Artificial Intelligence and the Brain: Is Innovation Getting Easier?

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Abstract

We develop an endogenous growth model in which artificial intelligence (AI) and the brain generate innovation. AI refines existing knowledge into a usable base, and the brain then recombines it into new ideas. AI's synthesis of information alleviates the brain's knowledge burdens but may weaken knowledge spillovers. Consequently, knowledge creation responds nonmonotonically to AI efficiency: at a modest level of AI efficiency, innovation slows down despite faster AI growth. Faster AI progress raises long-run growth, but its effects on research productivity and the R&D labor share are ambiguous. Finally, we characterize the conditions under which AI makes innovation easier.

Keywords: artificial intelligence, brain, knowledge spillovers, knowledge burden, economic growth

JEL Codes: O40, O33, E27

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1 Introduction

The similarities and differences between artificial intelligence and the brain have been central to pioneering work in computer science. 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). Recent advances in AI highlight its connection to the brain and its implications for economic development. When Geoffrey Hinton, the “Godfather of AI,” discussed his work on artificial neural networks (ANNs), he stated, “It’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 certain intelligence tasks, AI has already surpassed human capabilities. 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, significantly outperforming the human error rate of approximately 5% (Brynjolfsson et al., 2018). Furthermore, in tasks involving logical-mathematical intelligence, linguistic intelligence, and natural discriminative intelligence, employing AI is substantially cheaper than hiring skilled workers (Bao et al., 2024).

However, some scholars contend that AI cannot replicate human-like creativity. 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 analyzes the competitive dynamics and equilibrium between human- and AI-generated content.

To explore the roles of AI and humans in innovation, we divide the innovation process into two sequential stages, as illustrated in Figure 1. The first stage involves AI collecting, organizing, and refining vast amounts of existing knowledge to generate the refined knowledge necessary for innovation. This process aligns with the ancient philosophy that “simplicity is the ultimate sophistication.” Such a task cannot be accomplished by the brain alone. On the one hand, the brain is decentralized, and each individual is constrained by physiological limits that hinder their 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. On the other hand, 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.

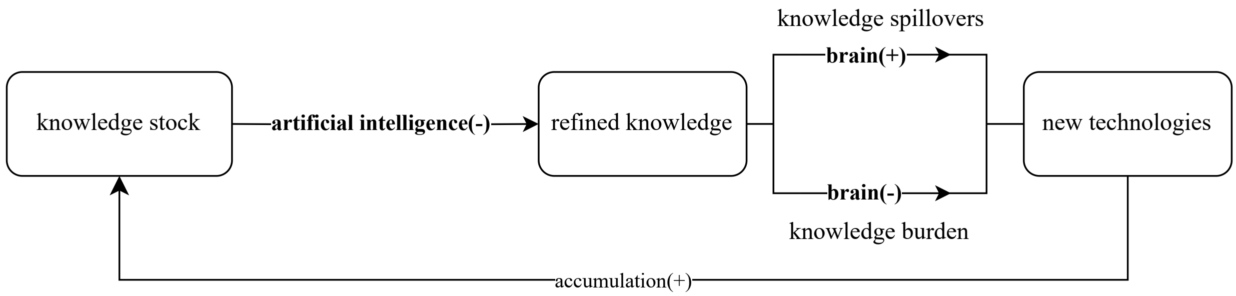

Figure 1: The roles of AI and brain in the innovation process of production technology

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 spillovers 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 spillovers, as discussed in endogenous growth models such as Romer (1990) and Jones (1995). However, when the amount of refined knowledge is too large, it burdens the creative thinking of the brain, hindering innovation. This phenomenon, termed knowledge burden, has been rarely noted in the literature on economic growth, with Jones (2009, 2010) being one of the few to study it.

We develop an endogenous growth model in which AI technology advances at an exogenous rate. Despite its simplified structure, the model effectively captures key characteristics of AI and the brain in the innovation process, enhancing our understanding of AI's economic impact. Under a general form of the research productivity function, we obtain several notable findings along the balanced-growth path (BGP). First, there exists a nonmonotonic response of the refined-knowledge stock to faster AI growth, revealing a distortion in the translation of collective knowledge into innovation. The endogenous deviation of the refined-knowledge stock from the brain's optimal performance level 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.

Second, faster AI growth raises long-run growth; yet, its effect on the R&D labor share is ambiguous. When refined knowledge is scarce, AI expands the set of knowledge humans can effectively process, strengthens spillovers, and boosts research productivity, yielding an R&D labor-saving effect. When refined knowledge is abundant, marginal spillover gains from AI weaken or reverse, so the R&D labor share increases in equilibrium.

Finally, we propose a criterion—based on relative elasticities—to assess whether innovation becomes easier as AI advances. We find that AI makes innovation easier in two regions: a strongly spillover-dominant region, where AI expands the set of knowledge humans can effectively process enough to realize spillovers despite selective discarding; and a burden-dominant region, where AI's second-order burden relief outweighs its first-order spillover loss. However, in the intermediate region (a weakly spillover-dominant region), AI makes innovation harder because filtering erodes spillovers more than it eases burden, lowering the returns to creative recombination.

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).[1]

From a theoretical perspective, Jones (2009) develops an idea-based growth model where 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 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 (991a), Grossman and Helpman (1991), 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, thus deepening our understanding of the role of AI in long-term growth.

Our work also contributes to the emerging literature on AI and innovation.[2] Among this literature,

[1]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.

[2]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).

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;[3] 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 use 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. However, the knowledge-burden-easing mechanism through which AI fosters innovation remains underexplored in theory. This paper seeks to fill that void.

2 The Model

In this section, we describe the model. For simplicity, we assume that AI technology evolves exogenously at a constant growth rate. Importantly, we incorporate both the advantages and limitations of the brain in the innovation process. Throughout the paper, 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 standard 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 good market is perfectly competitive. At time t, the production function for the final good is

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

[3] 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.

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:

$$N_z(t) = dz(t)^{\nu}, \tag{3}$$

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 an 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. The 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 respectively to research productivity and the number of researchers, similar to the formulation in Bloom et al. (2020). We specify the function $f(\cdot)$ as follows:

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

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 $f(\cdot)$:

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

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

AI technology. AI technology is upstream in the innovation process, as shown in Figure 1. As noted above, 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.

3 Equilibrium Analysis

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 stock of refined knowledge tends to 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 also define $\varepsilon(x^*) := \frac{f'(x^*)x^*}{f(x^*)}$ as the elasticity of research productivity with respect to refined knowledge.

To ensure the existence of the BGP equilibrium and the tractability of the model, we impose the following assumptions on the model parameters. Throughout the subsequent analysis, the following assumptions are always maintained.

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 results, as outlined in the following propositions. All proofs are provided in the Appendix.

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

Proposition 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 stock 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 hence into technological progress. Moreover, a straightforward observation is that, in BGP equilibrium, AI progress not only determines economic growth but also governs labor allocation and the accumulation of refined knowledge. Here, 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^*.

Proposition 2. *When $x^* < x_0 \exp(\frac{a-\gamma/\nu}{2b})$, the equilibrium stock of refined knowledge, x^*, is increasing in the AI growth rate m. When $x^* > x_0 \exp(\frac{a-\gamma/\nu}{2b})$, x^* is decreasing in m.*

Proposition 2 characterizes how the equilibrium stock of refined knowledge, x^*, responds to changes in the AI growth rate, m. When x^* is sufficiently low, accelerated progress in AI technology increases the equilibrium stock 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., $x^* < \hat{x}$). In contrast, when x^* is sufficiently high, faster AI progress reduces the equilibrium stock of refined knowledge. In particular, when $x_0 \exp(\frac{a-\gamma/\nu}{2b}) < x^* < \hat{x}$, additional refined knowledge remains physiologically productive, but AI-accelerated refinement selectively filters and discards information, weakening knowledge spillovers and underutilizing the brain's capacity for creative recombination. Once marginal spillovers decline sufficiently, the social planner optimally reduces the stock of refined knowledge even before cognitive performance reaches its physiological peak. Overall, the nonmonotonic response of the equilibrium refined-knowledge stock to faster AI growth reflects a distortion in the translation of collective knowledge into innovation. The endogenous wedge from the optimal level of brain performance $\hat{x}$—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.

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 $x^* > x_0 \exp(\frac{a}{2b} - \frac{m}{\rho})$.*

Proposition 3 has two implications. First, when the equilibrium stock of refined knowledge required for the brain's creative thinking is sufficiently low (i.e., $x_{\min} < x^* < x_0 \exp(\frac{a}{2b} - \frac{m}{\rho})$), faster AI growth expands the amount of knowledge that humans can process during innovation. This increases the equilibrium refined-knowledge stock and strengthens knowledge spillovers, thereby significantly raising research productivity and generating R&D labor-saving effects (note that Assumption 2 implies $x_0 \exp(\frac{a}{2b} - \frac{m}{\rho}) < x_0 \exp(\frac{a-\gamma/\nu}{2b})$). Second, when the marginal knowledge spillovers induced by faster AI growth are weak for $x_0 \exp(\frac{a}{2b} - \frac{m}{\rho}) < x^* < x_0 \exp(\frac{a-\gamma/\nu}{2b})$, decline for $x_0 \exp(\frac{a-\gamma/\nu}{2b}) < x^* < \hat{x}$, or when faster AI growth primarily alleviates the knowledge burden for $\hat{x} < x^* < x_{\max}$, the social planner allocates a higher fraction of labor to R&D to offset lower research productivity or insufficient marginal gains in research productivity.

In summary, the growth effect of AI technology is always positive because its knowledge-burden-alleviating effect is of higher order than its adverse effect on knowledge spillovers. However, the effects of faster AI growth on research productivity (i.e., the performance of the brain's creative thinking) and on the fraction of labor allocated to R&D are ambiguous, since AI technology may induce selective knowledge discarding (thereby weakening knowledge spillovers) or instead alleviate the knowledge burden.

3.1 Is Innovation Getting Easier?

As AI technology advances, does innovation become easier? To evaluate it, 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 4. *AI technology makes innovation easier (i.e., $\varepsilon_{g^*,m} > \varepsilon_{s^*,m}$) if $x^* < x_0 \exp(\frac{a-\gamma/\nu}{2b})$ or $x^* > \hat{x}$ holds; AI technology makes innovation harder (i.e., $\varepsilon_{g^*,m} < \varepsilon_{s^*,m}$) if $x_0 \exp(\frac{a-\gamma/\nu}{2b}) < x^* < \hat{x}$.*

Proposition 4 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 stock 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., $x_{\min} < x^* < x_0 \exp(\frac{a-\gamma/\nu}{2b})$), 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., $\hat{x} < x^* < x_{\max}$), 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 $x_0 \exp(\frac{a-\gamma/\nu}{2b}) < x^* < x_0 \exp(\frac{a}{2b})$, 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 in 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.

3.2 Further Discussion

Figure 2 summarizes the scenarios described in Propositions 3 and 4.[4] A key insight is that whether AI progress makes innovation harder or easier need not induce a monotonic change in the R&D labor share. When the equilibrium stock of refined knowledge is very low, faster AI growth raises this stock and facilitates innovation; yet because the increase in research productivity exceeds the increase in the AI growth rate, the marginal value of R&D labor can be lower than that of labor in the production of final goods, reducing the R&D labor share. Outside this region, once the equilibrium stock of refined knowledge is sufficiently

[4]The equilibrium in Figure 2 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 $\bar{x} < x_{\min}$, then $ds^*/dm < 0$ always holds. We, therefore, focus on the former case.

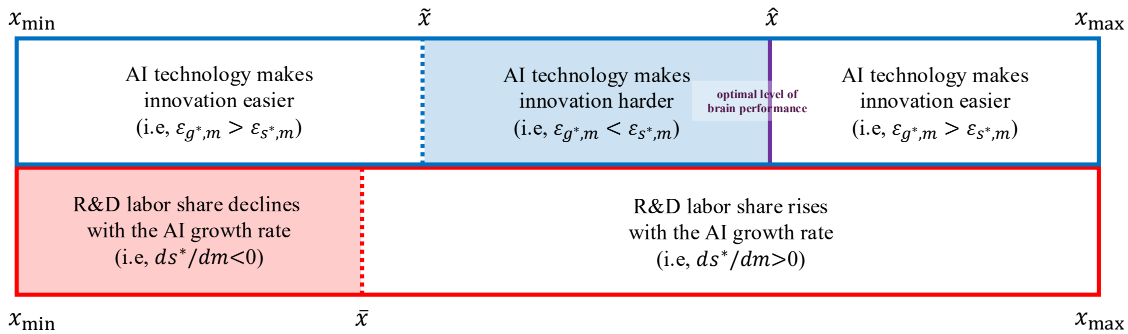

Figure 2: Effects of AI Technological Progress on R&D Performance over Different Ranges of x^*

Notes: For convenience, we provide new definitions: $\bar{x} \equiv x_0 \exp\left(\frac{a}{2b} - \frac{m}{\rho}\right)$ and $\tilde{x} \equiv x_0 \exp\left(\frac{a-\gamma/\nu}{2b}\right)$.

high, allocating a higher fraction of labor to R&D becomes more profitable regardless of whether AI makes innovation harder or easier.

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 (analogous to production technology) and increases the fraction of labor allocated to R&D. Second, the equilibrium stock 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 (or harder) when the relative degree of knowledge spillovers to knowledge burden is sufficiently high (or low). 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 with respect to refined knowledge as $\mathcal{E}(u(t)) := a - 2bu(t)$.

A Proof of Proposition 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, $u^l < u^* < u^h$, where $u^l = u(x^l)$ and $u^h = u(x_{\max})$. 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 $(u_{\min}, u^h)$ 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 2

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; otherwise, it is negative. 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 $\frac{a-\gamma/\nu}{2b} < u^* < u^h$, 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 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 4 and the last equality comes from (O9). Therefore,

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

We know the denominator is negative (recall the proof of Proposition 2), so $\frac{ds^*}{dm} < 0 \iff u^* < \frac{a}{2b} - \frac{m}{\rho}$. □

D Proof of Proposition 4

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, $\Delta E < 0$. □

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