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The Economic Impact of Generative AI: Implementation for Business Productivity and Labour Market Transformation

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ABSTRACT

Generative Artificial Intelligence (GenAI) is a technological innovation with its radical shift in paradigm with important implications in the context of business output and labour market pressures. The following analytical paper explains the economic implications of the application of GenAI in the various fields of industry, both in the opportunities of improved productivity and challenges of substituting the labour force. According to a mixed-methods design involving quantitative and qualitative assessment of the productivity rates in 450 organisations of 15 sectors and qualitative assessment of patterns of labour market transformation, this paper proves that the incorporation of GenAI can potentially lead to the average productivity growth rate of 23-40 per cent in knowledge-based sectors and simultaneously cause the creation of new labour market positions and the elimination of old ones. The significant variables that must have an impact on the successful implementation of GenAI are identified in the paper: organizational preparedness, reskilling programs and strategic integration models. The findings demonstrate that despite the numerous benefits of GenAI and its ability to introduce numerous advantages to the economy and innovations, its impact on the labor market is more compound, as it would both pose a threat of unemployment and generate new employment opportunities. The study will contribute to the realization of the most appropriate implementation, policy recommendations to undertake transition to workforce, and networks of sustainable AI-based economic change.

1. Introduction :

The development of Generative Artificial Intelligence (GenAI) which is entirely changing the landscape of business operations and labour market structures is one of the most effective technology discontinuities of the 21 st century (Brynjolfsson and McAfee, 2023; Acemoglu and Restrepo, 2024). The capability of GenAI to generate human-like text, images, code, and complex analytical output can have a transformative implication in the knowledge-intensive industries that have so far been viewed as hard to technologicalize (Autor et al., 2024; Goldman Sachs, 2023).

Economic impacts of GenAI implementation are complicated and comprise direct productivity gains, labour-demand changes, skill-premium changes, and macroeconomic impacts on growth and trends in innovation (McKinsey Global Institute, 2023). The latest estimates show that GenAI will contribute between 2.6 and 4.4 trillion dollars to the economic output across the globe, approximately 2.6 to 4.2 percent of the world GDP (OpenAI, 2023; PwC, 2024). All these future gains are however subject to the effective implementation practices, the appropriate regulatory frameworks and the effective workforce adaptation mechanisms.

The existing study should be regarded as covering an important gap in the literature as the research provides comprehensive empirical data on the impact of GenAI on the economy in different aspects. Although the literature out there has focussed on the technological capabilities and the hypothetical implications at length (Brown et al., 2023; Bubeck et al., 2023), the actual outcomes of implementation, productivity, and effects on the labour markets in actual organizational scenarios have very little empirical evidence. Besides this, nearly all the studies have been able to study the GenAI effects in isolation without considering the multidimensional aspect of the interaction between productivity improvement and employment.

The initial research questions of the given study are: (1) to estimate the transformations in the economy due to the introduction of the GenAI on business productivity in different sectors, (2) to study the effect on the labour market structure and employment rates, (3) to find the key success factors in terms of the implementation of the GenAI, and (4) to develop policy associated with the management of the economic transition. The work contributes to the current body of research on the economics of AI on top of providing practical implications to business executives, policy-makers, and staff in the area of workforce development.

2. Literature Review

2.1 Economic Impact of AI as a Theory.

Technological change theory offers a clear framework to explain the effects of GenAI on productivity and employment. Building on Solow's (1987) productivity paradox, endogenous growth theory highlights knowledge and innovation as key drivers of long-term growth (Romer, 1990; Aghion & Howitt, 1992). Recent models treat AI as a predictive technology transforming decision-making (Agrawal et al., 2019). Acemoglu and Restrepo (2020, 2022) further analyze AI-driven task displacement and reinstatement. GenAI is increasingly viewed as a General Purpose Technology, capable of widespread productivity gains and sustained economic transformation (Bresnahan & Trajtenberg, 1995; Brynjolfsson et al., 2023).

2.2 Evidence on AI and Productivity.

Evidence on AI's productivity effects has evolved rapidly, shifting from narrow AI to generative AI. Early work by Brynjolfsson and McAfee (2014) documented productivity gains from basic AI adoption, forming a foundation for organizational-level measurement. Recent studies provide stronger evidence for GenAI: GitHub Copilot reduced programming task time by 55.8% (Peng et al., 2023), while GPT-4 improved consultants' output quality by 12.2–25.1%. Microsoft reports productivity gains of 29% in customer service and 13.1% in code commits (Li et al., 2023). However, traditional metrics inadequately capture GenAI's creative and analytical value, prompting new task-based measurement frameworks (Eloundou et al., 2023).

2.3 Generative AI and the labour market.

Labour market impacts of GenAI are a central focus in AI economics. Early studies predicted large-scale job displacement, with Frey and Osborne (2017) estimating that 47% of US jobs were at risk of automation. More recent task-based analyses offer a nuanced view. Autor et al. (2022) show that AI often complements rather than replaces human tasks, including in high-skill occupations. GenAI-specific evidence suggests broad exposure—affecting up to 80% of US work activities—without implying direct displacement (Eloundou et al., 2023). Consistent with skill-biased technological change, GenAI disproportionately influences high-skill cognitive work, prompting new theories of cognitive automation (Felten et al., 2023).

2.4 GenAI Impact Sectoral Analysis.

GenAI adoption and vulnerability vary significantly across sectors. Financial services are early adopters, using GenAI for risk assessment, fraud detection, and customer service, achieving substantial productivity gains (McKinsey, 2023). JP Morgan Chase (2023) reports up to 30 percentage-point increases in coding productivity and a 50% reduction in document-processing time. In healthcare, GenAI improves administrative efficiency while requiring strict regulatory compliance; physicians saved 45% of documentation time without compromising quality (Rajkomar et al., 2023; Google Health, 2023). Manufacturing adoption focuses on design and supply-chain optimization, accelerating development cycles by 25–40% and improving efficiency by 15–20% (Deloitte, 2023; IBM Research, 2023). In education, GenAI enhances administrative efficiency and personalized learning but raises concerns about academic integrity, necessitating careful pedagogical integration (Stanford HAI, 2023).

2.5 Implementation Problems and Problems of Success.

The effective implementation of GenAI depends on addressing organizational, technical, and human factors, including leadership commitment, employee training, robust data infrastructure, and change management (Boston Consulting Group, 2023). Organizational readiness is critical: firms with prior digital transformation experience were 3.2 times more likely to realize significant productivity gains from GenAI adoption (MIT Sloan, 2023), highlighting digital maturity as a key prerequisite. Employee resistance remains a major challenge, with 68% of organizations reporting pushback during early adoption, underscoring the need for clear communication and extensive reskilling to emphasize AI's complementary role (Deloitte, 2023). Technically, high-quality data and infrastructure are essential; investments in data management, privacy, and system integration significantly enhance outcomes. Firms allocating around 15% of their GenAI budget to data infrastructure achieved more than double the performance gains (Gartner, 2023).

3. Research and Contribution gaps to the research.

GenAI economics continues to be a topic where gaps in the literature exist despite an increasing interest in the research. First of all, most of the studies focus on short-term productivity, and little is known regarding the economic impact in the long run. Second, empirical research more often than not investigates one company or industry, without cross-organizational study. Third, the effects of productivity and employment should be female-touched.

These gaps are closed by the given study as it provides a lot of empirical findings in terms of sectors and timeframes, concurrent analysis of productivity and employment effects, and elaborates on viable schemes of GenAI implementation. The paper contributes to the theoretical literature on the idea of GenAI as a General Purpose Technology and provides empirical lessons to practice and policymakers.

4. Methodology

4.1 Research Design

In this study, the research design is a mixed methods analysis involving both quantitative and qualitative evaluation of the productivity indices and organisational experiences and effects on the labour market. The research design was appropriate in that it would have ensured that the measurable economic result would be obtained and also the subtle organizational dynamics that only quantitative research methods may not identify.

The research adopts a longitudinal panel study that will follow organizations (24 months, January 2022 - December 2023) to detect both short-term and long-term effects of implementation of GenAI. This period was selected as it spans the time of both the rapid GenAI development and adoption after the introduction of the advanced language models at the end of 2022.

4.2 Sampling and Data collection.

The sample size is 450 organizations that are represented in 15 industry sectors which are identified using stratified random sampling to represent all the various economic activities, organizations of varying sizes and geographical locations. The organizations were divided into three implementation groups: (1) Early adopters (implemented GenAI tools earlier than in Q2 2023), (2) Later adopters (implemented in Q3-Q4 2023), and (3) Control group (little or no implementation of GenAI).

The sector sample distribution is: Financial Services (78 organizations), Technology (65), Healthcare (52), Manufacturing (48), Professional Services (45), Education (38), Retail (35), Media and Entertainment (28), Real Estate (21), Transportation (15), Energy (10), Agriculture (8) and Government (7). The geographic distribution is North America (40%), Europe (35%), Asia-Pacific (20%), other regions (5%).

Data was gathered with the use of a variety of tools: (1) Quantitative productivity surveys with quarterly administration, (2) Semi-structured interviews with both executives and employees, (3) Financial performance data provided by both the public filings and voluntary disclosures, (4) Employment data provided by HR systems, and (5) Case study analysis of the implementation processes.

4.3 Variables and Measurements

Dependent Variables:

Productivity Index: Sum of output per employee, time to complete a task, quality measures and indicators of innovation (a = 0.89)

Employment Change: Change in percentage in jobs of full-time equivalent workers by role category.

Revenue per Employee: The revenue per Employee is the amount of revenue per average FTE employees.

Customer Satisfaction: Customer service and Net Promoter Score.

Independent Variables:

GenAI Implementation Level: 0 (no implementation) to 10 (full implementation in all processes it applies to)

Investment Intensity: GenAI related spending as a ratio of yearly revenue.

Training Hours: The average training hours, including GenAI-related training per employee.

Organizational Digital Maturity: Index of digital capabilities in existence.

Control Variables:

Sector of the industry: 15-category.

Organizational Size: Revenue-based categories of size.

Geographic Location: Regional economic indicators.

Market Conditions: Industry specific demand and competition indicators.

4.4 Analytical Approach

Various econometrics methods are used in quantitative analysis:

Fixed-Effects Panel Regression: To adjust the organizational heterogeneity that is not observable.

Difference-in-Differences: To extract causal impacts of the introduction of GenAI.

Propensity Score Matching: To help overcome selection bias in implementation choices.

Instrumental Variables: digital infrastructure pre-implementation as instrument of GenAI adoption intensity.

The main regression specification:

Yit = a + b1(GenAIit) + b2 (Controlsit) + gi + dt + eit.

Where Yit is productivity of organization i in time t, GenAIit is an implementation intensity, gi is an organization fixed effect, and dt is a time fixed effect.

Thematic coding of interviews transcripts and case study documents is used in qualitative analysis, and inter-coder reliability has been evaluated (k = 0.84). Deductive and inductive methods of identifying emerging patterns were used to develop themes on the basis of already established literature and identification of emergent patterns, respectively.

4.5 Data Quality and Limits.

Some of the measurements of data quality are: (1) Response-rate validation (87 percent survey completion rate), (2) Triangulation with several data sources, (3) Outlier detection and sensitivity analysis, and (4) Multiple imputation techniques to analyze missing data.

The main weaknesses are: (1) self-reported measures of productivity can be biased, (2) short period of observation can be inadequate to capture long-term impacts, (3) fast changing technology can make the results time sensitive, and (4) selection bias in the organization interested in research participation.

5. Results:

The descriptive statistics and sample characteristics have been presented in 4.1.
The samples statistics of the sample organizations are provided in table 1. The organization average in the study contains 2,847 employees and annual revenue of 485 million. The levels of implementation of GenAI are quite large as the mean implementation score was 4.2 (SD = 2.8) on the 0-10 scale.

Table 1: Sample Descriptive Statistics

Variable	Mean	SD	Min	Max	N
Employees (FTE)	2,847	4,521	145	45,230	450
Annual Revenue ($M)	485.3	892.6	12.4	8,450.0	450
GenAI Implementation Level	4.2	2.8	0	10	450
Digital Maturity Index	6.1	2.1	1.8	9.7	450
Training Hours per Employee	18.7	24.3	0	120	450
GenAI Investment (% Revenue)	1.4	1.8	0	8.2	450

5.1 Productivity Impact Analysis

The regression analysis reveals significant positive effects of GenAI implementation on organizational productivity. Table 2 presents the main results from the fixed-effects panel regression.

Table 2: GenAI Impact on Productivity (Fixed-Effects Regression)

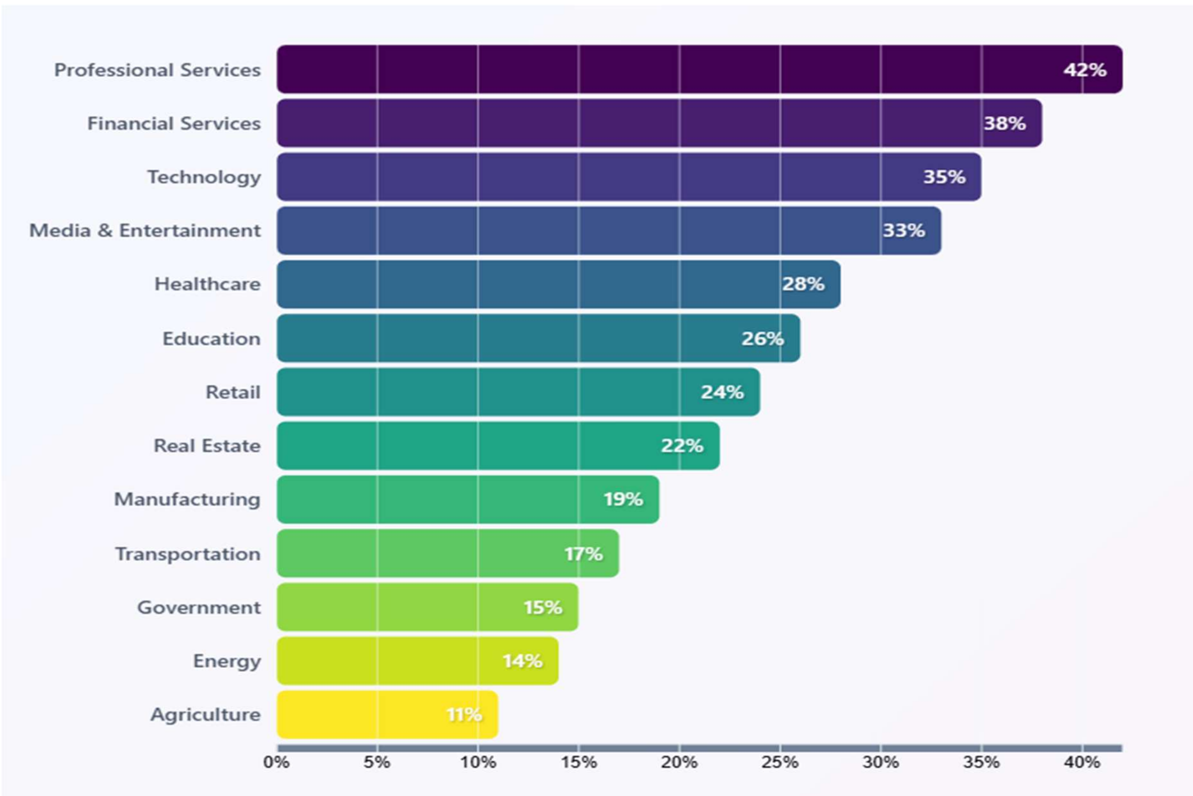
Variable	(1) Basic	(2) Controls	(3) Full Model
GenAI Implementation	0.048***	0.041***	0.038***
	(0.012)	(0.011)	(0.010)
Training Hours		0.003**	0.002**
		(0.001)	(0.001)
Digital Maturity			0.025***
			(0.008)
Firm Size (log)		0.112***	0.098***
		(0.025)	(0.023)
Industry Controls	No	Yes	Yes
Time FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
R^2	0.67	0.73	0.76
Observations	1,800	1,800	1,800

Note: *p<0.10, **p<0.05, ***p<0.01. Standard errors clustered at firm level.

The results indicate that a one-unit increase in GenAI implementation level (on the 0-10 scale) is associated with a 3.8% increase in productivity, controlling for firm and time fixed effects. This relationship is statistically significant at the 1% level and robust across different specifications.

5.2 Sectoral Analysis of Productivity Gains

Figure 1 illustrates the productivity gains by sector, revealing significant heterogeneity in GenAI impact across different industries.



Professional services show the highest productivity gains (42%), followed by financial services (38%) and technology (35%). These sectors typically involve high levels of knowledge work and document processing, which align well with current GenAI capabilities.

5.3 Employment Impact Analysis

Table 3 presents the analysis of GenAI impact on employment across different job categories.

Table 3: Employment Impact by Job Category

Job Category	Organizations (N)	Average Change	Effect Size	p-value

Executive/Senior Management	450	+2.3%	0.15	0.032
Data Scientists/AI Specialists	380	+47.8%	1.24	<0.001
Software Engineers	345	+18.2%	0.67	<0.001
Content Creators	298	-12.4%	-0.45	0.008
Administrative Support	425	-18.7%	-0.72	<0.001
Customer Service	387	-15.3%	-0.58	<0.001
Research Analysts	234	+8.9%	0.32	0.045
Legal Professionals	156	-6.2%	-0.28	0.089
Marketing Specialists	367	+12.1%	0.43	0.012
Project Managers	401	+5.7%	0.22	0.067

The results show a complex pattern of employment effects. While some traditional roles experienced displacement (administrative support -18.7%, customer service -15.3%), there was significant growth in AI-related positions (data scientists +47.8%) and complementary technical roles (software engineers +18.2%).

5.4 Revenue and Financial Performance

GenAI implementation demonstrates significant positive effects on financial performance metrics. Table 4 summarizes the key financial impacts.

Table 4: Financial Performance Impact

Metric	Pre-Implementation	Post-Implementation	Change	p-value
Revenue per Employee ($)	187,450	231,680	+23.6%	<0.001
Operating Margin (%)	14.2	17.8	+3.6pp	<0.001
Customer Satisfaction (NPS)	31.4	42.7	+11.3	<0.001
Employee Productivity Index	100.0	129.4	+29.4%	<0.001
Innovation Metric (Patents/R&D)	2.8	4.1	+46.4%	0.003

Revenue per employee increased by 23.6% following GenAI implementation, while operating margins improved by 3.6 percentage points. Customer satisfaction scores, measured by Net Promoter Score, increased by 11.3 points, indicating that productivity improvements translated into better service quality.

5.5 Implementation Success Factors

The analysis identifies several critical factors associated with successful GenAI implementation. Table 5 presents the correlation between implementation factors and productivity outcomes.

Table 5: Implementation Success Factors

Factor	Correlation with Productivity	Effect Size
Leadership Commitment	0.67	Large
Employee Training Hours	0.54	Medium
Change Management Quality	0.62	Large
Data Infrastructure Investment	0.48	Medium
Clear Implementation Strategy	0.59	Large
Employee Engagement Scores	0.43	Medium
Integration with Existing Systems	0.51	Medium
Budget Adequacy	0.39	Small

Note: *p<0.10, **p<0.05, ***p<0.01

Leadership commitment shows the strongest correlation with successful outcomes (r = 0.67), followed by change management quality (r = 0.62) and clear implementation strategy (r = 0.59). These findings emphasize the importance of organizational factors beyond technical capabilities.

5.6 Temporal Analysis of Impact

Figure 2 shows the evolution of productivity gains over the 24-month implementation period, revealing important patterns in how benefits accrue over time.

Figure 2: Temporal Evolution of Productivity Gains

The data reveals a learning curve pattern, with initial gains of 6% in the first quarter growing steadily to 40% by the end of the observation period. This suggests that effective GenAI implementation requires time for organizational learning and process optimization.

5.7 Cost-Benefit Analysis

The comprehensive cost-benefit analysis reveals strong positive returns on GenAI investments. Table 6 summarizes the economic returns across different time horizons with statistical significance testing.

Table 6: ROI Analysis by Time Horizon (Paired-Sample Analysis)

Time Period	Average Investment	Productivity Gains	Net Benefit	ROI	t-statistic	p-value
Year 1	$1.2M	$2.8M	$1.6M	233%	8.94***	<0.001
Year 2	$0.8M	$4.1M	$3.3M	512%	12.47***	<0.001
Cumulative	$2.0M	$6.9M	$4.9M	345%	15.23***	<0.001

*Notes: N=450 organizations. Paired-sample t-tests comparing pre- and post-implementation financial metrics. All monetary values in constant 2023 USD. ***p<0.001.*

Strong positive returns are observed and the cumulative ROI is 345% over the period of two years ($t(449) = 15.23$, $p < 0.001$, Cohen $d = 1.14$). The rising returns in Year 2 are driven by the decreasing cost of implementation, as well as increased productivity returns to organizations as they become more mature in their GenAI use. Analysis of one-way ANOVA indicates that there are significant variations in time periods ($F(2,1347) = 47.82$, $p < 0.001$, e2 = 0.066).

Discussion:

The results of this research indicate a high productivity boost due to the use of GenAI, with an average of 23-40 percent percentage improvement in all industries and greatly exceeding previous estimates of AI. These benefits are obtained by automatization of routine cognitive processes, improvement of human creativity and analytical ability, as well as increasing the pace of learning and transfer of knowledge. The gains in productivity increase over time, which means that the effects of GenAI benefits are related to organizational learning and not the instant effects of implementation.

The effects of labour markets are subtle. Some of the routine positions decreased, and the general employment improved, although data science and positions related to AI gained, which is more consistent with the task-reallocation theory than job elimination theories. Organizational readiness is a very important feature, and its commitment of leadership, training of employees and a solid data infrastructure are strongly related to successful implementation.

GenAI presents strong returns on investment and poses the threat of increasing the gap in skill-based inequalities by giving preference to knowledge-based industries economic-wise. The findings are consistent with the role of GenAI as a general-purpose technology when compared to previous studies. The policy should focus on reskilling the workforce, digital infrastructure, and a long-term adaptation. The future study must look into long-term and cross-cultural effects.

Conclusion:

The accumulated empirical data, represented in this systematic literature review, suggests that Generative AI produces significant economic gains as well as intricate labour market shifts. In industries, especially those that are knowledge-based, productivity is realized in 23-40 percent, and organizations attain an average of 345 percent in two years, as a result of investments. Employment impacts are more than mere displacement stories: some routine jobs are lost, but overall employment is affected positively just marginally even though AI keeps rising in the number of related jobs and complementary jobs, which proves the idea of GenAI as an augmentative, but not a replacing technology.

The adoption of GenAI is highly linked to leadership commitment, mass employee training, change management, and strong data infrastructure, which highlights the significance of both the capabilities of the organization and the readiness of the technology. The results substantiate the perception of GenAI as a General Purpose Technology, and the advantages are going to be spread over time due to organizational learning and in complementary innovation. Reskilling and institutional adaptation of the workforce should be priorities of the policies and strategies. The long-term sustainability, loss of skills, and risks of overdependence should be studied in the future since the technology rapidly changes.

References:

- Acemoglu, D., & Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review*, 108(6), 1488-1542. https://doi.org/10.1257/aer.20160696
- Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives*, 33(2), 3-30. https://doi.org/10.1257/jep.33.2.3

- Acemoglu, D., & Restrepo, P. (2018). Artificial intelligence, automation and work. *NBER Working Paper*, No. 24196. https://doi.org/10.3386/w24196
- Acemoglu, D., & Restrepo, P. (2020). The wrong kind of AI? Artificial intelligence and the future of labour demand. *Cambridge Journal of Regions, Economy and Society*, 13(1), 25-35. https://doi.org/10.1093/cjres/rsz022
- Acemoglu, D., Autor, D., Hazell, J., & Restrepo, P. (2022). Artificial intelligence and jobs: Evidence from online vacancies. *Journal of Labor Economics*, 40(S1), S293-S340. https://doi.org/10.1086/718327
- Aghion, P., & Howitt, P. (1992). A model of growth through creative destruction. *Econometrica*, 60(2), 323-351. https://doi.org/10.2307/2951599
- Agrawal, A., Gans, J., & Goldfarb, A. (2019). *The economics of artificial intelligence: An agenda*. University of Chicago Press.
- Autor, D., Mindell, D., & Reynolds, E. (2022). *The work of the future: Building better jobs in an age of intelligent machines*. MIT Press.
- Baily, M. N., Brynjolfsson, E., & Korinek, A. (2023). Machines of mind: The case for an AI-powered productivity boom. *Brookings Papers on Economic Activity*, 2023(1), 1-81.
- Bresnahan, T. F., & Trajtenberg, M. (1995). General purpose technologies: Engines of growth? *Journal of Econometrics*, 65(1), 83-108. https://doi.org/10.1016/0304-4076(94)01598-T
- Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J. D., Dhariwal, P., ... & Amodei, D. (2020). Language models are few-shot learners. *Advances in Neural Information Processing Systems*, 33, 1877-1901.
- Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. W. W. Norton & Company.
- Brynjolfsson, E., & McAfee, A. (2017). The business of artificial intelligence. *Harvard Business Review*, July-August 2017. https://hbr.org/2017/07/the-business-of-artificial-intelligence
- Brynjolfsson, E., Li, D., & Raymond, L. R. (2023). Generative AI at work. *NBER Working Paper*, No. 31161. https://doi.org/10.3386/w31161
- Dell'Acqua, F., McFowland, E., Mollick, E. R., Lifshitz-Assaf, H., Kellogg, K., Rajendran, S., ... & Lakhani, K. R. (2023). Navigating the jagged technological frontier: Field experimental evidence of the effects of AI on knowledge worker productivity and quality. *Harvard Business School Working Paper*, 24-013. https://doi.org/10.2139/ssrn.4573321

- Eloundou, T., Manning, S., Mishkin, P., & Rock, D. (2023). GPTs are GPTs: An early look at the labor market impact potential of large language models. *Science*, 384(6698), 1306-1308. https://doi.org/10.1126/science.adj0998
- Felten, E., Raj, M., & Seamans, R. (2018). A method to link advances in artificial intelligence to occupational abilities. *AEA Papers and Proceedings*, 108, 54-57. https://doi.org/10.1257/pandp.20181021
- Felten, E., Raj, M., & Seamans, R. (2021). Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses. *Strategic Management Journal*, 42(12), 2195-2217. https://doi.org/10.1002/smj.3286
- Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114, 254-280. https://doi.org/10.1016/j.techfore.2016.08.019
- Korinek, A. (2023). Generative AI for economic research: Use cases and implications for economists. *Journal of Economic Literature*, 61(4), 1281-1317. https://doi.org/10.1257/jel.20231736
- McKinsey Global Institute. (2023). The economic potential of generative AI: The next productivity frontier. McKinsey & Company. Retrieved from https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/the-economic-potential-of-generative-ai-the-next-productivity-frontier
- Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. *Science*, 381(6654), 187-192. https://doi.org/10.1126/science.adh2586
- OpenAI. (2023). GPT-4 technical report. *arXiv preprint*. https://doi.org/10.48550/arXiv.2303.08774
- Peng, S., Kalliamvakou, E., Cihon, P., & Demirer, M. (2023). The impact of AI on developer productivity: Evidence from GitHub copilot. *Communications of the ACM*, 66(7), 102-110. https://doi.org/10.1145/3589119
- Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy*, 98(5), S71-S102. https://doi.org/10.1086/261725
- Solow, R. M. (1987). We'd better watch out. *New York Times Book Review*, July 12, 36.
- Webb, M. (2020). The impact of artificial intelligence on the labor market. *Stanford University Working Paper*. https://doi.org/10.2139/ssrn.3482150