



Artificial Intelligence and Economic Transformation: Implications for Productivity, Employment, Innovation, and Sustainable Economic Growth

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ABSTRACT

This study systematically synthesizes the economic literature on artificial intelligence (AI), productivity, employment, and growth available up to 2024. An organizational framework based on a PRISMA approach is employed to structure 50 leading and citable research papers on productivity, innovation, labor demand, skills, distribution, and macroeconomic growth. The synthesis is based on the task-based technological change theory and the general-purpose technology perspective, with a focus on the differences between worker-, firm-, and economy-level evidence. There is growing evidence in the literature that AI complements work to boost the productivity of workers and firms, or that AI can assist in decision-making or product innovation. Aggregate productivity effects are less well agreed on, due to incomplete diffusion and measurement lags in the effect of complementary investments. Labor-market effects are heterogeneous, as displacement, augmentation, and new-task creation happen at the same time, and skill, occupation, sector, and firm characteristics condition exposure. The review integrates microeconomic, labor, and macroeconomic evidence in a single framework and outlines the research agenda on diffusion, developing economies, causal identification, generative AI, inequality, and long-run growth.



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1. Introduction

Artificial intelligence (AI) has shifted from a specialized computational technology to an increasingly general-purpose input into production, decision making and innovation. Machine learning, natural-language processing, computer vision and, more recently, generative AI can perform or support tasks that previously required substantial human judgment. This expansion has raised a central economic question: Will AI mostly increase productivity and facilitate the emergence of new activities or will the gains from AI be offset by displacement, concentration

and unequal access to it? The question is important because productivity growth is the source of long-run growth in living standards, and the distribution of productivity growth will decide if technological progress is a source for broadly distributed welfare.

The economics of AI is based on various older literatures. According to general purpose technology theory, large-scale technologies have widespread spillover effects, but the impact of a given technology takes time to occur as a result of complementary innovation (Bresnahan & Trajtenberg, 1995). Information technology research also demonstrates that organizational changes and intangible investments play a decisive role in the realization of productivity (Brynjolfsson & Hitt, 2000, 2003). Task-based models include a labor-market mechanism: technology can reduce the demand for labor in some tasks, increase it in others, and create new tasks that return labor demand (Acemoglu & Restrepo, 2018, 2019; Autor et al., 2003). From these perspectives comes the idea that the economic impact of AI is not solely dependent on technical capabilities.

This complexity is demonstrated in the light of recent empirical evidence. Firm-level studies report positive association between using AI and productivity (Czarnitzki & Rammer, 2023), and between investing in AI and product innovation, sales growth, employment growth, and market valuation (Babina, Fedyk, He & Hodson, 2024). The literature on generative AI, as well as the experimental and quasi-experimental evidence, indicates that tasks can be completed faster, and the quality of the output higher, and that the gains are larger for less-experienced workers (Brynjolfsson et al., 2023; Noy & Zhang, 2023). But macroeconomic evidence from across the country is more conservative. Parteka and Kordalska (2023) find that the measurable contribution of AI innovation to aggregate productivity remains limited, and 2024 OECD work stresses that macro gains depend heavily on adoption, sectoral diffusion and complementary capital.

The labor-market literature also is mixed. The exposure data shows that AI gets to many cognitive and non-routine tasks, but exposure is not equal to automation. Acemoglu, Autor, Acemoglu et al. (2022) reveal that AI impacts vacancy and skill demand, while OECD and ILO studies differentiate between task substitution and task augmentation. Generative AI will be especially significant, given the way it will increase technology exposure in writing, analysis, coding, and professional services. Consequently, traditional classifications of routine and nonroutine tasks have proven to be less adequate to describe technological change.

There are therefore three reasons for the need for a systematic review. First, the literature is spread throughout economics, management, innovation, labour studies, and labour policy research. Second, research is conducted at various levels of analysis and various conceptions of AI are used, which makes apparently opposing results hard to interpret. Thirdly, generative AI is an emerging technology that has produced significant new evidence stream with short-run productivity impacts that need to be separated from long-term macroeconomic impacts. This review seeks to tackle these issues with a cutoff date set to 2024.

The study asks four research questions: What does literature show about AI and productivity? What impact does AI have on jobs, work, skills, and pay? How does AI impact innovation and economic growth? What are the organizational, institutional and developmental conditions that influence these outcomes? The contribution is an integrated economic framework which connects adoption to task change, complementary investment, innovation, labor reallocation and aggregate growth and defines a targeted research agenda for the future.

2. Theoretical and Conceptual Background

The review is structured in three lenses, all of them theoretical. The first is that general-purpose-technology theory recognizes that AI could impact many sectors, and complementary

innovations will be required. Second, task-based technological-change theory breaks up jobs into tasks and then deploys technology to automate, augment or create tasks. Third, organizational complementarity: The same AI can have varying productivity impacts based on data quality, skills, workflows and managerial practices.

The integrated framework starts with AI capability and adoption. Adoption modifies the way tasks are done in terms of automation and augmentation, but it is mediated by complementary capital and organization redesign. These changes have an impact on process efficiency and product innovation, thus on firm productivity, labor demand and wages and market structure. Economy-wide growth comes after diffusion and reallocation from one firm to another and one sector to another. Each link is moderated by the institutions, competition, infrastructure and human capital.

This framework helps to explain an important difference between possibility and reality – technological possibility and economic realization. Adoption costs, incentives, demand and complementary investment are factors that determine realized productivity and employment effects, while exposure measures identify the tasks AI might impact. Hence, high levels of occupational exposure do not necessarily lead to job displacement, and positive findings on task productivity do not necessarily translate to aggregate productivity growth.

3. Review Methodology

The review is organized according to the logic of PRISMA 2020 and the structure adopted in international systematic reviews in economics, business and sustainability research. The goal is not to give an impressionistic story, but rather to make it reproducible. Evidence will be considered until 2024. Since the live Web of Science and Scopus subscription exports have not been provided with the manuscript, no attempt is made to create database specific identification counts. The final submission should be the search strategy documented in those databases with the PRISMA counts. Here the analytical corpus consists of 50 influential and traceable texts that are directly relevant to the research questions.

3.1. Search Strategy

The retained contributions were evaluated for relevance, clarity of data and methodology, appropriateness of identification or modelling approach, clarity of measures of outcome, and usefulness for the review questions. A numerical quality score was not applied since the corpus contains experiments, econometric studies, theoretical models and systematic reviews/institutional syntheses, all of which cannot be fairly ranked by one single metric. Rather, stronger causal designs receive more interpretive weight when causal claims are being discussed, and descriptive and modelling studies receive more interpretive weight when mechanisms are being discussed, as well as scenarios and context.

The coding framework documented publication year, setting, unit of analysis, exposure, outcome, method and principal finding and thematic contribution for each study. Thematic synthesis was selected in preference to meta-analysis as the effect measures, units, exposures and research designs are too diverse to combine in a single pooled coefficient without significant loss of meaning.

3.2. PRISMA Reporting and Reproducibility

The actual number of records identified in Web of Science and Scopus, records excluded due to duplication, records screened, full text evaluated and studies included should be reported in a submission-ready PRISMA flow diagram. These counts should be based on real database exports. This manuscript therefore offers the complete reporting structure and analytical synthesis but doesn't require database counts to be populated from the final

reproducible search. This method is the correct way to prevent the common and severe mistake of creating screening numbers.

3.3. Analytical Boundaries and Evidence Hierarchy

The review distinguishes between outcomes that have been observed and outcomes that are projections using models. Experimental studies of specific work tasks provide evidence of performance in the short run under controlled conditions, rather than the aggregate employment or aggregate GDP effects. Observational studies at the firm-level report on realized adoption and economic performance, but the selection into AI adoption could lead to biased estimates. Occupational exposure indices are a measure of technical feasibility and not observed displacement. Task exposure and adoption and substitution are assumed at the macroeconomic level and results of such simulations are regarded as conditional scenarios. This hierarchy stops the synthesis from considering exposure, adoption, productivity and long-run growth to be interchangeable outcomes.

4. Descriptive Profile of the Evidence

The evidence inventory should not be identified as the product of a complete database-wide screening exercise but is instead derived from 50 academic and institutional sources. Literature is interdisciplinary but economically coherent, from macroeconomics, labor economics, development economics to innovation and environmental economics/policy. There is an important rise in empirical studies and contributions in the 2020-2024 period, preceded by earlier works in theory and measurement. The corpus also highlights the geographical misbalance on the one hand, with advanced economies being more well represented in AI research, and on the other hand, with more developing countries and cross-country evidence in climate-growth research, but still significant gaps in low-income and fragile states.

4.1. Distribution of evidence by analytical scale

The collected studies cover four analytical scales: Worker and task studies explore time savings, output quality and individual capabilities. Firm-level studies analyze AI investment, innovation, employment and value added. Occupational and regional analyses look at the distribution of exposure and the evolving demand for skills in occupations. Macroeconomics research models economy-wide productivity, reallocation and distribution. The descriptive synthesis structures evidence in terms of the unit of observation, rather than a false average effect for two very different designs.

5. Thematic Findings

5.1. Productivity at Worker and Firm Levels

The one element of the literature that is consistently positive is micro evidence. According to Czarnitzki and Rammer (2023), German companies that use AI generate more sales and value added productivity. Damioli and Vertesy (2021) link AI-related technological capabilities to labor productivity and Babina et al. (2024) demonstrate that AI investment leads to future firm growth. Specific tasks can be strengthened from experiments with causal interpretation, such as reduced completion time and higher quality of professional writing by generative AI Noy and Zhang (2023), and higher productivity in customer support (Brynjolfsson et al., 2023). Notably, these improvements are heterogeneous and frequently smaller for more experienced workers, indicating that AI has the potential to spread good practices and somewhat narrow the performance gap between workers on a task.

In this theme, the differences in results can best be understood in terms of heterogeneity in exposure, adoption and complementarity. Technical exposure studies

generally measure potential exposure rather than realized use, while firm- and worker-level studies measure realized adoption, but typically over shorter time periods. The synthesis gives more weight to evidence that explicitly references adoption or task use and considers overall evidence indexes as evidence of potential effects.

5.2. Innovation, Intangible Capital and Firm Growth

AI is not only a process technology, Cockburn et al. (2019) define AI as a means of invention, implying that its greatest potential long-term impact could be the ability to speed up the process of discovery and product development. Babina et al. (2024) present evidence of how product innovation is a significant channel between AI investment and firm growth. This view can account for the fact that the short-term cost savings may be less than the economic value of the technology. Meanwhile, AI needs data, computing power, proficient human resources and organisational restructuring. The productivity J-curve Brynjolfsson et al. (2021) suggests that such complementary investment can be measured as a cost rather than a gain when it occurs, which slows the measurement of the aggregate productivity effect.

In this theme, variations in outcomes are most likely understood as variations in exposure, adoption and complementarity. Studies measuring technical exposure capture potential exposure; firm- and worker-level studies capture realized exposure, but typically at faster time horizons. This means that the synthesis is more heavily weighted towards evidence that specifies adoption or task use and uses broad exposure indices as a proxy for where effects might occur.

5.3. Employment, Task Displacement and Augmentation

A direct link between exposure to AI and job loss is not accepted in the literature. Task-based theory makes predictions about simultaneous displacement and reinstatement. AI can automate part of the work and increase productivity for other parts of the work, or create new activities or increase demand for existing activities. Acemoglu et al. (2022) identify the associated changes in vacancy and skill demand with AI exposure. Felten et al. (2021) and Webb (2020) demonstrate significant variation in exposures by occupation and industry. Studies by ILO and OECD also highlight that generative AI can be used to augment jobs more than to fully automate them. The employment effect is then linked to the elasticity of demand, firm growth, the composition of tasks within occupations and the rate at which new tasks are added.

In this theme, variations in outcomes should be understood in terms of the heterogeneity of exposure, adoption and complementarity. Studies reporting technical exposure measure potential adoption, while firm- and worker-level studies measure realized adoption but tend to cover shorter timeframes. The synthesis thus emphasizes evidence which mentions adoption or use of the task and evidence that implies exposure to extensive indices as evidence of possible exposures.

5.4. Skills, Wages and Inequality

AI changes the number and nature of skills needed. Technical capabilities of AI can give rewards in the labor market, but complementary managerial, social and domain knowledge also matter. According to Drydakis (2024), AI capital is correlated with better employment prospects. Green (2024) demonstrates the link between AI exposure and shifting demand for cognitive, digital, business and management skills. The distributional effects are unclear: If AI benefits disproportionately highly skilled workers, inequality could increase; if it passes on skills to less-experienced workers, gaps within occupations could decrease. Tools, training, data and organizational support are therefore key components of distribution.

In this theme, the differences in results are best understood in terms of heterogeneity in exposure and adoption and complementarity. Studies measuring potential exposure, rather than realized use, do not differ from firm/writer level studies, but the time frame may be shorter. The synthesis therefore gives greater weight to evidence that specifically identifies effects of adoption or task use and uses exposure indices that are broad in scope as indicators where effects may occur.

5.5. Aggregate Productivity and Growth

The evidence on the macro aspects is still less developed. Parteka and Kordalska (2023) report only minor aggregate productivity benefits from AI innovation, but the Oecd (2024) indicate that gains may be significant in more intense adoption and diffusion. The macroeconomic impact depends on the proportion of economically useful tasks impacted and the extent of the productivity gain, according to (Acemoglu, 2024). The findings are consistent with the general purpose-technology theory as aggregate gains are likely to be delayed due to the time lag required for adoption, complementary investment, reallocation. It is also important to note that there is a huge difference between impressive task-level effects and modest macro statistics; this gap is thus a key research problem and not just a contradiction.

In this theme, the differences in the results are best explained by the heterogeneity in exposure, adoption, and complementarity. Studies measuring potential exposure rather than use are studies of technical exposure; firm- and worker-level studies measure realized adoption but may have shorter exposure horizons. The evidence synthesis therefore places more importance on evidence which explicitly names adoption and/or task use and considers broad exposure indices as evidence of the potential for effects to occur.

5.6. Developing economies and institutional conditions

The evidence from the developing economies is considerably less dense than the evidence from the United States, Europe and other advanced economies. Korinek and Stiglitz (2021) highlight the impact of AI on comparative advantage and development strategies and Saba and Ngepah (2024) demonstrate how governance can shape relationships between AI and employment growth in BRICS economies. Leapfrogging and “low-cost” knowledge service are possibilities for developing countries, but also present some infrastructure, skill, financing and data challenges. International distribution of capabilities for AI may therefore affect convergences, offshoring’s, and high-value activities.

The differences between results in this theme should be interpreted from the point of view of heterogeneity in exposure, adoption and complementarity. Technical exposure studies measure potential exposure, while firm- and worker-level studies measure realized exposure, but over shorter timeframes. The synthesis gives greater weight to evidence that specifically references adoption or task use and takes the exposure indices as evidence of where effects may occur.

5.7. Reconciling seemingly contradictory findings

The finding of positive employment relationships at the firm level does not contradict the possibility of displacement of workers in specific tasks. A company that automates some things may lower the cost per unit, bring new products to market and ultimately hire more people. However, it could be that a firm who is implementing productivity growth sees a decrease in jobs relative to other firms in the same industry or its suppliers. Likewise, an occupation that is heavily exposed to AI could see both a rise and fall in wage rates depending on whether AI fills in the gaps for a scarce skill or replaces a standardized one. The sign of the reported coefficient is as important as the unit of analysis or the counterfactual.

5.8. Implications of study design and measurement

There are multiple measurement problems that reappear in the evidence. Inventive activity can be determined by patent counts but does not imply commercial deployment. Employer intentions are more evident on job announcements than in actual hiring. The perception of AI may differ by respondents, leading to different self-reported adoption. Task experiments tend to have short time horizons and narrow work environments, and aggregate productivity data are sluggish in reacting to organizational changes. A more robust future literature would connect software-use logs, with employer/employee records, with product innovation and value added, and would explicitly differentiate between predictive and generative AI.

6. Discussion

The review comes with four broad conclusions. First, the impact of AI on productivity is already measurable in certain firms and tasks but is not yet proportionate at the economy-wide level to the most impressive results on the micro-level. This micro/macro gap is in line with diffusion lags and complementary investment, and not with the illusion of micro gains. Secondly, employment impacts are essentially task related. By replacing task content, AI can also boost output, generate complementary tasks, and boost demand for complementary workers.

Third, innovation is likely to be an important, long-term channel. When AI mainly reduces the cost of performing current tasks, its impact could be like traditional automation. The dynamic growth effect can be greater if it helps to speed up product discovery, scientific research, software development and organizational experimentation. Last, Distribution is endogenous to Institutions and Access. Those that have more complementary skills between firms and workers are likely to realise more of the gains, potentially increasing concentration unless it is diffused in the broad sense.

The conclusions also help explain the apparently conflicting results found in the literature. There are various studies that report on various phases of the same adjustment process. Exposure studies look for potential changes in tasks, experiments measure immediate productivity impacts, firm studies measure adoption and organizational impacts, and macro studies measure diffusion and general-equilibrium impacts. These levels need to be connected rather than chosen as the definitive level of interpretation.

6.1. An integrated explanation of heterogeneous economic outcomes

An integrated reading of the literature indicates a series of 'conditional' mechanisms. First, AI changes the task production functions, decreasing the cost of performing certain cognitive or operational tasks. These are then chosen by the organizations which redesign the work, retrain the employees, introduce new products, or reduce labour inputs. Those decisions have an impact on the productivity of the firms and the proportion of the market that they occupy. This leads to sectoral diffusion and consequently to a change in relative prices, entry, competition and demand for factors. Finally, the percentage of activity affected and the extent to which productivity gains results in investments and new demand affect aggregate growth. Each phase is different, each with its own level of complexity, and a gain at the task level cannot be multiplied across an economy.

6.2. Interpretation for lower-income economies

In developing economies, the evidence is even more fragile to informal work, inequality on electricity and connectivity, high costs of imported technologies, lack of computing

infrastructure and uneven distribution of language resources. While AI can enhance access to knowledge and reduce the expenses of certain exchangeable services, companies lacking the resources to invest in complementary skills and data could be left out. There is also a difference between the gains of domestic AI users and the gains of foreign technology providers. Future research should consider the domestic value added as well as worker outcomes and productivity, not just adoption as an indicator of development.

7. Conclusion

To date (at the end of 2024), the economic literature shows evidence of the benefits of AI for productivity and innovation, and further evidence of the potential aggregate and distributional implications of AI adoption. In addition to firm-level gains, which are becoming more apparent, particularly where AI is used to complement human abilities, macroeconomic impacts are less certain, as diffusion and complementary investment takes time. Task is the more appropriate unit than occupation for the description of employment outcomes, because they are heterogeneous. The key policy challenge is thus not only to speed up AI adoption, but to develop the skills, infrastructure, organizational capacities, competition, and governance needed to ensure that the productivity benefits spread widely. Future research should focus on causal evidence in developing economies, long-run impacts of generative-AI, distribution and explicit connections between micro productivity and macro growth.

7.1. Theoretical Contributions

Conceptually, the general purpose-technology and task-based approaches are combined in the review, adding value. GPT theory is used to explain diffusion lags and complementary investments, task theory is used to explain the effects of heterogeneous labor, and organizational complementarity is used to explain the variation among firms. They integrate into a multilevel account, and the first thing they change is how tasks are done and how organizations are organized, then innovation and productivity, and then their contribution to the number's overall growth.

7.2. Policy Implications

The focus of productivity policy should be on complementary skills, rather than numbers of adoptions. The effectiveness of AI tools as valuable instruments hinges on a range of factors, including digital infrastructure, data management, employee training, and management competence and organizational restructuring.

Labour market policy should be job specific. Training systems must adapt to new task packages and to facilitate transitioning without taking it for granted that entire occupations will cease to exist. In algorithmic management, worker consultation and monitoring of job quality are especially pertinent forms of use.

Competition policy is important because AI benefits can be added to those with better data, computing power, talent and financial resources. The distribution of productivity gains may be influenced by interoperability, contestability, and diffusion to smaller firms.

In the case of developing economies, the focus should be the digital foundations and human capital that foster innovation as well as public policy that is not uncritical transplants of advanced economy estimates. Local data on firms, occupations and informal employment are needed.

7.3. Limitations

There are limitations to this review. The methods and outcomes of the evidence base are diverse, and a defensible, pooled effect cannot be obtained without more stringent eligibility requirements. The review also incorporates important institutional and working-paper documents that are relevant to the rapidly evolving economics issues; future versions may limit the volume of documents to peer-reviewed articles, depending on the requirements of the target journal. Finally, PRISMA identification and exclusion counts need to be done via final Web of Science and Scopus exports. The cutoff date of 2024 is purposefully not followed by later evidence.

Authors' Contribution

Prince Chukwuemeka Ekeocha: Conceptualization, methodology, investigation, writing – original draft, and project administration.

Mariam Biodun Kolapo: Literature review, data curation, formal analysis, writing – original draft, and visualization.

Stephen Alaba John: Validation, supervision, writing – review and editing, and critical revision of the manuscript.

Conflict of Interests/Disclosures

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- Stanford Institute for Human-Centered, A. I. (2024). *Ai Index Report 2024*.
- Wang, Q., Liu, X., & Huang, K. W. (2024). Employees' Occupational Risks and Benefits Resulting from Artificial Intelligence. *Information & Management* 61(08). <https://doi.org/https://doi.org/10.1016/j.im.2024.104036>
- Webb, M. (2020). *The Impact of Artificial Intelligence on the Labor Market*.
- Wilson, H. J., & Daugherty, P. R. (2018). Collaborative Intelligence: Humans and Ai Are Joining Forces. *Harvard Business Review* 96(04), 114-123.
- Xie, X., & Yan, J. (2024). *How Does Artificial Intelligence Affect Productivity and Agglomeration? International Review of Economics & Finance*
- Yuan, Q., Jin, Z., Zha, D., & Dennis, C. (2024). Artificial Intelligence and Firm Performance: A Systematic Literature Review and Future Research. *Academy of Management Proceedings* (01). <https://doi.org/https://doi.org/10.5465/AMPROC.2024.18903>

Appendix A: Study-level Evidence Inventory

The main scholarly contributions are juxtaposed with their main analytical roles in this appendix. It is intended to be used as a "helpful aid" to a screening log exported from a database, not as a replacement. Bibliographic information and eligibility need to be confirmed with the publisher. Once the full-text screening is done, the representative contributions cited in the thematic discussion should be replaced with a table with included studies based on actual extraction.

No.	Publication / contribution	Relevance to the synthesis
1	Acemoglu (2024).The simple macroeconomics of AI. NBER Working Paper 32487.	Conceptual, measurement or policy context
2	Acemoglu et al. (2022). Artificial intelligence and jobs: Evidence from online vacancies. <i>Journal of Labor Economics</i> , 40(S1), S293-S340.	Labor demand, tasks and skills
3	Acemoglu and Restrepo (2018).The race between man and machine. <i>American Economic Review</i> , 108(6), 1488-1542.	Conceptual, measurement or policy context
4	Acemoglu and Restrepo (2019). Automation and new tasks. <i>Journal of Economic Perspectives</i> , 33(2), 3-30.	Conceptual, measurement or policy context
5	Acemoglu and Restrepo (2020). Robots and jobs. <i>Journal of Political Economy</i> , 128(6), 2188-2244.	Labor demand, tasks and skills
6	Aghion et al. (2019). Artificial intelligence and economic growth. In <i>The Economics of Artificial Intelligence</i> . University of Chicago Press.	Innovation, growth and distribution
7	Agrawal et al. (2019). <i>The Economics of Artificial Intelligence</i> . University of Chicago Press.	Conceptual, measurement or policy context
8	Arntz et al. (2016).The risk of automation for jobs in OECD countries. <i>OECD Working Paper</i> 189.	Labor demand, tasks and skills
9	Autor (2015). Why are there still so many jobs? <i>Journal of Economic Perspectives</i> , 29(3), 3-30.	Labor demand, tasks and skills
10	Autor et al. (2003). The skill content of	Conceptual, measurement or policy context

	recent technological change. Quarterly Journal of Economics, 118(4), 1279-1333.	
11	Babina et al. (2024). Artificial intelligence, firm growth, and product innovation. Journal of Financial Economics, 151 (01)	Innovation, growth and distribution
12	Bessen (2019). AI and jobs: The role of demand. NBER Working Paper 24235.	Labor demand, tasks and skills
13	Bick et al. (2024). The rapid adoption of generative AI. NBER Working Paper 32966.	Conceptual, measurement or policy context
14	Bresnahan and Trajtenberg (1995). General purpose technologies. Journal of Econometrics, 65(1), 83-108.	Conceptual, measurement or policy context
15	Brynjolfsson and Hitt (2000). Beyond computation. Journal of Economic Perspectives, 14(4), 23-48.	Conceptual, measurement or policy context
16	Brynjolfsson and Hitt (2003). Computing productivity. Review of Economics and Statistics, 85(4), 793-808.	Worker/firm productivity
17	Brynjolfsson et al. (2023). Generative AI at work. NBER Working Paper 31161.	Worker/firm productivity
18	Brynjolfsson et al. (2021). The productivity J-curve. American Economic Journal: Macroeconomics, 13(1), 333-372.	Worker/firm productivity
19	Cockburn et al. (2019). The impact of artificial intelligence on innovation. In The Economics of Artificial Intelligence. University of Chicago Press.	Innovation, growth and distribution
20	Comunale and Manera (2024). The economic impacts and regulation of AI. IMF Working Paper 2024/065.	Conceptual, measurement or policy context
21	Czarnitzki and Rammer (2023). Artificial intelligence and firm-level productivity. Journal of Economic Behavior & Organization, 211, 188-205.	Worker/firm productivity
22	Damioli and Vertesy (2021). The impact of artificial intelligence on labor productivity. Eurasian Business Review, 11, 1-25.	Worker/firm productivity
23	Drydakis (2024). Artificial intelligence capital and employment prospects. Oxford Economic Papers, 76(4), 901-919.	Labor demand, tasks and skills
24	Eloundou et al. (2023). GPTs are GPTs. arXiv preprint.	Conceptual, measurement or policy context
25	Felten et al. (2021). Occupational, industry, and geographic exposure to artificial intelligence. Strategic Management Journal, 42(12), 2195-2217.	Conceptual, measurement or policy context
26	Filippucci, Gal, Jona-Lasinio, et al. (2024). The impact of artificial intelligence on productivity, distribution and growth. OECD AI Papers 15.	Worker/firm productivity
27	Filippucci, Gal and Schief (2024). Miracle or myth? Assessing macroeconomic productivity gains from AI. OECD AI Papers 29.	Worker/firm productivity
28	Frey and Osborne (2017). The future of employment. Technological Forecasting and Social Change, 114, 254-280.	Labor demand, tasks and skills
29	Gmyrek et al. (2023). Generative AI and jobs. ILO Working Paper 96.	Labor demand, tasks and skills
30	Graetz and Michaels (2018). Robots at work. Review of Economics and Statistics, 100(5), 753-768.	Conceptual, measurement or policy context

31	Green (2024). Artificial intelligence and the changing demand for skills. OECD AI Papers 14.	Labor demand, tasks and skills
32	Korinek and Stiglitz (2021). Artificial intelligence, globalization, and strategies for economic development. NBER Working Paper 28453.	Conceptual, measurement or policy context
33	Lane (2024). Who will be the workers most affected by AI? OECD AI Papers 26.	Conceptual, measurement or policy context
34	Noy and Zhang (2023). Experimental evidence on the productivity effects of generative artificial intelligence. Science, 381(6654), 187-192.	Worker/firm productivity
35	Oecd (2023). OECD Employment Outlook 2023: Artificial Intelligence and the Labour Market. OECD Publishing.	Labor demand, tasks and skills
36	Oecd (2024). Using AI in the workplace: Opportunities, risks and policy responses. OECD AI Papers.	Labor demand, tasks and skills
37	Parteka and Kordalska (2023). Artificial intelligence and productivity: Global evidence. Technovation, 125(07).	Worker/firm productivity
38	Saba and Ngepah (2024). The impact of artificial intelligence on employment and economic growth in BRICS. Research in Globalization, 8, 100213.	Labor demand, tasks and skills
39	Stanford Institute for Human-Centered (2024). AI Index Report 2024. Stanford University.	Conceptual, measurement or policy context
40	Webb (2020). The impact of artificial intelligence on the labor market. Stanford working paper.	Labor demand, tasks and skills
41	Yuan et al. (2024). Artificial intelligence and firm performance: A systematic literature review and future research. Academy of Management Proceedings, 2024(1).	Conceptual, measurement or policy context
42	Choi and Leigh (2024). Artificial intelligence's creation and displacement of labor demand. Technological Forecasting and Social Change, 209(12).	Labor demand, tasks and skills
43	Xie and Yan (2024). How does artificial intelligence affect productivity and agglomeration? International Review of Economics & Finance, 94(07).	Worker/firm productivity
44	Chen et al. (2024). Does artificial intelligence promote common prosperity within enterprises? Technological Forecasting and Social Change, 200(3).	Conceptual, measurement or policy context
45	Wang et al. (2024). Employees' occupational risks and benefits resulting from artificial intelligence. Information & Management, 61(8).	Conceptual, measurement or policy context
46	Masoud (2024). Artificial intelligence and unemployment dynamics. Technological Sustainability, 4(1), 30-50.	Labor demand, tasks and skills
47	Hampton and et al. (2024). Mapping the landscape of the economics of AI literature: Gaps and opportunities for research and policy. Journal of Economic Surveys (online record through 2024 corpus).	Conceptual, measurement or policy context
48	Raisch and Krakowski (2021). Artificial	Conceptual, measurement or policy context

	intelligence and management: The automation-augmentation paradox. <i>Academy of Management Review</i> , 46(1), 192-210.	
49	Jarrahi (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. <i>Business Horizons</i> , 61(4), 577-586.	Conceptual, measurement or policy context
50	Wilson and Daugherty (2018). Collaborative intelligence: Humans and AI are joining forces. <i>Harvard Business Review</i> , 96(4), 114-123.	Labor demand, tasks and skills
