

Automation vs. Augmentation: Examining the normative-empirical divide in AI adoption

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KEYWORDS	ABSTRACT
Artificial Intelligence Augmentation Automation AI adoption	Artificial Intelligence (AI) is shaping how human work is defined and where the human role is still required. Academic literature frequently argues that human abilities should be augmented by AI to optimize welfare outcomes. Business behavior, however, suggests that automation initiatives are pursued in practice. This essay explains this divergence by building a conceptual framework. It argues that differences in tasks (decision versus creation tasks), as well as organizational perspective (macro versus firm level), influence which narrative prevails. The essay identifies tensions between the macro and the firm level across both task types. As AI outperforms humans in decision tasks, companies pursue automation initiatives, while the macro-level suggests negative societal and macroeconomic outcomes due to displacement effects. Humans outperform AI in creation tasks, but companies still reduce headcount, a phenomenon the essay calls ‘speculative automation’. The essay argues that the macro and firm level perspectives are misaligned due to the tax preference for capital over labor.

1. Introduction

Artificial Intelligence (AI) has arrived at the workplace, with 88% of companies using this technology in at least one business function (McKinsey & Company, 2025). This substantially changes how organizations operate and how human roles are defined (Bankins et al., 2024). While academic research warns about long-term job automation, there is widespread understanding in the literature that the best results arise from humans and machines working together. This means AI should augment human capabilities rather than automate human work (Agrawal et al., 2018; Brynjolfsson et al., 2023; Brynjolfsson & McAfee, 2014). Similar claims are made at the macro and societal level.

Acemoglu & Restrepo (2019), analyzing the labor market impact of automation technology, find no evidence for the end of human work or for the unconditional superiority of technology over human labor, emphasizing the strength of augmentation.

In contrast to this normative view, business practice shows different behavior. In March 2026, 25% of all job cuts in the United States were attributed to automation by AI¹. This aligns with continuous news headlines that portray AI as the cause of layoffs, especially in the technology sector².

This raises the question: Why does the AI augmentation narrative persist in academic discourse while business practice pursues

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automation?

To answer this research question, the paper uses a conceptual analysis drawing on secondary literature from peer-reviewed academic sources as well as practitioner discourse (e.g., Harvard Business Review). While this approach allows for comprehensive discussion, it is not based on new, unique data, and builds some arguments on non-peer-reviewed reports. Further, this essay focuses on task-level and level-of-analysis explanations rather than attributing the gap to corporate communication strategies, which fail to account for systematic divergence.

As an opinion piece, this framing is built upon a simplified observation that does not sufficiently acknowledge the more nuanced reality. Economic literature also examines automation and its implications across different levels of analysis, including the firm-level (e.g., Chen & Wang, 2026), while firms besides automation also invest in AI-human collaboration. For example, US retailer Walmart has designed an AI strategy that is built upon human-centered design principles³. Thus, this paper does not suggest a simple binary decision towards automation or augmentation but relative emphasis.

2. Task-based perspective

The first major theoretical argument emerges from the task-based perspective on automation technology. It examines which tasks are conducted by humans or capital, respectively. Automation in this context is referred to as the adoption of technology which leads to the reallocation of tasks to capital instead of labor which is called the replacement effect. On the contrary, the introduction of AI can also lead to new tasks in which labor offers comparative advantages and, thus, increases labor demand which is called the reinstatement effect (Acemoglu & Restrepo, 2019). Augmentation in

this essay refers to both the reinstatement effect (Acemoglu & Restrepo, 2019) and close human-AI collaboration (Raisch & Krakowski, 2021; Vaccaro et al., 2024).

The question of whether automation or augmentation prevails depends on the comparative advantage (Acemoglu & Restrepo, 2019). Accordingly, organizations choose the strategy that maximizes task-level productivity. Raisch & Krakowski (2021) extend this logic, arguing that the combination of automation and augmentation initiatives simultaneously leads to the highest performance.

Vaccaro et al. (2024) support this theoretical distinction empirically through a meta-analysis of 106 experimental studies published between 2020 and 2023. Productivity results depend on context and whether AI or humans alone perform better on a task. For tasks in which AI performs better than humans alone, human-AI collaboration does not create sufficient synergies to outperform AI. Only in cases in which humans alone outperform AI, the human-AI collaboration provides additional benefits. That stands in contrast to the widespread academic assumption that augmentation is universally better than automation.

However, a pure task-based perspective leaves the technology untheorized, implicitly assuming that there is no difference between AI types and context beyond whether labor or capital is more efficient. It is central to understand what makes AI superior, and in which tasks. One popular differentiation is between decision tasks, for deciding between several options such as whether a bank transaction is fraudulent or not, and creation tasks, for creating output such as text, images, or videos. Automation strategies outperform augmentation in decision tasks but underperform in creation tasks (Vaccaro et al., 2024). AI has the advantage in decision tasks, as they resemble optimization problems in which pattern recognition is crucial (Agrawal et al.,

2018; Russell & Norvig, 2022). Deep learning models, for example, trained on large datasets possess an inherent advantage in this area (LeCun et al., 2015). On the contrary, creation tasks do not possess a clear right or wrong answer and depend on contextual judgment and novelty. As AI models are trained on historical data and recombine existing patterns, they are currently still lagging in this area (Doshi & Hauser, 2024). While Generative AI has expanded content generation capabilities over the last couple of years, it is still dependent on human-AI collaboration for achieving the best results. In these areas, humans alone and human-AI collaboration still outperform automation (Noy & Zhang, 2023; Vaccaro et al., 2024).

3. Level of Analysis

The second major debate divides along the level of analysis, contrasting the individual firm perspective and the macro/societal perspective. Following the doctrine of economist Milton Friedman, a company's goal is to increase profits and maximize shareholder value (Friedman, 1970). Companies should consequently pursue automation initiatives in cases in which AI offers task-level advantages (Vaccaro et al., 2024). However, a recent practitioner-oriented study across over 1000 executives suggests that 89% of organizations are reducing headcount or slowing their hiring process based on AI's expected potential rather than proven implementation success. This questions the assumption of rational-acting firms and suggests capital-market-driven pressure to cut costs, for which AI provides a more acceptable justification (Davenport & Srinivasan, 2026).

Academic discussions seem more interested in the macro-perspective and what automation means for national economies and society. Even when automation is individually rational, aggregated effects on the macro-level become negative as the displacement effect outweighs

the reinstatement effect. Particularly problematic are situations in which automation technologies displace human labor without increasing labor productivity, nor achieving economic benefits. As no additional tasks or jobs are created, the simple displacement leads to a lower number of jobs and rising inequality, favoring capital owners (Acemoglu et al., 2020; Acemoglu & Restrepo, 2020).

These suboptimal social outcomes suggest market failures driven by three main factors: First, augmentation and the creation of new tasks require innovation, which can be used by other firms as well, potentially discouraging radically innovative firms. Second, there is bias among major tech firms towards automation and removing the human factor. Third, tax policies in many countries actively subsidize capital while taxing employment (Acemoglu et al., 2020; Acemoglu & Restrepo, 2020). For example, in the United States, effective labor tax lands between 25.5 and 33.5 percent, while effective tax on capital has been steadily reduced from 20 percent in the 1990s to roughly 5 percent in 2020 (Acemoglu et al., 2020). This essay deliberately draws the comparison between the firm and macro-level while avoiding discussions at the industry level, which might provide a more nuanced discussion.

4. Discussion

Having introduced the task-based perspective and differences in the level of analysis, this section explains how these factors combined explain the divergence.

4.1 The question of technology

As demonstrated, the tasks and consequently the technology used must not be treated as given. Different types of AI offer different implications and fundamentally different propositions. This aligns with Huang & Rust's (2021) typology of mechanical, thinking, and feeling AI.

Mechanical AI refers to traditional rule-based or simple machine learning models designed for standardization and minimal variability. Thinking AI (e.g., advanced machine learning) learns and adapts from data while feeling AI (e.g., Generative AI) responds to context and individual-specific experiences.

These capability levels loosely map onto task distinction. Decision tasks are typically best performed by mechanical AI or thinking AI where pattern recognition is required. Creation tasks require high-level capabilities of thinking AI and feeling AI, but automation potential is limited and conditional. Generative AI increasingly supports creative work but still requires human contextual judgment (Vaccaro et al., 2024). That reinforces the point that the automation-augmentation choice is task- and technology-dependent. This is also the distinction that Acemoglu & Restrepo (2020) emphasize when warning of the ‘wrong kind of AI’.

However, this raises the question whether these assumptions remain true when AI systems improve further in the future. Agentic AI, for example, already has the potential to remove some of the limitations discussed for creation tasks. Agentic AI can be understood as a technology that possesses intelligence and is designed to make rational decisions to achieve the best expected outcome without direct human intervention (Baird & Maruping, 2021). Literature distinguishes AI Agents, that perform narrow tasks independently by integrating large language models (LLMs) with external tools, and Agentic AI systems, characterized by multi-agent architecture to pursue complex, organization-wide tasks (Sapkota et al., 2026). Agentic AI, thus, both creates and decides likewise within a workflow. In a fully ‘agentic organization’, AI augmentation might just represent an intermediary step on the way to full AI automation in the future (Raisch &

Krakowski, 2021). However, while Agentic AI’s abilities are much broader than that of traditional Gen AI models, the focus is still on mechanical tasks and accelerating existing workflows. Further, within an agentic workflow, goals are decomposed into smaller tasks which depend on different capabilities (Sapkota et al., 2026). The comparative advantage logic between automation vs. augmentation (Acemoglu & Restrepo, 2019) is simply shifted from a high-level workflow perspective to sub-tasks without diminishing its validity.

The introduction of Artificial General Intelligence (AGI), defined as “an AI system that is at least as capable as a human at most tasks” (Morris et al., 2023, p. 1) could shift boundaries even further. While systems with superhuman intelligence have been developed for narrow sets of tasks (e.g., AlphaFold for protein structures, or AlphaZero for Chess and Go), they are still unable to perform on a human level in general non-physical tasks that require metacognitive abilities like acquiring new skills. Research has identified five levels of AGI depending on the performance percentile compared to skilled adults. If AGI were to reach expert level, corresponding to the 90th percentile (Morris et al., 2023), task distinction could become obsolete. In this scenario, the AGI can learn the required skills even for creation tasks at a level surpassing most human workers. However, it remains unclear when these types of technology will become available (Acemoglu et al., 2026). Consequently, I argue that the decision-creation task distinction remains useful in the foreseeable future for conceptualizing automation versus augmentation discussions.

4.2 Conceptual framework

Fundamentally, whether firms automate or augment is explained by technology, specifically, AI’s selective superiority. This arises because AI can automate certain tasks very efficiently, while it is currently unable to replace the creative

capacity of humans. Figure 1 illustrates the normative-empirical divide across task types and levels of analysis. The matrix reveals two distinct tensions:

In decision tasks, in which AI outperforms human capabilities (Vaccaro et al., 2024), companies pursue *full automation* to maximize individual gains. The essay defines this as pursuing automation initiatives for all decision tasks that can be performed more economically by AI. In contrast, the macro-level perspective advocates for *selective automation*, which considers displacement concerns and avoids ‘so-so automation’ without productivity gains (Acemoglu & Restrepo, 2019).

In creation tasks, the macro level advocates for a clear *augmentation priority*, which keeps societal benefits at the macro level as human work is enhanced (Acemoglu et al., 2026). This should align with firms’ shareholder interests as they achieve the highest productivity from augmentation in these areas (Vaccaro et al.,

2024). Yet the question remains why companies pursue automation initiatives regardless, seemingly against rational business behavior. Industry studies find 60% of firms are reducing headcount based on AI potential, while only 2% of companies are doing so based on AI implementation success (Davenport & Srinivasan, 2026). I propose to call this phenomenon ‘speculative automation’, which is characterized by the removal of the human factor based on expected future AI automation capabilities. AI initiatives at the firm-level prioritize automation, while ignoring the potential of human-AI collaboration, which could enable new task creation and skill acquisition (Acemoglu et al., 2026). Headlines of rehiring after initial AI-related lay-off waves (e.g., at the Fintech Klarna⁴), however, suggest that these practices are either premature given the technological state or the assumption that AI can catch up with humans in creation tasks does not hold.

Figure 1. Automation vs. Augmentation Explanation Framework

	Decision Tasks	Creation Tasks
Macro Perspective	Selective automation Consider displacement effects and focus on areas requiring humans	Augmentation priority Preserve the human role and create new tasks
Individual Firm Perspective	Full automation AI is superior and replaces human labor	Speculative automation AI is expected to become superior; humans are replaced

The misalignment between optimal decisions at the macro and individual firm-level raises the question whether policy changes are required to better align firm- and societal-level outcomes. A potential solution is the removal of incentives and preferential treatment of capital (Acemoglu & Restrepo, 2019, 2020) as included in many tax systems. However, I argue that AI-related policies aiming to foster augmentation need to take specific tasks into account. As context and technology matter, blanket recommendations and policies are ill-suited to deliver the desired effect. For example, decision tasks that can be completed by mechanical AI are best left unaddressed by policies while the focus should be on areas in which humans can genuinely perform better and more efficiently than technology alone.

The taxation argument depends on the assumption that tax incentives are the primary driver of excessive automation. However, if path dependencies create lock-in effects for automation technology, the automation narrative might prevail even after conducting tax reforms. This might be because of implicit knowledge accumulated by technology over time that cannot be easily learnt and understood by humans.

5. Conclusion

This essay analyzes the normative-empirical divide between automation and augmentation narratives to explain why both coexist. The answer lies in distinguishing organizational level of analysis from task types. The augmentation narrative arises from a macro-level view that focuses on creation tasks in which humans can outperform AI, leading to human jobs being secured. Automation initiatives are shaped by firm-level rationale that focuses on tasks in which AI is superior to humans. While this is empirically supported for decision tasks, corporate automation initiatives also include

creation tasks. The literature assessed suggests that companies do so based on expected future technological breakthroughs, such as Agentic AI or AGI. To describe this phenomenon, this essay introduces the term ‘speculative automation’. It argues that there is a misalignment between firm-level and macro-level objectives, leading to inefficient behavior and excessive use of capital over labor at the firm level. The consequence is a steadily increasing share of capital in the economy, posing the threat of increasing winner-takes-all scenarios. To address this, the essay follows Acemoglu et al. (2020) in calling for policy change by increasing the historically low taxation of capital while reducing the labor-tax burden.

The results offer important implications for scholars and practitioners. Scholars gain insights into why augmentation is not a realistic goal for mechanical decision tasks, while practitioners receive guidance on when to opt for augmentation or automation. Further, it aims to sensitize managers that following the bandwagon might not be the right choice, and a more mindful approach toward automation of creation tasks is required.

Notes

1. Challenger, Gray & Christmas. (2026, April 2). Challenger Report: March Cuts Rise 25% From February, AI Leads Reasons. Challenger Report. <https://www.challengergray.com/blog/challenger-report-march-cuts-rise-25-from-february-ai-leads-reasons/>
2. For example: Georgiadis, P., Heikkilä, M., & Rosner-Uddin, R. (2026, January 28). Amazon to axe another 16,000 corporate jobs. <https://www.ft.com/content/c6055c9d-5229-4cfc-9f75-c7d96e021929>
3. Walmart example: Scoble-Williams, N., Cantrell, S., Mallon, D. & Besana, S. (2026). Getting human and machine relationships right. Deloitte Insights.

<https://www.deloitte.com/us/en/insights/topics/talent/human-capital-trends/2026/human-ai-interaction-design.html>

4. Klarna example: The Economic Times (18 May 2025). After firing 700 employees for AI, Swedish company admits their mistake and plans to rehire humans. What went wrong?
https://economictimes.indiatimes.com//magazines/panache/after-firing-700-employees-for-ai-swedish-company-admits-their-mistake-and-plans-to-rehire-humans-what-happened/articleshow/121252776.cms?utm_source=contentofinterest&utm_medium=text&utm_campaign=cppst

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