Artificial Intelligence and the Brain: Is Innovation Getting Easier?

Kevin Mi* Danxia Xie† Buyuan Yang‡ Hanzhe Zhang§

March 9, 2026¶

Abstract

Artificial intelligence (AI) synthesizes existing knowledge into refined knowledge, which the human brain then recombines to generate new ideas. By lowering the cognitive burden of information processing, AI can accelerate discovery, but it may also reduce knowledge spillovers by filtering out valuable information. We show that research productivity varies nonmonotonically with AI efficiency: AI boosts innovation when knowledge is very scarce or very abundant yet may create a mid-knowledge-level *AI trap* where faster AI progress *slows down* innovation and *lowers* productivity. In our endogenous growth model, faster AI raises long-run growth, but its effect on R&D labor share is ambiguous.

Keywords: AI trap, endogenous growth, knowledge spillovers, knowledge burdens

JEL Codes: O40, O33, O41, O31

*Department of Economics, Michigan State University; kwmi@msu.edu.

†Institute of Economics, School of Social Sciences, Tsinghua University; xiedanxia@tsinghua.edu.cn.

‡School of International Trade and Economics, Central University of Finance and Economics; yangbuyuan@cufe.edu.cn.

§Department of Economics, Michigan State University; hanzhe@msu.edu.

¶We thank Yao Hou, Jinglei Huang, and Longtian Zhang, as well as participants at the 2026 ASSA Annual Meeting, for comments. Xie acknowledges the National Natural Science Foundation of China (72373079, 72342008, and 72442027) and Tsinghua University Initiative Scientific Research Program (2024THZWYY06); Yang acknowledges the National Natural Science Foundation of China (72403265), the National Social Science Fund of China (24&ZD053), the 75th batch of the General Program of CPSF (2024M753813), and the Program for Innovation Research in Central University of Finance and Economics; and Zhang acknowledges the National Science Foundation (1928278) and Amazon Science. Yang is the corresponding author.

1 Introduction

The similarities and differences between artificial intelligence and the human brain have been central to pioneering work in computer science (Turing, 1950; Von Neumann and Kurzweil, 1958).[1] Recent advances in AI highlight its connection to the brain and its implications for economic development. Geoffrey Hinton, the "Godfather of AI," stated, "[AI]'s going to be like the Industrial Revolution—but instead of our physical capabilities, it's going to exceed our intellectual capabilities" (BBC News, 2024). However, existing economic studies have rarely examined the implications of AI's foundational philosophy—its relationship with the brain—for innovation and growth.

Given the recent rapid advances in AI, we seek to explore the intricate relationships between AI and the brain in the innovation process. In many intelligence tasks, AI has already surpassed human capabilities.[2] However, some scholars contend that AI alone cannot replicate human-like creativity.[3] That is, although AI excels at acquiring and processing existing knowledge, it lacks the capacity for fundamentally novel idea generation. In contrast, the human brain is indispensable for creating new knowledge, despite it being comparatively less efficient at processing large volumes of information.

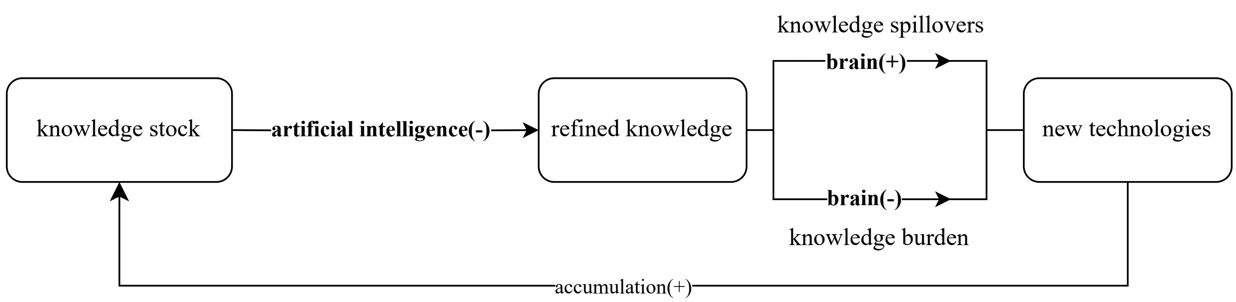

Figure 1: AI and the Brain in the Innovation Process

In this paper, we develop an endogenous growth model to capture the key roles of AI and the brain

[1]For example, the seminal frameworks of the Turing Test (Turing, 1950) and the von Neumann architecture (Von Neumann and Kurzweil, 1958) emphasize the imitation of brain functions by computers, laying the foundations for modern computing and artificial intelligence (AI). J. C. R. Licklider, who introduced the concept of man-computer symbiosis, argued that collaboration between computers and the brain would drive advances in formalized reasoning, scientific decision-making, and complex situation management (Licklider, 1960; Campbell-Kelly et al., 2023).

[2]For example, deep learning algorithms reduced image-labeling error rates on ImageNet—a dataset developed by Stanford researchers that comprises over 10 million images—from over 30% in 2010 to less than 5% in 2016, reaching 2.2% by 2017 and significantly outperforming the human error rate of approximately 5% (Brynjolfsson et al., 2018). In tasks involving logical and mathematical intelligence, linguistic intelligence, and natural discriminative intelligence, employing AI is substantially cheaper than hiring skilled workers (Bao et al., 2024). Furthermore, Charness and Grieco (2026) provide experimental evidence that AI-generated responses score higher than human-generated responses in closed tasks.

[3]Searle (1980) maintains that intentionality emerges from the causal properties of the brain and cannot be duplicated merely through the execution of computer programs. Consequently, Searle argues that strong AI, relying solely on programs without intrinsic causal powers, cannot achieve genuine cognition. Felin and Holweg (2024) argue that AI, as a data-driven predictive tool, is inherently backward-looking and imitative, lacking the theory-driven causal reasoning and forward-looking capacities intrinsic to human cognition, thus incapable of generating authentic novelty or original knowledge. Yao et al. (2024) highlight concerns regarding the potential marginalization of human creativity resulting from generative AI and analyze the competitive dynamics and equilibrium between human-generated and AI-generated content.

in innovation. Figure 1 illustrates our proposed two-stage innovation process. The first stage involves AI collecting, organizing, and refining vast amounts of existing knowledge to generate the refined knowledge necessary for innovation. Such a task cannot be accomplished by the brain alone. Each individual brain is constrained by physiological limits that hinder its ability to synthesize, analyze, and organize high-dimensional knowledge. In contrast, AI, supported by parallel processing chip architectures, is capable of handling these tasks efficiently. Even if the brain could process existing knowledge, its efficiency would be significantly lower, and relying solely on it to manage vast amounts of information is restrictive.

The second stage centers on the creative thinking of the brain as it builds upon refined knowledge. This creative capacity distinguishes the brain from AI, ultimately delivering the "final blow" to generate new production technologies. In this stage, two effects emerge within the processing of refined knowledge in the brain: *knowledge spillover* and *knowledge burden*. When the amount of refined knowledge is small, its increase provides more ideas for creative thinking, facilitating innovation—this is known as *knowledge spillover*, as discussed in endogenous growth models such as Romer (1990) and Jones (1995). However, when the amount of refined knowledge is too large, it hinders the brain's creative thinking and, consequently, innovation. This phenomenon, termed *knowledge burden*, has been rarely noted in the literature on economic growth, with Jones (2009, 2010) among the few studies that examine it.

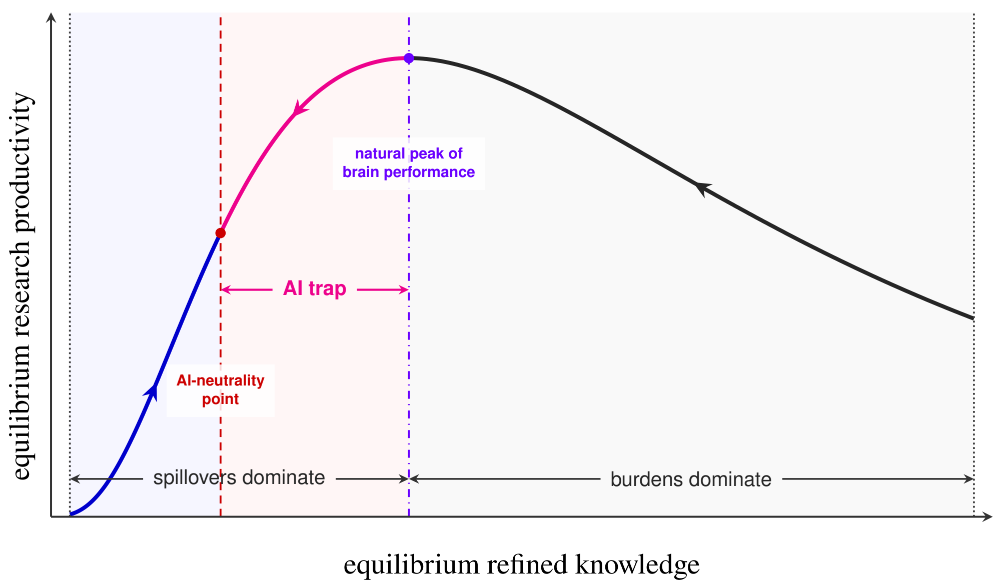

Figure 2: Effects of Faster AI Progress on Refined Knowledge and Research Productivity

Along the balanced growth path (BGP), we establish three results. First, as shown in Figure 2, refined knowledge and research productivity are *nonmonotonic* in AI progress. There is an optimal amount of refined knowledge for the brain to reach peak research productivity, at which level the knowledge spillovers and knowledge burdens effects balance. Starting from a relatively low level of refined knowledge, the faster growth of AI will increase refined knowledge but will plateau before reaching the refined knowledge needed for peak brain performance. Even the maximum speed of AI progress leads to a strictly lower amount of equilibrium refined knowledge, which we call the *AI-neutrality point*. This implies a waste of social intelligence: valuable knowledge remains unexploited, or the informational load exceeds the brain's capacity. This inefficiency reflects distorted social resource allocation rather than physiological constraints. In the region of intermediate levels of equilibrium refined knowledge, this distortion generates an *AI trap* in which faster AI progress leads to a *decline* in research productivity.

Second, we propose an elasticity-based criterion to assess whether innovation becomes easier as the AI growth rate increases. We find that faster AI growth makes innovation easier in two regions: a strongly spillover-dominant region, where AI expands the set of knowledge that humans can effectively process enough to sustain spillovers despite selective discarding; and a burden-dominant region, where second-order burden relief outweighs first-order spillover loss. In the weakly spillover-dominant region—the AI trap region—faster AI growth makes innovation harder because filtering erodes spillovers more than it eases burdens, reducing the returns to the brain's creative thinking.

Finally, faster AI growth raises long-run growth, but its effect on the R&D labor share is ambiguous. When refined knowledge is scarce, faster AI growth expands the set of knowledge that humans can effectively process, strengthens spillovers, and raises research productivity, generating an R&D labor-saving effect. When refined knowledge is abundant, the marginal spillover gains from faster AI progress weaken or turn negative, so the R&D labor share increases.

The rest of the paper is organized as follows. The remainder of this section reviews the related literature. Section 2 presents the model, solves the Pareto-optimal problem, and establishes the existence of equilibrium. Section 3 discusses our three main results on the effects of faster AI progress on research productivity, the ease of innovation, and the R&D labor share. Section 4 concludes.

Related Literature. Our paper contributes to the literature on the economics of science and innovation. A notable phenomenon in this field is the decline in research productivity over the past decades. For example, Bloom et al. (2020) document substantial declines across sectors such as semiconductors, agriculture, and medicine. Some scholars attribute this decline to the increasing depth and breadth of scientific knowledge. Jones (2009) presents stylized facts showing that the expansion of knowledge raises cognitive burdens on researchers, leading to a shift from individual to team-based innovation, prolonged training periods, and delayed peak productivity. Subsequent studies corroborate the trend of later-life innovation among leading inventors and scientists (Jones, 2010), and document rising co-authorship in economics as a response to increasing specialization and knowledge complexity (Jones, 2021; Chen et al., 2025), as well as the discouraging effect of the knowledge burden on disruptive and novel innovation (Park et al., 2023; Grashof and Kopka, 2023).[4]

From a theoretical perspective, Jones (2009) develops an idea-based growth model in which innovators incur rising costs to assimilate frontier knowledge, leading to prolonged education, greater specialization, and greater reliance on teams. For quantitative analysis, Bloom et al. (2020) propose a simple growth model that decomposes economic growth into two multiplicative factors: research productivity and the number of researchers. This model implies that sustained technological progress—and thus economic growth—requires exponentially increasing R&D investment. In contrast, we develop an endogenous growth

[4] There is also evidence to the contrary. Ando et al. (2025) find that, in U.S. manufacturing, R&D has become more effective at generating productivity-enhancing ideas; they attribute the decline in productivity growth to rising technological rivalry and obsolescence.

model that explicitly incorporates the knowledge burden. Building on Bloom et al. (2020), we further decompose research productivity into two components: a negative effect from the knowledge burden and a positive effect from knowledge spillovers. This tractable framework allows us to examine the effect of AI on innovation and growth through two distinct channels.

Our study advances growth theory from a broader perspective. Since Romer (1990) introduced an endogenous growth model based on the nonrivalry of knowledge, subsequent developments—whether in the expanding-variety framework (e.g., Rivera-Batiz and Romer (1991) and Jones (1995)) or the quality-ladder framework (e.g., Grossman and Helpman (1991a,b) and Aghion and Howitt (1992))—have uniformly assumed purely positive knowledge spillovers. Beyond Jones (2009), who examines the economic implications of knowledge burden within a growth framework, Xie and Yang (2022, 2025) identify frictions in spatial and intertemporal knowledge spillovers—stemming from underdeveloped information carrier technologies—as constraints on innovation and growth. In contrast, to the best of our knowledge, our model is the first to incorporate both knowledge burden and AI into the expanding-variety framework, thereby deepening our understanding of the role of AI in long-term growth.

Our work also contributes to the emerging literature on AI and innovation.[5] Among this literature, empirical studies have linked AI to innovation. Cockburn et al. (2019) documents a rapid shift in the U.S. toward learning-oriented research since 2009, coinciding with breakthroughs in deep learning for tasks such as computer vision.[6] Babina et al. (2024) show that AI investment promotes firm growth through product innovation. A few theoretical studies explore the relationship between AI and innovation (Aghion et al., 2019; Agrawal et al., 2019, 2023, 2024; Gans, 2025). Aghion et al. (2019) examine the role of AI as a capital input in idea production, its interaction with research labor, and the resulting implications for economic growth. Agrawal et al. (2019), building on Weitzman (1998), analyze how AI affects search and combination processes within complex knowledge spaces during innovation. Agrawal et al. (2023, 2024) model innovation as a two-stage process—combinatorial prediction and hypothesis testing—and uses survival analysis to assess the effects of AI adoption on innovation success probability, search duration, and expected profits. Gans (2025) argues that AI reshapes research incentives by introducing complementarity between scientific novelty and decision-making effectiveness, showing that sufficiently advanced AI tools encourage more novel rather than incremental research. Jones (2025) characterizes AI's role in R&D as the automation of research tasks. However, the knowledge-burden-easing mechanism through which AI fosters innovation remains underexplored in theory. This paper seeks to fill that void.

[5] In recent years, rapid advances in and the widespread adoption of AI have spurred growing interest in its economic implications, including employment (Acemoglu and Restrepo, 2018; Acemoglu et al., 2022; Felten et al., 2023; Sun and Zhang, 2025), finance (Babina et al., 2024; Cao et al., 2024), risk and regulation (Jones, 2024; Acemoglu and Lensman, 2024), productivity (Noy and Zhang, 2023; Aghion and Bunel, 2024; Brynjolfsson et al., 2025), economic growth (Aghion et al., 2019; Agrawal et al., 2019; Lu, 2021; Trammell and Korinek, 2023; Bao et al., 2024), and international trade (Goldfarb et al., 2019; Sun and Trefler, 2023).

[6] Cockburn et al. (2019) argue that among the three key AI trajectories—robotics, symbolic systems, and deep learning—only deep learning, due to its general-purpose nature, is likely to transform the innovation process; symbolic systems have stagnated with limited future relevance, and robotics, while capable of substituting for labor, is unlikely to fundamentally reshape innovation.

2 The Model

Our endogenous growth model incorporates both the advantages and limitations of the brain in the innovation process. We focus on equilibrium outcomes under the Pareto optimal allocation.

2.1 Economic Environment

The representative consumer. The economy consists of a constant mass $L > 0$ of homogeneous consumers who supply labor inelastically. Each consumer has constant relative risk aversion (CRRA) preferences. By choosing the consumption path $c(t)$ for $t \in (0, \infty)$, a representative consumer maximizes her discounted lifetime utility

$$\int_0^\infty e^{-\rho t} \frac{c(t)^{1-\gamma} - 1}{1 - \gamma} dt, \tag{1}$$

where $\rho > 0$ is the subjective discount rate, $\gamma > 0$ is the coefficient of relative risk aversion, and $c(t)$ denotes per capita consumption.

Final goods producers. The final goods market is perfectly competitive. At time t, the production function for the final good is

$$Y(t) = z(t)(1 - s(t))L, \tag{2}$$

where $Y(t)$ denotes the total output of the final good in the economy, $z(t)$ represents the production technology, and $s(t) \in (0, 1)$ indicates the fraction of labor allocated to R&D for production technology. Thus, $1 - s(t)$ is the fraction of labor allocated to final good production. As a result, the final good output per capita, defined as $y(t) \equiv Y(t)/L$, is given by $z(t)(1 - s(t))$.

Production technology. As a downstream technology, the advancement of production technology depends on AI technology, R&D labor input, and the existing knowledge base. At time t, the stock of production knowledge, $N_z(t)$, depends on the level of production technology, $z(t)$, as follows:

$$N_z(t) = d \cdot z(t)^\nu, \tag{3}$$

where $d > 0$ captures the strength, and $\nu \in (0, 1]$ governs the scale effect in converting production technology into knowledge stock.

The brain typically filters knowledge to enable thought. Licklider (1960) argues that approximately 85% of his "thinking" time is spent on clerical or mechanical tasks that prepare for actual thinking, decision-making, or learning, including searching, calculating, plotting, transforming, determining the logical or dynamic consequences of a set of assumptions or hypotheses, and preparing the way for a decision or insight. The renowned communication theorist Marshall McLuhan distinguishes hot from cool media, defining hot media as high definition (the state of being well filled with data), thereby limiting audience participation (McLuhan, 1994). He argues that high-definition experiences must be forgotten, censored, and cooled before they can be assimilated. Censorship is crucial for learning; without it, unfiltered exposure to shocks would result in mental collapse.

Motivated by these insights, we formalize innovation as a two-stage process. The first stage involves AI technology $A(t)$ processing the stock of production knowledge $N_z(t)$ to generate refined knowledge $x(t)$. This process is represented as

$$x(t) = h\left(N_z(t), A(t)\right) \equiv \frac{N_z(t)}{A(t)}, \tag{4}$$

where the function $h(\cdot,\cdot)$ satisfies $\partial h(N_z, A)/\partial N_z > 0$ and $\partial h(N_z, A)/\partial A < 0$. To make the model tractable, we define this function as $h(N_z, A) \equiv N_z/A$ throughout the paper.

The second stage involves R&D labor expanding the frontier of innovative possibilities in production technology. This process is expressed as:

$$\frac{\dot{z}(t)}{z(t)} = \underbrace{f(x(t))}_{\text{research productivity}} \times \underbrace{s(t)L}_{\text{number of researchers}}, \tag{5}$$

where the function $f(\cdot)$ captures the contribution of each brain to technological innovation. Here, $f(x)$ and sL correspond to research productivity and the number of researchers, respectively, similar to the formulation in Bloom et al. (2020). We specify the function $f(\cdot)$ as follows:

$$f(x(t)) = F_0 \exp\left(\underbrace{-b\left[\ln\frac{x(t)}{x_0}\right]^2}_{\text{knowledge burden}} + \underbrace{a\ln\frac{x(t)}{x_0}}_{\text{knowledge spillovers}} \right), \tag{6}$$

where $F_0 > 0$ is a scale constant, $a > 0$ parameterizes knowledge spillovers, $b > 0$ captures the knowledge burden, and $x_0 > 0$ is a reference level used to normalize $x(t)$. We can readily observe the following properties of the function $f(\cdot)$:

$$\lim_{x\to 0^+} f(x) = 0, \quad \lim_{x\to +\infty} f(x) = 0, \quad \frac{\partial f(x)}{\partial x} > 0 \text{ for } x < \widehat{x}, \quad \frac{\partial f(x)}{\partial x} < 0 \text{ for } x > \widehat{x},$$

where $\widehat{x} \equiv x_0 \exp(\frac{a}{2b})$ is the threshold at which the monotonicity of the function changes and can be interpreted as the level of refined knowledge at which the brain operates at optimal performance. Thus, $f(x)$ is an inverted-U in x, shaped by positive knowledge spillovers and negative knowledge burdens.

AI technology. AI technology is upstream in the innovation process, as shown in Figure 1. AI technology progresses exogenously at a constant rate $m > 0$. Thus, at time t, the level of AI technology is:

$$A(t) = A(0)\exp(mt), \tag{7}$$

where $A(0) > 0$ is the initial level of AI technology. This setup is sufficient to explore the core mechanisms by which AI technology and the brain influence innovation and growth.

Resource constraint. The two resources involved are labor and the final good. The labor constraint has been implicitly accounted for by allocating $1 - s(t)$ of labor to the final good production. Thus, the only remaining resource constraint is the final good constraint:

$$c(t)L = Y(t). \tag{8}$$

2.2 Pareto Optimal Problem

The dynamic optimization problem of a social planner is:

$$\max_{\{c,s,x,z\}} \int_0^\infty e^{-\rho t} \frac{c(t)^{1-\gamma} - 1}{1-\gamma} dt, \tag{9}$$

subject to

$$c(t) = z(t)(1 - s(t)), \tag{10}$$

$$x(t) = \frac{dz(t)^\nu}{A(t)}, \tag{11}$$

$$\dot{z}(t) = z(t)s(t)Lf(x(t)). \tag{12}$$

Here, the combination of equations (2) and (8) leads to equation (10), equation (11) follows from equations (3) and (11), and equation (12) is the equivalent transformation of equation (5). Thus, the current-value Hamiltonian of this maximization problem can be expressed as:

$$\mathcal{H}(s, z, \lambda) = \frac{[z(t)(1 - s(t))]^{1-\gamma} - 1}{1-\gamma} + \lambda(t)z(t)s(t)Lf(x(t)), \tag{13}$$

where $x(t) = \frac{dz(t)^\nu}{A(t)}$; $A(t)$ grows exogenously as in equation (7); and $\lambda(t)$ is the current-value costate variable. We explicitly incorporate $f(x(t))$ as defined in equation (6) below.

2.3 Existence of Equilibrium

In the model, the balanced growth path (BGP) equilibrium is defined as one in which the growth rates of per capita consumption, production technology, and per capita output of the final good converge to the same constant value, the labor allocation between final good production and R&D for production technology approaches constant ratios, and the level of refined knowledge tends toward a constant value. Throughout the paper, g_k denotes the growth rate of any variable k, and k^* denotes the equilibrium value of any variable k. We define the *innovation ease* by $\varepsilon(x^*) := \frac{f'(x^*)x^*}{f(x^*)}$, the elasticity of research productivity with respect to refined knowledge.

For model tractability, we impose two technical assumptions on the parameters. The first rules out a corner solution for the fraction of labor allocated to R&D versus production, while the latter ensures the transversality condition and streamlines the equilibrium characterization. These assumptions are maintained throughout the subsequent analysis.

Assumption 1. $f(x_{\min}) \geq \frac{m}{\nu L}$ *where* $x_{\min} \equiv x_0 \exp[\frac{a}{2b} - \frac{\rho+(\gamma-1)m/\nu}{2bm}]$.

Assumption 2. *$\rho\nu > m$ and $\min\{a, 2\sqrt{2}\sqrt{b}\} > \frac{\rho}{m} + \frac{\gamma}{\nu}$.*

Next, we analyze the BGP equilibrium, as outlined in the following theorem and propositions. All proofs are provided in the Appendix.

Theorem 1. *There exists a unique BGP equilibrium such that $g_c^* = g_z^* = g_y^* = \frac{m}{\nu}$ and $s^* = \frac{m}{L\nu f(x^*)}$, where x^* solves $\frac{m}{\nu} = \frac{1}{\gamma}[Lf(x^*) + m\varepsilon(x^*) - \rho]$.*

Theorem 1 demonstrates that the model admits a unique BGP equilibrium. Specifically, the BGP growth rates of per capita consumption, production technology, and per capita output are identical at $\equiv m/\nu$, determined by the AI technology progress rate m and the parameter ν (which captures the scale effect of converting production technology into knowledge). Faster AI progress supports faster growth in productive knowledge, consistent with the BGP equilibrium in which the refined-knowledge level remains constant. In the absence of sufficiently rapid AI advances, the accumulation of productive knowledge cannot be effectively converted into the creative-thinking stage and, thus, into technological progress. Moreover, in equilibrium, faster AI progress not only raises economic growth—because its higher-order burden relief outweighs the spillover loss from selective discarding—but also shapes labor allocation and the level of refined knowledge. Although the form of $f(x^*)$ is unspecified thus far, important insights follow from the equilibrium equality $m/\nu = [Lf(x^*) + m\varepsilon(x^*) - \rho]/\gamma$ for solving x^*.

3 Effects of Faster AI Progress

3.1 On Refined Knowledge and Research Productivity

Proposition 1 characterizes how the equilibrium level of refined knowledge, x^*, responds to changes in the AI growth rate, m, as illustrated in Figure 2. When x^* is sufficiently low, accelerated progress in AI technology increases the equilibrium level of refined knowledge in the second stage of the innovation process—the creative thinking stage—and thus enhances research productivity (since x^* lies in the region where knowledge spillovers dominate, i.e., $x^* < \widehat{x}$). In contrast, when x^* is sufficiently high, faster AI progress reduces the equilibrium level of refined knowledge.

Proposition 1. *When $x^* < \widetilde{x} \equiv x_0 \exp(\frac{a-\gamma/\nu}{2b})$, the equilibrium level of refined knowledge, x^*, is increasing with the AI growth rate m. When $x^* > \widetilde{x}$, x^* is decreasing in m. At $x^* = \widetilde{x}$, AI neutrality obtains: any change in m does not alter x^*.*

In particular, when $\widetilde{x} < x^* < \widehat{x}$, additional refined knowledge remains physiologically productive; however, AI-accelerated refinement selectively filters and discards information, thereby weakening knowledge spillovers and underutilizing the brain's capacity for creative recombination. We refer to this region as the "AI trap" region. Once marginal spillovers decline sufficiently, the social planner optimally reduces refined knowledge even before brain performance reaches its physiological peak. In particular, at $x^* = \widetilde{x}$, AI neutrality obtains: any change in AI growth rate does not alter equilibrium refined knowledge and hence research productivity. Overall, the nonmonotonic response of refined knowledge—and thus research productivity—to

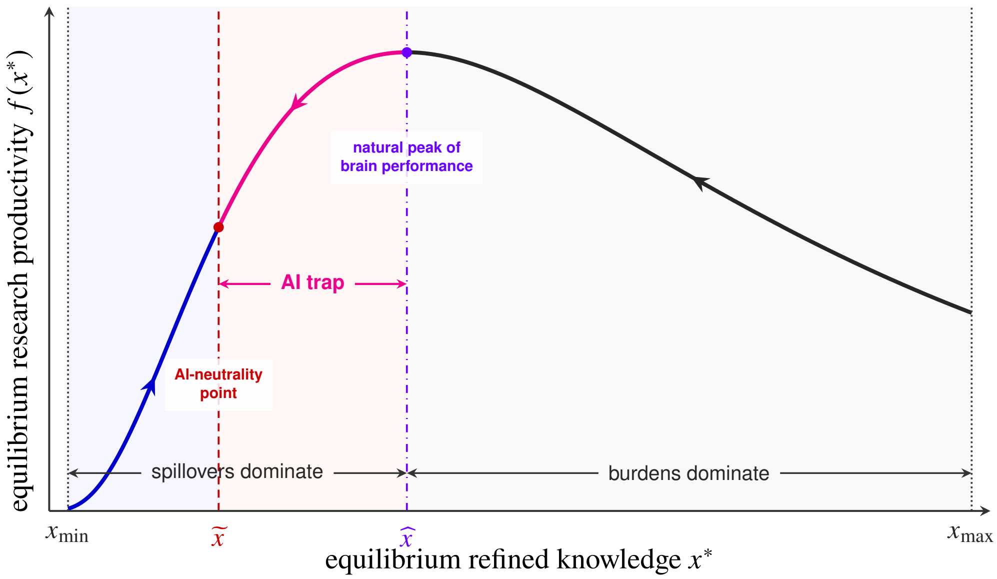

Figure 3: Effects of Faster AI Progress on Refined Knowledge and Research Productivity

faster AI growth reflects a distortion in translating collective knowledge into innovation. The endogenous wedge from the refined knowledge base needed for the optimal level of brain performance $\widehat{x}$—which faster AI growth need not eliminate—implies a waste of social intelligence: potentially useful knowledge remains unexploited, or the knowledge burden outpaces the brain's capacity. This waste stems from a distortion in social resource allocation rather than physiological limits.

3.2 On the Ease of Innovation

As AI technology advances, is innovation becoming easier? To evaluate this, we propose a criterion based on relative elasticities:

$$\varepsilon_{g^*,m} \equiv \frac{\partial g^*/g^*}{\partial m/m} > \varepsilon_{s^*,m} \equiv \frac{\partial s^*/s^*}{\partial m/m}, \tag{14}$$

where $\varepsilon_{g^*,m}$ represents the elasticity of g^* with respect to m, and $\varepsilon_{s^*,m}$ represents the elasticity of s^* with respect to m. The relation $g^* = f(x^*) \times s^*L$ implies that $\varepsilon_{g^*,m} - \varepsilon_{s^*,m}$ corresponds to the elasticity of research productivity with respect to m. The criterion that AI technology makes innovation easier can also be equivalently interpreted as the elasticity of research productivity $f(x^*)$ with respect to m being positive. Thus, we obtain the following proposition.

Proposition 2. *AI technology makes innovation easier (i.e., $\varepsilon_{g^*,m} > \varepsilon_{s^*,m}$) if either $x^* < \widetilde{x}$ or $x^* > \widehat{x}$; AI technology makes innovation harder (i.e., $\varepsilon_{g^*,m} < \varepsilon_{s^*,m}$) if $\widetilde{x} < x^* < \widehat{x}$.*

The proposition characterizes the conditions under which AI technology makes innovation easier. Whether AI facilitates innovation depends on both (i) the relative importance of the knowledge burden versus knowledge spillovers for research productivity and (ii) how the equilibrium level of refined knowledge responds to faster AI growth. We identify two cases in which AI makes innovation easier. First, when knowledge spillovers substantially dominate the knowledge burden (i.e., $x^* < \widetilde{x}$)), faster AI growth enables humans to process more knowledge, thereby allowing these spillovers to be realized despite selective knowledge discarding. Second, when the knowledge burden dominates spillovers (i.e., $x^* > \widehat{x}$), faster AI growth reduces the knowledge burden through a second-order channel; this higher-order relief dominates the first-order spillover loss.

In contrast, when $\widetilde{x} < x^* < \widehat{x}$, the knowledge-burden relief from faster AI growth is insufficient to offset the substantial weakening of knowledge spillovers; thus, faster AI progress makes innovation harder. The intuition is that AI diminishes knowledge spillovers significantly—due to the selective discarding of knowledge—relative to its effect on easing the knowledge burden during the innovation process. To understand how such a scenario may occur, consider the idea of cross-industry innovation, where solutions developed in one industry have historically been found to be useful in other industries. For example, groove patterns initially designed for space shuttle runways were later utilized for highways to improve traction and reduce hydroplaning and accidents. While humans may exchange information and share "wasteful" knowledge in the R&D process, AI tools may discard information they deem obsolete, as AI tools in corporate R&D are often highly specialized or proprietary. In turn, as AI technology progresses and AI usage increases, serendipitous cross-industry innovation will be harder if knowledge and insights from other fields are overlooked or discarded during the innovation process.

3.3 On R&D Labor Share

Proposition 3. *The proportion of labor allocated to the R&D sector decreases with the growth rate of AI technology if $x^* < x_0 \exp(\frac{a}{2b} - \frac{m}{\rho})$ and increases if $x^* > x_0 \exp(\frac{a}{2b} - \frac{m}{\rho})$.*

The proposition has two implications. First, when the equilibrium level of refined knowledge required for the brain's creative thinking is sufficiently low (i.e., $x^* < x_0 \exp(\frac{a}{2b} - \frac{m}{\rho})$, for convenience, let $\overline{x} \equiv x_0 \exp\left(\frac{a}{2b} - \frac{m}{\rho}\right)$), faster AI growth expands the amount of knowledge that humans can process during innovation. This increases the equilibrium refined-knowledge level and strengthens knowledge spillovers, thereby significantly raising research productivity and generating R&D labor-saving effects (note that Assumption 2 implies $\overline{x} < \widetilde{x}$). Second, when the marginal knowledge spillovers induced by faster AI growth are weak for $\overline{x} < x^* < \widetilde{x}$, decline for $\widetilde{x} < x^* < \widehat{x}$, or when faster AI growth primarily alleviates the knowledge burden for $x^* > \widehat{x}$, the social planner allocates a higher fraction of labor to R&D to offset lower research productivity or insufficient marginal gains in research productivity.

The equilibrium implications stated in Propositions 2 and 3 are summarized in Figure 4.[7] In summary, whether AI progress makes innovation harder or easier need not induce a monotonic change in the R&D labor share. When refined knowledge is very low, faster AI growth raises it and facilitates innovation. Yet because research productivity increases by more than the AI growth rate, the marginal returns to R&D labor can fall below those to labor in final-goods production, reducing the R&D labor share. Outside this region, once refined knowledge is sufficiently high, allocating a higher fraction of labor to R&D becomes more profitable, regardless of whether AI makes innovation harder or easier.

[7]The equilibrium in Figure 4 is characterized by $b < \frac{1}{2}\left(\frac{\rho}{m} + \frac{\gamma-1}{\nu}\right)\frac{\rho}{m}$. If instead $b > \frac{1}{2}\left(\frac{\rho}{m} + \frac{\gamma-1}{\nu}\right)\frac{\rho}{m}$—which implies $\overline{x} < x_{\min}$—then $ds^*/dm < 0$ always holds. We therefore focus on the former case.

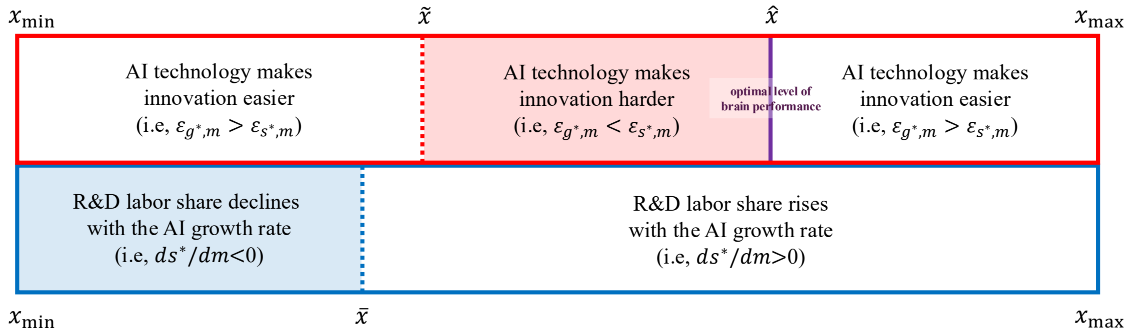

Figure 4: Effects of AI Technological Progress on R&D Performance over Different Ranges of x^*

4 Conclusion

In this paper, we incorporate the mechanism through which AI alleviates the knowledge burden—thus fostering innovation and growth—into an endogenous growth framework. We decompose research productivity, as characterized in Bloom et al. (2020), into two components: (positive) knowledge spillovers and (negative) knowledge burdens. This approach enriches the micro mechanism of technological innovation in the AI era. In our model, the innovation process consists of two sequential stages: AI-driven refinement of existing knowledge and human creative thinking. This structure enables a theoretical assessment of whether innovation becomes easier. Our analysis delivers three takeaways. First, faster AI growth raises the growth rate of per capita consumption (and, analogously, production technology), but its effect on the fraction of labor allocated to R&D is ambiguous. Second, the equilibrium level of refined knowledge may fall short of the level required for optimal brain performance, leading to a waste of social intelligence. This arises because, while faster AI growth mitigates the brain's knowledge burden, it also diminishes knowledge spillovers by selectively discarding information. Third, AI makes innovation easier when spillovers survive filtering or burden relief dominates, but harder in the intermediate region where spillover loss outweighs burden reduction. Future research may examine decentralized economies to assess the impact of AI on market failures and the design of optimal government policies. AI may also facilitate the second-stage creative thinking proposed in this paper, and its micro mechanisms merit further analysis.

Appendix: Proofs

We introduce some notation that will simplify the analysis in the following proofs. Let $u(t) := \ln \frac{x(t)}{x_0}$, $\psi(u(t)) := au(t) - b[u(t)]^2$, and $\mathcal{F}(u(t)) := F_0 \exp[\psi(u(t))]$. That is, we can rewrite $f(x(t))$ as $\mathcal{F}(u(t))$. Note that the mapping between x^* and u^* is bijective and strictly increasing. Assumption 1 can also be restated as

Assumption 1′. *$\mathcal{F}(u_{\min}) \geq \frac{m}{\nu L}$ where $u_{\min} = \frac{a}{2b} - \frac{\rho+(\gamma-1)m/\nu}{2bm}$.*

Finally, we can rewrite the elasticity of research productivity concerning refined knowledge as $\mathcal{E}(u(t)) := a - 2bu(t)$.

A Proof of Theorem 1

Proof. The social planner's maximization problem, characterized by the current-value Hamiltonian in equation (13), implies that the time paths of $s(t)$, $z(t)$, and $\lambda(t)$ must satisfy the following first-order necessary conditions:

$$\mathcal{H}_s(s,z,\lambda) = -z(t)[z(t)(1-s(t))]^{-\gamma} + \lambda(t)z(t)Lf(x(t)) = 0, \tag{O1}$$

$$\mathcal{H}_z(s,z,\lambda) = (1-s(t))[z(t)(1-s(t))]^{-\gamma} + \lambda(t)s(t)L[f(x(t)) + \nu f'(x(t))x(t)] = \rho\lambda(t) - \dot{\lambda}(t), \tag{O2}$$

$$\dot{z}(t) = \mathcal{H}_\lambda(s,z,\lambda) = z(t)s(t)Lf(x(t)). \tag{O3}$$

The transversality condition is $\lim_{t\to\infty}[\exp(-\rho t)\lambda(t)z(t)] = 0$.

To prepare for the equilibrium analysis, we rearrange the above conditions as follows. First, when expressed in growth rates, equation (O1) yields

$$-\gamma\left[g_z(t) + \frac{-\dot{s}(t)}{1-s(t)}\right] = g_\lambda(t) + \frac{\dot{f}(x(t))}{f(x(t))}. \tag{O4}$$

Equation (O1) also implies

$$\frac{[z(t)(1-s(t))]^{-\gamma}}{\lambda(t)} = Lf(x(t)). \tag{O5}$$

Second, incorporating equation (O5) into equation (O2) gives

$$Lf(x(t)) + \nu s(t)Lf'(x(t))x(t) = \rho - g_\lambda(t). \tag{O6}$$

Third, equation (O3) directly implies

$$g_z(t) = s(t)Lf(x(t)). \tag{O7}$$

Next, we determine the BGP equilibrium. Recall the definition of the BGP equilibrium. As $t \to \infty$, $x(t)$ converges to a constant value x^*. Therefore, equation (11) implies $g_z^* = \frac{m}{\nu}$. In the BGP equilibrium, the fraction of labor allocated to R&D tend to a constant value s^*, which, by condition (10), implies $g_c^* = g_z^*$. Since $y(t) = z(t)(1 - s(t))$, it follows that $g_y^* = g_z^*$. Taking into account equation (O4) in BGP equilibrium, we obtain: $g_c^* = g_z^* = g_y^* = \frac{m}{\nu}$ and $g_\lambda^* = -\frac{\gamma m}{\nu}$. It follows immediately that $g^* \equiv g_c^* = g_z^* = g_y^*$ increases in m. Thus, condition (O7) yields the fraction of labor allocated to the R&D sector in the BGP equilibrium as $s^* = \frac{m}{L\nu f(x^*)}$. Moreover, substituting the full expressions for s^* and g_κ^* into equation (O6) yields

$$\frac{m}{\nu} = \frac{1}{\gamma}[Lf(x^*) + m\varepsilon(x^*) - \rho]. \tag{O8}$$

Thus, once x^* is obtained from this equation, all equilibrium outcomes are determined. It remains to prove that equation (O8) admits at least one solution for x^*.

We further define $x_l := \min\{x \mid f(x) = \frac{m}{L\nu}\}$ and $x_{\max} := \max\{x \mid f(x) = \frac{m}{L\nu}\}$. To ensure that s^* lies within $(0, 1)$, it must hold that $f(x^*) > \frac{m}{L\nu}$, or equivalently, $L\mathcal{F}(u^*) > m/\nu$. This condition implies $x_l < x^* < x_{\max}$, or equivalently, $u_l < u^* < u_{\max}$, where $u_l = u(x_l)$ and $u_{\max} = u(x_{\max})$. The existence of x^* is equivalent to that of u^*, as the mapping between them is bijective and strictly increasing. Equation (O8) can be rewritten as

$$L\mathcal{F}(u^*) = -m\mathcal{E}(u^*) + \gamma m/\nu + \rho. \tag{O9}$$

Consider that in the equation, the left-hand side $H(u^*) := L\mathcal{F}(u^*)$ is inverted-U in u^*, whereas the right-hand side $h(u^*) := -m\mathcal{E}(u^*) + \gamma m/\nu + \rho$ is linear and strictly increasing in u^*. It follows that the intersection of $h(u^*)$ with m/ν occurs at $u_{\min}$ (Assumption 2 ensures that $u_{\min} > 0$). By Assumption 1′, $\mathcal{F}(u_{\min}) > \frac{m}{L\nu}$. Thus, the intersection of $H(u^*)$ and $h(u^*)$ lies above m/ν on the vertical axis and within $(u_{\min}, u_{\max})$ on the horizontal axis. Hence, there exists a unique u^* satisfying equation (O9), and consequently, a unique x^* satisfying equation (O8). □

B Proof of Proposition 1

Proof. As established in the proof of Proposition 1, equation (O9) holds in equilibrium. We have that

$$u_{\min} = \frac{a}{2b} - \frac{\frac{\rho}{m} + \frac{\gamma - 1}{\nu}}{2b} < u^* < u^h = \frac{a}{2b} + \frac{\sqrt{a^2 - 4b \ln\left(\frac{m}{\nu}\frac{1}{LF_0}\right)}}{2b}.$$

Let $\phi := L\mathcal{F}(u^*) + m\mathcal{E}(u^*) - \gamma m/\nu - \rho = 0$. By the implicit function theorem, we have $\frac{du^*}{dm} = -\frac{\partial \phi}{\partial m} \Big/ \frac{\partial \phi}{\partial u^*}$ where the partial derivatives are

$$\frac{\partial \phi}{\partial m} = (a - 2bu^*) - \gamma/\nu \text{ and } \frac{\partial \phi}{\partial u^*} = LF_0 \exp(au^* - bu^{*2})(a - 2bu^*) - 2bm.$$

Thus, we obtain

$$\frac{du^*}{dm} = \frac{2b\left(u^* - \frac{a-\gamma/\nu}{2b}\right)}{LF_0 \exp(au^* - bu^{*2})(a - 2bu^*) - 2bm}.$$

Using the equilibrium condition from (O9), the derivative becomes

$$\frac{du^*}{dm} = \frac{2b\left(u^* - \frac{a-\gamma/\nu}{2b}\right)}{-4b^2mu^{*2} + 2b(2am - \gamma m/\nu - \rho)u^* + [m(a\gamma/\nu - a^2 - 2b) + a\rho]}. \tag{O10}$$

Next, we examine the sign of $\frac{du^*}{dm}$. First, it is evident that if $u^* > \frac{a-\gamma/\nu}{2b}$, the numerator is positive; if $u^* < \frac{a-\gamma/\nu}{2b}$, it is negative; and if $u^* = \frac{a-\gamma/\nu}{2b}$, AI neutrality obtains, so u^* (and hence x^*) does not vary with m. Second, the denominator remains strictly negative because $2\sqrt{2}\sqrt{b} > \frac{\gamma}{\nu} + \frac{\rho}{m}$ in Assumption 2. Thus, we can conclude that: if $\frac{a-\gamma/\nu}{2b} < u^* < u_{\max}$, there is $\frac{du^*}{dm} < 0$; if $u_{\min} < u^* < \frac{a-\gamma/\nu}{2b}$, there is $\frac{du^*}{dm} > 0$. Moreover, since $u^* = \ln(\frac{x^*}{x_0})$, it follows that

$$\frac{du^*}{dm} = \underbrace{\frac{1}{x^*}}_{>0}\frac{dx^*}{dm}, \tag{O11}$$

which implies $sign\left\{\frac{dx^*}{dm}\right\} = sign\left\{\frac{du^*}{dm}\right\}$, establishing the result. □

C Proof of Proposition 2

Proof. Recall the equilibrium results: $g^* = \frac{m}{\nu}$ and $s^* = \frac{m}{L\nu f(x^*)}$. The definitions of elasticities imply:

$$\varepsilon_{g^*,m} = 1 \text{ and } \varepsilon_{s^*,m} = 1 - m\frac{f'(x^*)}{f(x^*)}\frac{dx^*}{dm} = 1 - m\mathcal{E}(u^*)\frac{du^*}{dm}.$$

where the last equality follows from (O11). We have

$$\begin{aligned}\Delta E &:= \varepsilon_{g^*,m} - \varepsilon_{s^*,m} \\ &= m\mathcal{E}(u^*)\frac{du^*}{dm} \\ &= \frac{m(a - 2bu^*)(\frac{\gamma}{\nu} - (a - 2bu^*))}{LF_0 \exp[au^* - bu^{*2}](a - 2bu^*) - 2bm}\end{aligned}$$

where the last equality uses (O10). Therefore,

$$sign\{\Delta E\} = sign\{\mathcal{E}(u^*)\} \times sign\left\{\frac{du^*}{dm}\right\}$$

which gives us $\Delta E > 0$ if $u^* < \frac{a-\gamma/\nu}{2b}$ or $u^* > \hat{u}$. Otherwise, $\Delta E < 0$. □

D Proof of Proposition 3

Proof. Based on the expression of s^* in BGP equilibrium, we obtain

$$\frac{ds^*}{dm} = \underbrace{\frac{1}{L\nu f(x^*)}}_{>0} \left(\underbrace{1 - m\frac{f'(x^*)}{f(x^*)}\frac{dx^*}{dm}}_{=\mathcal{E}_{s^*,m}} \right) < 0 \iff \mathcal{E}_{s^*,m} < 0.$$

We have

$$\begin{aligned}
\mathcal{E}_{s^*,m} &= 1 - m\mathcal{E}(u^*)\frac{du^*}{dm} \\
&= 1 - \frac{m\mathcal{E}(u^*)(\frac{\gamma}{\nu} - (a - 2bu^*))}{LF_0 \exp[au^* - bu^{*2}](a - 2bu^*) - 2bm} \\
&= 1 - \frac{m\mathcal{E}(u^*)(\frac{\gamma}{\nu} - \mathcal{E}(u^*))}{L\mathcal{F}(u^*)\mathcal{E}(u^*) + m\mathcal{E}'(u^*)} \\
&= \frac{\mathcal{E}(u^*)(L\mathcal{F}(u^*) + m\mathcal{E}(u^*) - \frac{\gamma m}{\nu}) + m\mathcal{E}'(u^*)}{L\mathcal{F}(u^*)\mathcal{E}(u^*) + m\mathcal{E}'(u^*)} \\
&= \frac{\rho\mathcal{E}(u^*) + m\mathcal{E}'(u^*)}{L\mathcal{F}(u^*)\mathcal{E}(u^*) + m\mathcal{E}'(u^*)}
\end{aligned}$$

where the first line follows from the proof of Proposition 2 and the last equality comes from (O9). Therefore,

$$\frac{ds^*}{dm} < 0 \iff \frac{\rho\mathcal{E}(u^*) + m\mathcal{E}'(u^*)}{L\mathcal{F}(u^*)\mathcal{E}(u^*) + m\mathcal{E}'(u^*)} < 0.$$

Since the denominator is negative (see the proof of Proposition 1), $\frac{ds^*}{dm} < 0$ if and only if the numerator is positive, which is equivalent to $u^* < \frac{a}{2b} - \frac{m}{\rho}$. ◻

References

Acemoglu, D., Autor, D., Hazell, J., and Restrepo, P. (2022). Artificial intelligence and jobs: Evidence from online vacancies. *Journal of Labor Economics*, 40(S1):S293–S340.

Acemoglu, D. and Lensman, T. (2024). Regulating transformative technologies. *American Economic Review: Insights*, 6(3):359–376.

Acemoglu, D. and Restrepo, P. (2018). Artificial intelligence, automation, and work. In *The economics of artificial intelligence: An agenda*, pages 197–236. University of Chicago Press.

Aghion, P. and Bunel, S. (2024). AI and growth: Where do we stand? Mimeo.

Aghion, P. and Howitt, P. (1992). A model of growth through creative destruction. *Econometrica*, 60(2):323–351.

Aghion, P., Jones, B. F., and Jones, C. I. (2019). Artificial intelligence and economic growth. In *The Economics of Artificial Intelligence*, pages 237–290. University of Chicago Press.

Agrawal, A., McHale, J., and Oettl, A. (2019). *Finding Needles in Haystacks: Artificial Intelligence and Recombinant Growth*, pages 149–174. University of Chicago Press.

Agrawal, A., McHale, J., and Oettl, A. (2023). Superhuman science: How artificial intelligence may impact innovation. *Journal of Evolutionary Economics*, 33(5):1473–1517.

Agrawal, A., McHale, J., and Oettl, A. (2024). Artificial intelligence and scientific discovery: A model of prioritized search. *Research Policy*, 53(5):104989.

Ando, Y., Bessen, J., and Wang, X. (2025). The rising returns to R&D: Ideas are not getting harder to find. Mimeo.

Babina, T., Fedyk, A., He, A., and Hodson, J. (2024). Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics*, 151:103745.

Bao, C., Yang, B., Zhang, X., and Zhong, T. (2024). Artificial intelligence, knowledge spillovers, and growth. Mimeo.

BBC News (2024). Pioneers in AI win nobel prize in physics. *BBC News*. Accessed 28 Dec. 2025.

Bloom, N., Jones, C. I., Van Reenen, J., and Webb, M. (2020). Are ideas getting harder to find? *American Economic Review*, 110(4):1104–44.

Brynjolfsson, E., Li, D., and Raymond, L. (2025). Generative AI at work. *Quarterly Journal of Economics*, page qjae044.

Brynjolfsson, E., Rock, D., and Syverson, C. (2018). Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics. In *The economics of artificial intelligence: An agenda*, pages 23–57. University of Chicago Press.

Campbell-Kelly, M., Aspray, W. F., Yost, J. R., Tinn, H., and Díaz, G. C. (2023). *Computer: A History of the Information Machine*. Taylor & Francis.

Cao, S., Jiang, W., Wang, J., and Yang, B. (2024). From man vs. machine to man+ machine: The art and AI of stock analyses. *Journal of Financial Economics*, 160:103910.

Charness, G. and Grieco, D. (2026). Creativity and AI. *The Economic Journal*. Forthcoming.

Chen, W., Qiao, X., and Zhang, H. (2025). Over a century of economics research collaboration. Mimeo.

Cockburn, I. M., Henderson, R., and Stern, S. (2019). The impact of artificial intelligence on innovation: An exploratory analysis. In *The Economics of Artificial Intelligence: An Agenda*, pages 115–146. University of Chicago Press.

Felin, T. and Holweg, M. (2024). Theory is all you need: AI, human cognition, and causal reasoning. *Strategy Science*.

Felten, E. W., Raj, M., and Seamans, R. (2023). Occupational heterogeneity in exposure to generative ai. Mimeo.

Gans, J. S. (2025). A quest for AI knowledge. Mimeo.

Goldfarb, A., Trefler, D., et al. (2019). Artificial intelligence and international trade. *The Economics of Artificial Intelligence: An Agenda*, pages 463–492.

Grashof, N. and Kopka, A. (2023). Artificial intelligence and radical innovation: an opportunity for all companies? *Small Business Economics*, 61(2):771–797.

Grossman, G. M. and Helpman, E. (1991a). *Innovation and Growth in the Global Economy*. MIT press.

Grossman, G. M. and Helpman, E. (1991b). Quality ladders in the theory of growth. *Review of Economic Studies*, 58(1):43–61.

Jones, B. F. (2009). The burden of knowledge and the “death of the renaissance man": Is innovation getting harder? *Review of Economic Studies*, 76(1):283–317.

Jones, B. F. (2010). Age and great invention. *Review of Economics and Statistics*, 92(1):1–14.

Jones, B. F. (2021). The rise of research teams: Benefits and costs in economics. *Journal of Economic Perspectives*, 35(2):191–216.

Jones, B. F. (2025). Artificial intelligence in research and development. Mimeo.

Jones, C. I. (1995). R&D-based models of economic growth. *Journal of Political Economy*, 103(4):759–784.

Jones, C. I. (2024). The AI dilemma: Growth versus existential risk. *American Economic Review: Insights*, 6(4):575–590.

Licklider, J. C. (1960). Man-computer symbiosis. *IRE Transactions on Human Factors in Electronics*, HFE-1(1):4–11.

Lu, C.-H. (2021). The impact of artificial intelligence on economic growth and welfare. *Journal of Macroeconomics*, 69:103342.

McLuhan, M. (1994). *Understanding Media: The Extensions of Man*. MIT Press, Cambridge, MA.

Noy, S. and Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. *Science*, 381(6654):187–192.

Park, M., Leahey, E., and Funk, R. J. (2023). Papers and patents are becoming less disruptive over time. *Nature*, 613(7942):138–144.

Rivera-Batiz, L. A. and Romer, P. M. (1991). Economic integration and endogenous growth. *Quarterly Journal of Economics*, 106(2):531–555.

Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy*, 98(5, Part 2):S71–S102.

Searle, J. R. (1980). Minds, brains, and programs. *Behavioral and Brain Sciences*, 3(3):417–424.

Sun, H. and Zhang, C. (2025). (Generative) AI in production economy. Mimeo.

Sun, R. and Trefler, D. (2023). The impact of AI and cross-border data regulation on international trade in digital services: A large language model. Mimeo.

Trammell, P. and Korinek, A. (2023). Economic growth under transformative AI. Mimeo.

Turing, A. M. (1950). Computing machinery and intelligence. *Mind*, 59(236):433–460.

Von Neumann, J. and Kurzweil, R. (1958). *The Computer and the Brain*. Yale University Press.

Weitzman, M. L. (1998). Recombinant growth. *Quarterly Journal of Economics*, 113(2):331–360.

Xie, D. and Yang, B. (2022). Endogenous information carrier technology. Mimeo.

Xie, D. and Yang, B. (2025). Information carrier technology and growth. *Scandinavian Journal of Economics*, 127(4):912–944.

Yao, F., Li, C., Nekipelov, D., Wang, H., and Xu, H. (2024). Human vs. generative AI in content creation competition: Symbiosis or conflict? *arXiv preprint arXiv:2402.15467*.