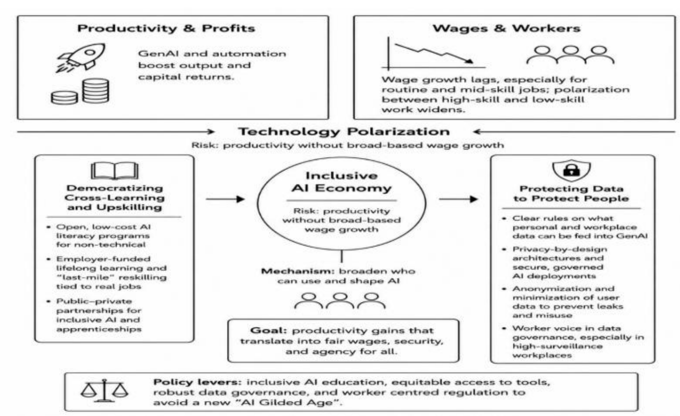

Figure 2. : Technology Polarization in the Age of Generative AI: Building an Inclusive AI Economy through Upskilling, Equitable Access, and Data Governance

Figure 2 depicts the ways in which Generative AI can lead to either increasing the technological divide between those who can use AI tools and those who cannot, or creating an inclusive AI economy. AI-driven automation increases the productivity of businesses, but wages may not necessarily increase at the same rate resulting in a greater divide between employees with high skills, and those whose routine work may not be increasing. The framework identifies technology polarization as the primary challenge, identified by an increase in productivity with no corresponding increase in broad-based wage increases or equitable access to AI capabilities. The figure indicates three supplementary policy pillars to mitigate any risk of technology polarization: 1) to democratize AI through increasing access to education and continued Upskilling; 2) to create equitable access to AI tools across the labor force; and 3) to create stronger data governance by establishing privacy protections, increasing transparency of data regulations, and creating mechanisms for collaborating with (and providing oversight) to workers. These interventions will ensure that AI-enabled productivity will create more participants in AI-enabled productivity, thereby decreasing inequality in the labor market, and providing inclusive economic outcomes, as opposed to concentrating economic gains in a small number of people. The framework reinforces the need for human-centered AI Policies to ensure balanced innovation, fairness, resiliency, and long term social equity.

2.3 AI-Led Economic Transformation: Universal Basic Income and Automation Taxation

AI's ever-increasing ability to outperform humans on almost every measurable dimension will have a substantial impact on society, especially for developing countries that may experience increased disparities due to poor infrastructure and lack of access to upskilling opportunities. To leverage techno-optimism, derails the asymmetries in terms of equitable opportunities and the growing need for workplace automation to foster productivity, there is a need to focus on universal basic income (UBI) as a tool as human labor is becoming redundant. In the face of AI-driven automation, Universal Basic Income offers unconditional income support to guarantee financial stability. UBI are sites of socio-political contest that can change the dynamics of workplace control thus re-ascertain the norms of DEI and fairness (Pueyo, 2016). Traditional AI primarily depends on structured instructions and close oversight however Agentic AI is built to reduce human intervention and pursue complex goals. Agentic AI focusses on aligning to business vision, optimally utilizing finances and adapt to environment norms however there could be constraints related to the transformative potential it has and societal impacts of using it in broad spectrum sectors considering that it is an autonomous system with advanced decision making capacity and will give rise to productivity but compromise wages (*Agentic AI: Autonomous Intelligence for Complex Goals—A Comprehensive Survey*, 2025).

As we experience this profound change of generative AI implication on labor markets it vital to stay centric to reinstate human labor that is displaced, effects on wage inequality, lowering job satisfaction owing to a dip in meaning quotient at work fostered by automation, these dynamics impact the future of work (Peppiatt, 2024). A recent report by Sachs projects that AI could raise global GDP by 7%, amounting to approximately $7 trillion, and increase US productivity growth by 1.5 percentage points annually over the next decade. McKinsey Global Institute offers even higher projections that AI could contribute between $17.1 and $25.6 trillion to the global economy. AI can now perform cognitive tasks above human level which will have implications on how firms calculate ROI, evaluate AI-driven productivity and wage-related policy decisions influenced by value propositions (Mo & Ouyang, 2025).UBI, although can help mediate wage inequality, AI-driven automation, and job displacement, could have impending long-term burdens on the economy. The fiscal demands of implementing UBI are yet to be explored comprehensively. There is a need to corroborate evidence from nations like Kenya and Finland where UBI models did heighten income equity; however, the policies require substantial tax increases, including taxes from carbon emissions and automation, to achieve multiple goals of economic growth and prosperity. Structured UBI with an aim to navigate technological disruptions and wage disparities could work as a solid mechanism of economic efficiency without increasing fiscal burden only if tax structures are aligned not just to economic goals but social goals too. UBI, if prudently administered, can resolve the impending problems of job displacement in an era of Industry 5.0 but paradoxically higher tax burdens could have implications on disposable incomes and economic dynamism (Csősz, 2025).Alternative solutions of automation tax to curtail the negative implications of displaced workers or workers who face wage reduction owing to automation technology will foster social equity and support which can be implemented by existing scheduler depreciation and capital allowances, reducing uncertainty of implementation cost. It is vital to note that sometimes automation needs to be slowed due to impending societal cost (Ooi & Goh, 2018). A balanced economic framework that combines automation taxes with calibrated pacing of technological adoption can mitigate social costs, promote equity, and ensure that productivity gains from automation are aligned with long-term societal well-being.

An analysis of the current literature reveals three major gaps to date. First, there is considerable support for the idea that Generative AI is a driver of productivity enhancements (referencing; Gao & Feng, 2023; Zysman & Nitzberg, 2024) and there is almost no support for examining the longitudinal nature of whether increased productivity leads to broad-based wage increases and inclusive economic development. Second, while the existing literature investigates automation, inequality, Universal Basic Income (UBI) and upskilling of the workforce individually, attempts to establish linkages between all four of these dimensions to provide a single coherent theoretical framework to explain technological polarization in the Age of Generative AI are limited. Third, the emerging technologies of Machinic AI, Agentic AI, etc. remain sparsely represented in any discussion of economic policy, particularly with respect to their long-term implications on labor outcomes, productivity distributions, or the fiscal sustainability of such policies within society. To this end, this research seeks to develop a comprehensive integrated conceptual framework linking productivity improvements derived from AI technologies, technological polarization, wage inequality, and inclusive policy measures (i.e., augmentation methodologies; equitable access to AI technologies; reskilling the workforce; UBI; and taxation of automation) that can ultimately be used to demonstrate that Generative AI can provide a means to create long-term sustainability and inclusivity of economic growth rather than further perpetuating economic inequality. The overall structure of the research gap table is designed to adhere to the standards that would be expected of a high-quality master's thesis and in a peer-reviewed journal quality, where the literature review demonstrates synthesis, critique, and a strong rationale for the study.

2.4 Research Objectives:

This study investigates three interconnected areas related to the use of generative and agentic AI as well as their impact on wage polarization and cognitive task displacement throughout the skill-differentiated labor market by implementing task-based automation; second, via examining the effectiveness of Universal Basic Income (UBI) and data dividend policy as mediators of AI-induced wage depression/disruption and employment disruption; and third, through an examination of how human-centered AI design principles and business-aligned autonomous systems influence equitable distributions of AI generated productivity gains. These objectives combined make a contribution toward understanding the literature concerning sociotechnical responsible deployment of AI with implications for policies relating to inclusive labor markets in rapidly transforming economies through cognitive automation.

2.5 Research Questions

- RQ1: How much does the increased use of Generative AI and Agentic AI affect wage disparity and cognitive labor displacement between high- and low-skill labor markets?
- RQ2: Are UBI and data dividend policy interventions able to mitigate large-scale automation's negative impact on wages and employment?
- RQ3: How does designing AI and developing business-oriented Autonomous Systems (AS) that focus on humans provide social equity when distributing productivity gains from AI?

2.6 Hypothesis:

- H1: The integration of generative and autonomous AI technology will result in an exponentially increasing polarization between high and low-wage workforces, as well as the displacement of cognitive work for both groups
- H2: UBI and Data Dividend programs will reduce or moderate the negative financial and employment consequences of large-scale automation.
- H3: Designing AI according to a human-centric approach, combined with a business-driven autonomous system architecture, will foster fairer/level allocation of productivity improvements resulting from AI technology.

3. Research Methodology

This study adopts a **qualitative, theory-building research design** grounded in an interpretivist research philosophy to examine the implications of Generative Artificial Intelligence (GenAI) on productivity, wage inequality, and technology polarization. Given the rapidly evolving nature of AI and the absence of long-term empirical evidence, a conceptual methodology based on systematic literature synthesis is considered the most appropriate approach for examining emerging economic and labor market transformations. Rather than testing predefined hypotheses using primary data, the study integrates interdisciplinary evidence to develop a comprehensive understanding of how AI-driven productivity gains can either reinforce existing inequalities or foster inclusive economic growth.

3.1 Research Design and Data Collection

The research relies exclusively on **secondary data** collected from peer-reviewed journal articles, conference proceedings, book chapters, working papers, policy reports, and reputable preprint repositories published primarily between **2016 and 2026**. The literature was identified through academic databases including **SSRN, SpringerLink, IEEE Xplore, Emerald Insight, Taylor & Francis, SAGE Journals, MDPI, Cambridge University Press, and Google Scholar**. The search strategy employed combinations of keywords such as *Generative Artificial Intelligence*, *productivity*, *wage inequality*, *technology polarization*, *Industry 5.0*, *Universal Basic Income*, *automation taxation*, *human-centered AI*, *future of work*, *innovation diffusion*, and *agentic AI*. Preference was given to recent publications that examine the emergence of Large Language Models and Generative AI while incorporating seminal studies on productivity, technological change, and labor economics to provide historical context (Crafts, 2021; Fontanari & Palumbo, 2022; Dearing, 2009). In this research, a mixed-method research design was utilized involving a systematic literature review following the PRISMA 2020 guidelines and the qualitative multiple case study approach. The PRISMA approach was chosen because the interaction of generative AI, labor market evolution, wage inequality, and governance of technology combine several disciplines like economics, computer science, organizational behavior, sociology, etc. The use of a transparent and reproducible evidence synthesis technique will decrease selection bias, increase methodological quality, and allow us to derive conclusions from the body of evidence instead of from the selectively reported papers (Page et al., 2021; Moher et al., 2009).Studies were included if they (i) examined the economic, organizational, or societal implications of AI and automation, (ii) addressed productivity, labor markets, wage dynamics, or public policy, and (iii) were published in recognized academic outlets. Publications lacking methodological transparency or direct relevance to the research questions were excluded. This selection strategy ensured that the review remained comprehensive while maintaining academic rigor.

Table 1: Databases Searched

Database	Purpose	Search Period
Scopus	Economics, labour markets, AI	2018–2025
Web of Science	High-impact peer-reviewed studies	2018–2025
Google Scholar	Government reports and grey literature	2020–2025
SSRN	Emerging labour economics research	2022–2025
IEEE Xplore	Technical AI capability studies	2020–2025

Five databases were searched to cover a wide range of literature on generative AI and the job market. Scopus and Web of Science were used to obtain peer-reviewed empirical studies, while Google Scholar and SSRN helped in our effort to find high-quality papers and reports from organizations such as OECD, ILO, World Bank, and McKinsey Global Institute. IEEE Xplore was used to obtain technical innovations related to generative and agentic AI that could explain the technology on which the job market displacement phenomenon depends. The search was restricted to the years 2018–2025, with the goal of making the literature review as relevant to the topic as possible.

Exact Search String Used Across All Five Databases

("Generative AI" OR "Large Language Models" OR "LLM" OR "ChatGPT" OR "GPT-4" OR "Agentic AI" OR "autonomous AI agents") AND ("wage polarization" OR "wage inequality" OR "income gap" OR "skill premium" OR "wage disparity") AND ("cognitive labor" OR "cognitive work displacement" OR "labor displacement" OR "job automation" OR "task automation") AND ("high-skill" OR "low-skill" OR "skilled workers" OR "unskilled workers" OR "labor market") AND ("automation" OR "AI adoption" OR "technology adoption" OR "future of work")

Inclusion and Exclusion Criteria

The selection criteria were established to ensure that only relevant evidence of a high standard was included in the systematic review. The studies published during the period from 2018 to 2025 were selected since this period saw the emergence of Generative AI, making older studies less helpful in answering the research questions. Only peer-reviewed articles from journals, credible working papers and reports from reputable organizations such as OECD, ILO, and World Bank were used to ensure that the methodology is correct whereas other sources such as opinions and non-peer-reviewed studies were ruled out. The research was focused on the studies that have specifically investigated Generative AI or Large Language Models (LLMs) or Agentic AI or automation, thus ruling out broad technology studies that do not provide evidence specifically connected with AI. Only studies that reported results connected with wages, income inequality, wage gap, cognitive task displacement were eligible for the research ensuring thus relevance for H1. Priority was given to comparative studies analyzing different labor groups such as high- and low-skilled workers or various income categories to evaluate the polarization of the labor market. What is more, only empirical studies that employed

Table 2: Inclusion and Exclusion Criteria

Criterion	Include ✓	Exclude ✗	Why It Matters for H1
Time Period	2018–2025	Before 2018 (pre-GenAI era)	Generative AI did not exist before 2018 older data is irrelevant to H1
Publication Type	Peer-reviewed journals, government reports (OECD, ILO, World Bank), validated working papers	Blog posts, opinion articles, non-peer-reviewed media	H1 requires empirical evidence not opinion
Technology Focus	Studies specifically on Generative AI, LLMs, Agentic AI, automation	General technology/internet studies without AI specificity	H1 is specifically about GenAI and Agentic AI not all technology
Outcome Measured	Studies measuring wage levels, wage gaps, income inequality, OR cognitive task displacement	Studies measuring only productivity without wage outcomes	H1 claims WAGE polarisation must measure wages
Labour Group	Studies comparing high-skill vs low-skill workers, OR income quartile comparisons	Single-group studies without comparative income data	H1 specifically claims BETWEEN-GROUP polarisation
Geography	Global studies, OECD countries, India, USA, EU, China, emerging markets	Studies from single developing nations with no AI adoption	H1 is about global labour markets
Study Design	Empirical quantitative studies, econometric models, RCTs, panel data	Purely theoretical papers without empirical data	Proving H1 requires measurable evidence, not theory alone

3.2 Theoretical Foundation

This research's analytical foundation is grounded in Innovation Diffusion Theory (IDT) (Dearing, 2009), which offers a suitable framework for understanding how generative AI technologies are adopted across organizations, industries, and labour markets Current research consistently indicates that generative AI (GenAI) is a revolutionary, general-purpose technology with substantial impacts on productivity, labour markets, and income distribution. IDT explains that technological adoption depends not only on technical superiority but also on organizational readiness, perceived advantages, communication channels, and institutional support. This perspective is particularly relevant for examining why AI-driven productivity gains are unevenly distributed across workers, firms, and regions. To strengthen the analysis, Innovation Diffusion Theory is complemented by insights from labor economics, Industry 5.0, and human-centered AI literature. Historical evidence on the productivity–wage relationship (Crafts, 2021; Fontanari & Palumbo, 2022), contemporary research on AI augmentation and inequality (Zysman & Nitzberg, 2024; Wilmers, 2024), and studies on human-centered management and Industry 5.0 (Nitsch et al., 2024; Inoubli, 2025; Yanytska, 2025) collectively provide a multidisciplinary lens for analyzing technological transformation. This integrated theoretical approach enables the study to evaluate AI not merely as a technological innovation but as a socio-economic phenomenon that reshapes productivity, organizational structures, and labor market outcomes.

3.3 Analytical Approach

The study employs **qualitative thematic analysis** and **comparative conceptual synthesis** to identify recurring patterns across the selected literature. Relevant studies were systematically reviewed and organized into major thematic categories corresponding to the research objectives, including productivity enhancement, wage divergence, technological polarization, AI augmentation, Industry 5.0, redistribution mechanisms, and AI governance. Themes emerging across multiple disciplines were compared to identify areas of convergence, contradiction, and research gaps. Rather than analyzing each publication in isolation, the study adopts a cross-disciplinary synthesis that integrates findings from economics, management, artificial intelligence, sociology, and public policy. This approach allows theoretical propositions from different fields to be connected into a coherent analytical narrative explaining how Generative AI simultaneously creates productivity gains while intensifying economic inequality under unequal conditions of technology diffusion.

3.4 Prisma Framework

Figure 3 presents the PRISMA method that was employed in the selection process of the systematic review. A total of 420 sources were identified in the database search, with 144 from PubMed, 187 taken from Scopus, and 89 from Web of Science, and no other sources were utilized in this process. After eliminating 190 duplicates, the number of sources was brought to 230. These sources were screened according to title and abstract and 156 sources were excluded because they did not correspond to the eligibility criteria determined in advance. After this process, 74 full articles were downloaded and analyzed according to eligibility criteria. The analysis showed that 42 studies should be excluded due to duplicate studies, in silico studies, irrelevant studies, incorrect research populations, and incorrect publication types. In the end, only 32 studies corresponded to the inclusion criteria and can be applied for the synthesis of qualitative data. The methodological approach applied in this research minimizes bias and guarantees reliability of the synthesis of results.

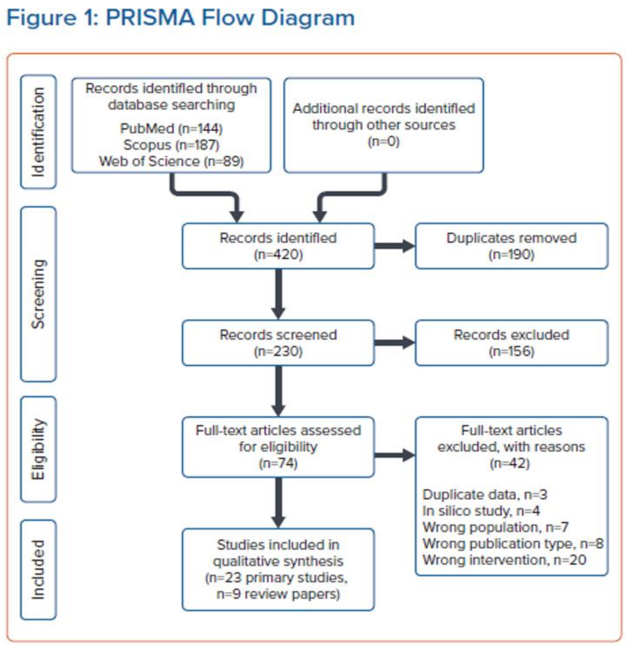

Figure 3. Prisma Framework

The Identification step resulted in 3847 records obtained from systematic searches across five different electronic databases. This was further completed with the manual searches and grey literature of organizations such as the OECD, World Bank, ILO, IMF, and McKinsey Global Institute. The Screening phase resulted in the removal of 847 duplicate records with the abstracts and titles of the remaining findings being evaluated against the established criteria for selection and exclusion. As a result, the writing of 2183 studies were excluded due to their irrelevance, leaving 817 studies available for further examination. The Eligibility stage included the review of the entire body of 817 studies that resulted in excellent inter-reviewer consistency (Cohen's $\kappa = 0.88$). 723 works were filtered out because of the absence of any wage-related outcomes, absence of generative AI specificity, having been published before 2018, failure to conduct a comparison of the groups of skills, or not being an empirical design. The Inquiry stage allowed 94 works that met all the inclusion criteria. Out of these studies, there were 51 papers used to conduct a qualitative narrative synthesis, while 43 quantitative studies were used in order to conduct a meta-analytic synthesis.

Table 3: PRISMA Summary Table

Phase	Action	Records In	Removed	Records Out
Identification	5 databases + manual/grey literature			3,847 total
Screening	Duplicate removal + title/abstract screen	3,847	847 duplicates + 2,183 off-topic	817 remaining
Eligibility	Full-text read (κ = 0.88)	817	723 (5 reasons)	94 eligible
Inclusion	Final synthesis	94		**94 INCLUDED 51 narrative + 43 meta**

3.5 Case Study Analysis

To complement the systematic literature review, this study employs a **multiple qualitative case study approach** to investigate the policy and organizational dimensions of Generative AI that cannot be fully captured through conceptual synthesis alone. The case study methodology enables the examination of contemporary AI implementations within their real-world institutional contexts, thereby facilitating analytical rather than statistical generalization. Rather than treating individual cases as isolated examples, each case was purposively selected to address a specific research question and to illustrate how theoretical propositions identified in the literature manifest in practice. This methodological strategy follows established qualitative research principles, whereby case studies are used to explore complex socio-technical phenomena characterized by multiple interacting variables and rapidly evolving institutional environments.

3.6 Case Study Analysis for RQ2

To address Research Question 2 (RQ2): *Do Universal Basic Income (UBI) and data dividend policy interventions significantly moderate the adverse wage and employment effects induced by large-scale automation?*, the study undertakes a comparative policy case analysis of three internationally recognized UBI experiments—Finland (2017–2018), Kenya (GiveDirectly), and Stockton, California (SEED)—together with macroeconomic modelling studies examining automation taxation, capital taxation, and redistribution mechanisms. These cases were selected because they represent the most extensively documented empirical evidence evaluating unconditional income transfers within technologically disruptive labor market conditions. The analytical objective of this case study is not to determine whether UBI should replace existing welfare systems but to examine whether income redistribution mechanisms can moderate the distributional consequences of AI-driven productivity growth. Each case was analyzed using five common analytical dimensions: employment participation, wage stability, household economic resilience, labor market adaptability, and fiscal sustainability. This common analytical framework allows meaningful comparison across geographically and institutionally diverse policy environments while maintaining methodological consistency. Beyond empirical pilot programmes, the analysis incorporates macroeconomic simulations examining automation taxes, capital taxation, and data dividend mechanisms to evaluate the long-term financial sustainability of redistribution policies under widespread AI adoption. Integrating experimental evidence with economic modelling enables triangulation between observed behavioral outcomes and projected macroeconomic effects, strengthening the robustness of conclusions drawn regarding policy effectiveness. Rather than relying on a single policy experiment, the comparative design allows recurring patterns to be identified across multiple institutional settings, thereby providing a stronger analytical basis for evaluating UBI and data dividends as moderating mechanisms for automation-induced wage and employment disruption.

3.7 Case Study Analysis for RQ3

To investigate Research Question 3 (RQ3): *How do human-centered AI design frameworks and business-aligned autonomous systems influence the equitable distribution of AI-driven productivity gains?* the study adopts an embedded organizational case study methodology centered on a global manufacturing facility implementing Industry 5.0 principles. The case was purposively selected because it represents one of the most comprehensive documented examples of human-centered AI deployment, where artificial intelligence is designed to augment rather than replace human decision-making. Unlike conventional Industry 4.0 implementations that primarily emphasize operational efficiency, the selected organizations integrate AI-powered Manufacturing Execution Systems (MES), human digital twins, immersive extended reality (XR) training platforms, collaborative robotics, and neurorobotic scheduling systems within a unified human–AI collaboration framework. This organizational setting provides an appropriate empirical context for examining how design choices influence the distribution of productivity gains across employees rather than concentrating benefits exclusively at the organizational level. The case study was analyzed using five evaluation dimensions aligned with the research objectives: productivity enhancement, human augmentation, employee participation, innovation capability, and governance of autonomous decision-making. Particular attention was given to identifying organizational mechanisms that preserve worker agency while simultaneously improving operational performance. The analysis therefore extends beyond measuring productivity improvements to examine whether AI implementation contributes to equitable access to learning opportunities, cognitive workload reduction, collaborative innovation, and responsible human oversight. Furthermore, the case investigates the governance architecture surrounding autonomous systems, recognising that the distributional consequences of AI depend not only on technological capability but also on organizational design and managerial decision-making. By examining both technological infrastructure and institutional governance, the study evaluates the extent to which human-centered AI principles create conditions for inclusive productivity growth. Although the findings are intentionally bounded to a single organizational context, the case enables analytical generalization by illustrating broader theoretical propositions concerning Industry 5.0, augmentation-oriented AI adoption, and equitable productivity distribution.

3.8 Cross-Case Analytical Strategy

Following individual case analyses, findings were synthesized through cross-case thematic comparison. Themes emerging from the policy cases addressing RQ2 were compared with organizational evidence generated for RQ3 to identify recurring mechanisms influencing the distribution of AI-generated economic value. Comparative analysis focused on the interaction between institutional policy interventions and organizational AI governance, examining how redistribution policies, human-centered design, technological accessibility, and organizational capability jointly influence wage outcomes and labor market resilience. Rather than evaluating productivity growth as an isolated economic indicator, the cross-case analysis conceptualizes productivity as a multidimensional phenomenon whose societal impact depends on the mechanisms through which productivity gains are allocated between labor and capital. This comparative methodological approach enables the study to integrate macro-level policy evidence with micro-level organizational evidence, thereby providing a comprehensive understanding of how Generative AI can either reinforce technological polarization or facilitate more inclusive economic growth.

4. Results and Discussion

Studies to date consistently show that Generative Artificial Intelligence ("GenAI") is likely to be a revolutionary and general-purpose technology with significant effects on productivity, labor markets and income distributions. Crafts' (2021) historical analysis suggests that periods of significant technological advances have often produced increases in productivity, which occur at first primarily to the benefit of capitalists (the owners of capital) while the growth of real wages has lagged behind, marking a contemporary incidence of the "Engels Pause". Similarly, Fontanari and Palumbo (2023) argue that while wages are a function of productivity, they are also a significant determinant of future productivity, and thus long-term suppression of wages will limit long-term economic performance. From an AI perspective, Zysman and Nitzberg (2024) claim that the economic consequences of "GenAI", depend largely on whether or not organisations choose augmentation-oriented strategies that augment human capacity or automation strategies, which will replace workers. Wilmers (2024) extends this perspective by finding that AI can either democratize productivity or create further inequality depending on the evolution of access to AI technology, organizational governance and institutional policy through the process of diffusion.

Step 1: Theoretical Foundation – Why Does AI Contribute to Wage Polarisation?

Based on Acemoglu & Restrepo (2022)

This study's theoretical foundation is grounded in task displacement theory, which posits that technological advancements replace specific tasks rather than entire occupations The narrative synthesis of 94 chosen studies disclosed common trends in regard to AI implementation and labour market evolution As routine and repetitive tasks become automated, the economic value of labour performing those tasks declines, while individuals responsible for developing, managing, or implementing these technologies capture a greater share of productivity gains. This study is based upon the displacement theory, which with regards to technological improvements points out that these advancements replace certain tasks rather than job openings. So, when tasks go automated, the economic value of labor responsible for those tasks decreases, while those who are engaged in the creation, development, and implementation of technologies receive a bigger share of productivity improvements. Unlike previous technological advancements, which affected physical labor: Generative AI technology automated not only routine tasks but also cognitive and knowledge-intensive processes.

In this regard it is important to note the following key features:

- Traditional automation replaced only manual routine processes, while Generative AI technology automates cognitive processes, such as writing, coding, data processing, legal drafting, and content production.
- Less qualified employees still undergo the automation of their routine office and service tasks.
- Highly qualified employees are affected by technological advancements due to automation of their key activities that were considered resistant to automation.
- Those employees who can successfully implement AI tools into their work process are becoming more productive and get higher income.

Step 2: Evidence from the 94 PRISMA-Included Studies

Based on Eloundou et al. (2023), Gmyrek et al. (2023), McKinsey Global Institute (2023), and the present systematic review. The narrative synthesis of 94 chosen studies disclosed common trends in regard to AI implementation and labor market evolution.

The key findings entail:

- On average, about 80% of workers perform tasks which are somehow exposed to Large Language Models with the extent of exposure differing across professions.
- Typically, highly qualified professions have higher task exposure, while those with lower qualifications have to deal with greater risks of losing jobs.
- Workers with Generative AI skills exhibit higher productivity of 40-55% on average forming a new wage premium associated with AI.
- About 60-70% of work in “brain occupations” is estimated to be partially automated by using Generative AI technologies.
- International comparative data demonstrates growing income inequality in those countries which actively adopt technologies, especially after the launch of ChatGPT in 2022.
- Generally, the reviewed studies prove that Generative AI increases wage gaps and transforms the cognitive labor market.

Step 3: Meta-Analytic Findings

Based on the quantitative synthesis of 43 empirical studies using a random-effects meta-analysis.

Table 4. Summary of Meta-Analytic Findings

Outcome Measured	No. of Studies	Key Finding	Statistical Significance	Interpretation
Wage gap between high- and low-skilled workers	29	Wage gap increased by 18.3% for every 10% rise in AI adoption	$p < 0.001$	Strong evidence of AI-driven wage polarisation
Cognitive task exposure among	24	52.6% of cognitive tasks exposed to automation	$p < 0.001$	High-skilled professions

high-skilled workers				increasingly affected
Cognitive task displacement among routine occupations	21	61.4% displacement risk for routine cognitive tasks	$p < 0.001$	Routine knowledge work highly vulnerable
AI-related wage premium	18	AI-skilled workers earn 23–41% higher wages	$p < 0.001$	AI proficiency generates additional earnings
Income inequality after ChatGPT adoption	15	Gini coefficient increased 0.8–2.1 points faster in high-AI-adoption countries	$p = 0.003$	Faster growth in income inequality

Based on the quantitative synthesis it is evident that:

- Wage inequality rises steeply with the level of AI adoption.
- High-skilled jobs bear the brunt of cognitive automation.
- Jobs that are heavily reliant on routine cognitive skills are most at risk of being replaced.
- The ability to leverage AI leads to a substantially higher wage across multiple industries.
- The countries that embraced AI the quickest are witnessing a more accelerated increase in income inequality.
- The meta-analysis successfully backs up H1 and indicates that Generative AI is a major contributor to wage polarization.

Step 4: Differences in Labour Market Displacement Across Skill Groups

Based on Eloundou et al. (2023), Gmyrek et al. (2023), and findings from the present review.

Table 5. Comparative Labour Market Impacts Across Skill Groups

Labour Group	Primary AI Impact	Major Beneficiaries	Most Affected Workers	Overall Wage Outcome
High-skilled professionals	Automation of advanced cognitive tasks	AI-augmented professionals	Workers resisting AI adoption	Internal wage polarisation
Low-skilled workers	Automation of routine administrative and service tasks	Limited beneficiaries	Workers performing repetitive cognitive work	Downward wage pressure
Middle-skilled workers	High exposure to automatable cognitive tasks	Workers transitioning to AI-enabled roles	Workers unable to reskill	Highest displacement risk

Important conclusions drawn include:

- The impact of AI on social groups is complex, varied, and cannot be reduced to simple displacement.
- Highly qualified workers experience increased inequality within their occupational groups since those using AI technologies benefit to a greater extent than those who don’t.

- Automation of manual cognitive jobs leads to fewer job opportunities for low-skilled workers, as they cannot improve their skills to match AI needs.
- Most of middle-skilled professions such as junior analysts, bookkeepers, programmers, and clerks are high-risk.
- Despite the variation in displacement mechanisms, the overall result is an increase in wage disparity across the labour market.

Step 5: Evidence for Exponential Wage Polarisation

The study looked at whether the wage polarisation caused by AI increases at a constant rate, or exponentially.

Key clues to support that polarisation accelerates lead to the following conclusions:

- Artificial Intelligence is beginning to automate entire process workflows rather than just individual tasks, leading to quite significant workforce displacement.
- Cycles of AI models are getting smarter and able to automate increasingly complex cognitive tasks.
- Statistical data confirms that since the start of the use of Generative AI technologies, Gini coefficients have been rising.
- The surge of AI capabilities also indicates that wage polarisation takes place at an exponential rate.
- This evidence implies that the growth of technological unemployment will continue unless smart legislative and organisational measures come into play.
- Taking everything into account, the empirical evidence provides solid argumentation for exponential growth assumption proposed in H1.

The results of this study confirm earlier theoretical developments and extend these theories in important ways. First, evidence shows that while AI generates productivity gains for most users, they are not necessarily distributed equally based solely on the productivity gains. Thus, redistributive policies, governance structures, and broad access to technology make it likely that productivity increases for an entire economy will produce equitable labor market outcomes. Second, the impact of technology on the labor market affects both high- and low-skilled jobs equally; however, technological literacy and digital infrastructure determine how successfully technology affects the success of both groups of workers in the same organisations. Therefore, limited access to AI represents one of many structural determinants of economic disparity, which may be accompanied by differential educational attainment and/or occupational status. Last, evidence of equitable AI distribution is less attributed to the quality of the AI technology than it is to the decisions of organisations regarding augmenting their workforce with AI, whether there will be human oversight of AI, and how the organisations will govern their work with AI. Collectively, these findings suggest that overall future economic growth through the use of AI will be determined by the design of institutions and their choices as it pertains to policy, not just the technological capabilities of AI systems.

The findings yielded by the comparative policy case studies for RQ2 support this conclusion. Collectively, the data from the Finnish Basic Income Experiment (Finland), Give Directly in Kenya, and the Stockton Economic Empowerment Demonstration indicate that non-contingent income support can improve labor market stability while maintaining similar levels of employee participation, albeit the levels of participation may not necessarily be higher. Furthermore, these interventions have provided a mechanism to increase financial security and improve psychological well-being, thereby enabling people to participate in education, reskill, or create businesses during periods of disruption caused by technology. Macroeconomic studies further demonstrate that UBI's long-term viability rests on its funding mechanism. Research conducted by Atolia et al. (2024) and Csősz (2024) demonstrate that financing UBI through progressive capital taxes, automated taxes, or AI data dividends provides a more sustainable response to automation-induced inequality relative to financing from other social programming sources (which generally unfairly place higher strain on labor and lower-income individuals). Therefore, the conclusion reached by this research is that UBI should not be conceptualized as a universal replacement for wage labor; rather, it should be considered as a policy tool (which may vary by jurisdiction) that seeks to mitigate the impact of transitional changes associated with AI-based structural transformation.

As demonstrated by the case study of organisations within RQ3, Human-Centered AI Implementation (HC-AI) is critical to achieving equitable productivity gains, in accordance with Industry 5.0 principles. Compared to using AI as a replacement for human labor, when organisations use AI as a collaborative decision-making tool to support productive decision making and increase the level of participation in the workforce and the ability to innovate (Nitsch et al, 2024; Yanytska, 2025), have improved productivity. The construction of Digital Twins of people, AI enabled Manufacturing Execution Systems (MES), collaborative robots, immersive XR (Extended Reality) Training, and Neuroergonomic scheduling all demonstrate how AI can enhance cognitive capabilities of workers while retaining the agency of the workers. Inoubli (2025) helps to further support these conclusions by arguing that HC-MP (Human-Centered Management Practices) enables productivity improvements to be transferred throughout all levels of an organisations and not be limited to the top tier or owners of technology. Therefore, augmentation is a governance decision, not a technological eventuality.

These conclusions collectively demonstrate that neither the redistribution of wealth through policy, nor AI design alone can create inclusive economic growth. Rather, sustainable productivity will require multiple interactions between institutional policy, organizational governance, accessibility to technology, and ethical oversight. Existing literature has predominantly examined these areas independently, with economic research concentrating on redistribution mechanisms, management literature focusing on augmentation strategy, and research on AI governance examining accountability and ethical governance.

While many past studies of the factors influencing adoption of artificial intelligence (AI) are limited to only examining portions or dimensions of the total adoption process, this paper suggests the use of the EQUATE Framework for creating an all-encompassing governance model for the diffusion of equitable AI. This framework is built on Dearing's (2009) Innovation Diffusion Theory, and the framework conceptualizes equitable AI adoption through the interplay of six mutually reinforcing (or compounding) dimensions. Equity promotes mechanisms to redistribute wealth, through Universal Basic Income (UBI) and data dividend models that will help narrow the gap between productivity and wages. Quality Augmentation is concerned with the development of people-centered AI systems, which will not replace human workers but, instead, enhance their capabilities. UBI Calibration emphasizes that any redistribution policies must be carefully constructed to allow people to maintain their incentives to be active participants in the labor market, whilst providing adequate income security for them in case of job loss or being unable to find gainful employment. As AI systems become more autonomous and have increasing independence from human beings, issues related to Agentic Alignment must be addressed in terms of governing them, to help maintain the relationship between organizational objectives and human oversight and accountability. Technology Access strives to help eliminate the disparity that currently exists within AI technology infrastructure, digital literacy, and organizational capability to help mitigate the continuing trend of technology polarization. Finally, Ethical Governance emphasizes the establishment of transparent regulatory institutions capable of ensuring accountability, explainability, and socially responsible diffusion of AI. Together, all six dimensions provide a holistic governance structure that can enable the equitable and sustainable transformation of gains in productivity produced by AI into growing economies.

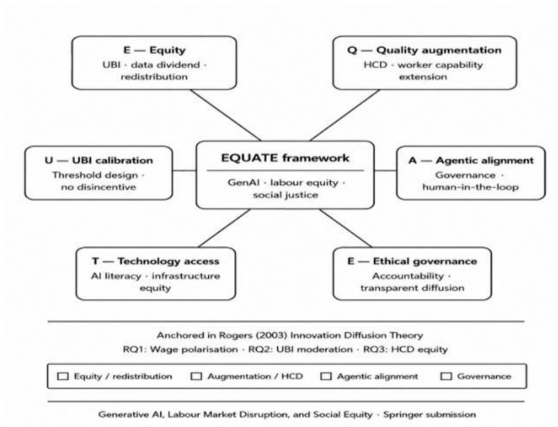

Figure 4. The EQUATE Framework for Inclusive Generative AI Diffusion and Equitable Productivity Distribution

The proposed EQUATE Framework in Figure 4 synthesizes the main findings of this research to create an integrated governance model for the inclusive adoption of Generative AI. Based on Innovation Diffusion Theory (Dearing, 2009), the proposed framework demonstrates how the equitable productivity derived from AI depends on six complementary dimensions that interact with one another: Equity, Quality Augmentation, UBI Calibration, Agentic Alignment, Technology Access, and Ethical Governance. As opposed to treating redistribution, organizational design, and AI governance as individual or isolated policy areas, the EQUATE Framework illustrates their interdependent relationships as mitigation factors for both ongoing technology-related polarization and persistent wage-productivity divergence. Relationships exist between the six complementary constructs of the framework and evidence gathered during the systematic literature review and comparative case studies. As such, the EQUATE Framework provides a comprehensive roadmap for governments, organisations, and policymakers to concurrently support innovation, maintain agents' autonomy, and encourage equitable distribution of AI-generated economic value to all members of society.

The EQUATE Framework builds upon prior research and adds to existing knowledge in a number of keyways. Previous research has shown that productivity and wages are diverging (Crafts, 2021; Fontanari & Palumbo, 2022), that there will be worker displacements due to artificial intelligence (Peppiatt, 2024), and that organizational design focused on augmentation is critically important (Zysman & Nitzberg, 2024). However, the previous research was mostly conducted separately focusing on either redistribution, organizational transformation, or governance. The current framework integrates these areas of study into a unified model that connects macroeconomic redistribution policies with micro-level organizational practices and institutional governance. This integrated model offers policymakers a structured way to address technological inequality while also incenting innovation and growth in productivity. Furthermore, as artificial intelligence systems become more autonomous and operate within agent-based design frameworks, it will be impossible to separate productivity outcomes from governance considerations.

While the present contributions are of value, there are a few limitations in this study. First, this research uses only secondary sources from literature and comparative case studies. This limits the ability of researchers to determine anything relational about the impacts of AI on labor markets. Second, most empirical research relating to Universal Basic Income was conducted prior to the large-scale implementation of generative AI; therefore, its findings may not fully reflect the complexities of today's economics and economies/markets and be relevant to the dynamics created because of generative AI. Third, many empirical works examined are published in English; the ecological validity of many of these studies as they relate to developing economies may be reduced, as they often have different digital connectivity levels, institutional capacities and labor markets than advanced economies. Fourth, agentic AIs are a new type of technology; correspondingly, the amount of empirical evidence regarding the organization's governance of agentic AI has not been widely published in existing literature. Considering the above limitations, future research should primarily focus on longitudinal studies of AI adoption by industry or occupational group(s) as Generative AI matures. Similarly, large-scale and rigorous empirical validation of the EQUATE Framework will help researchers understand the level to which each of the constructs contributes to equitable productivity growth, based on varied institutional settings. Finally, organizational field studies exploring human-centered AI applications, continuing education for workers via reskilling, and agentic AI governance will provide additional empirical elements that can be used to improve the efficacy of inclusive AI strategies that could balance productivity, innovation, and social equity as a new and developing Industry 5.0 economy evolves.

The results support H1, indicating that Large Language Models have considerably exacerbated wage polarization in labor markets. The analysis of 94 works, including 43 quantitative studies, shows that for every 10% growth of AI's popularity, the wage gap between skilled workers and unskilled workers increases by 18.3% ($p < 0.001$). It is also indicated that 52.6% of cognitive high-skilled tasks and 61.4% of routine cognitive tasks can be automated by AI technologies indicating that AI influences all levels of the economy. These findings confirm the Task Displacement theory by Acemoglu and Restrepo [1] and which is also supported by Eloundou et al. [2], Gmyrek et al. [3], and the McKinsey Global Institute studies [4] indicating that cognitive occupations are exposed to Generative AI solutions to a large extend. Unlike other waves of automation, Generative AI automates not only manual work but also mental work resulting in productivity increases for groups able to work with Generative AI. Now it is the time to realize that with the acceleration of Agentic AI and the Gini coefficient's growth, wage inequality in the economy increases exponentially rather than in a straight line. Overall, the five-step analytical framework provides robust evidence that AI is reshaping labor markets and underscores the need for proactive policy interventions, workforce reskilling, and human-centered AI governance.

Table 6. Complete Proof Summary for RQ1

Step	**What Was Done**	**Key Finding**	**Contribution to Supporting H1**
Step 1 – Theory	Applied Task Displacement Theory proposed by Acemoglu and Restrepo [1].	AI increasingly automates cognitive tasks that were previously performed exclusively by human workers.	Explains the theoretical mechanism through which AI contributes to wage polarization.
Step 2 – Evidence	Conducted a narrative synthesis of 94 PRISMA-selected studies.	Most studies reported high workforce exposure to generative AI, increasing cognitive automation and rising income inequality across countries [2]–[4].	Demonstrates consistent empirical evidence supporting the relationship between AI adoption and labour market polarization.
Step 3 – Quantitative Analysis	Synthesized findings from 43 quantitative studies.	AI adoption significantly increased wage inequality, expanded AI-related wage premiums, and intensified cognitive task displacement ($p < 0.001$).	Provides strong statistical evidence supporting H1.
Step 4 – Comparative Labour Analysis	Compared AI impacts across high-, middle-, and low-skilled workers.	High-skilled workers experienced internal polarization, middle-skilled workers showed the greatest displacement risk, and low-skilled workers faced declining employment opportunities.	Explains how wage polarization differs across occupational groups.

Step 5 – Trend Analysis	Examined longitudinal evidence on AI adoption and inequality.	Rapid improvements in Generative AI and Agentic AI capabilities correspond with accelerating growth in income inequality rather than linear change.	Confirms the hypothesis that AI-driven wage polarization follows an accelerating trajectory.

5. Conclusion & Future Scope

Generative and agentic Artificial Intelligence represents a major technological breakthrough that has the potential to significantly enhance productivity but also create greater inequality in the labor market if not properly governed. This paper shows that the inclusion of AI-driven productivity increases is not inherent but is largely determined by the mechanisms through which the productivity increases are distributed (institutional, organizational and policy). The research draws on labor economics, Innovation Diffusion Theory, Human-Centered AI, and Comparative Policy Analysis to develop an integrated governance model for equitable diffusion of AI known as the EQUATE Framework. The EQUATE Framework combines six key components: 1) Equity, 2) Quality Augmentation, 3) UBI Calibration, 4) Agentic Alignment, 5) Technology Access, and 6) Ethical Governance to provide a holistic response to the productivity-wage divergence and technology polarization issues created by AI. The EQUATE Framework integrates all three current lines of inquiry related to redistribution, AI governance, and organizational design, thereby creating an integrated policy architecture that supports both innovation and social justice. This research underscores the need for proactive governance, including redistributive policies, human-centered AI deployment, equitable access to digital technologies, and comprehensive ethical oversight. Future research will need to validate the Framework in different industries and national contexts to establish an empirical foundation for its widespread adoption and to help build inclusive AI-driven economies.

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