KIER DISCUSSION PAPER SERIES

KYOTO INSTITUTE
OF
ECONOMIC RESEARCH

Discussion Paper No.1125

"AI Investment and Economic Growth:
Exploring the Divergence of Equilibria"

Nobuyasu Suzusho

Feb 2026

KYOTO UNIVERSITY

KYOTO, JAPAN

AI Investment and Economic Growth: Exploring the Divergence of Equilibria

Nobuyasu Suzusho[1*]

[1*]Graduate School of Economics,Kyoto University,Yoshida Honmachi,Sakyo-ku, Kyoto,606-8501,Japan.

Corresponding author(s). E-mail(s): suzusho.nobuyasu.52a@st.kyoto-u.ac.jp;

Abstract

This paper focuses on the role of strategic complementarity between artificial intelligence (AI) investment and human capital accumulation, analyzing how they interact to shape long-term economic growth. Our model introduces an explicit threshold investment level necessary for viable AI adoption and demonstrates how its existence, along with agents' expectations, generates multiple equilibria. The paper concludes with policy recommendations to lower AI adoption barriers, bolster human capital, and align public and private expectations to foster a sustained, AI-driven growth trajectory.

Keywords: Artificial Intelligence (AI), Economic Growth, Human Capital, Threshold Investment, Multiple Equilibria, Strategic Complementarity

JEL Classification. O33; O40; O41; J24

Acknowledgments. The authors are grateful to Professor Akihisa Shibata of Osaka University of Economics, Professor Hiroshi Teruyama of the Institute of Economic Research, Kyoto University, and Associate Professor Shuhei Takahashi of the Institute of Economic Research, Kyoto University, for their invaluable guidance and encouragement throughout this research. Their insightful comments and unwavering support have been essential to the completion of this paper.

1 Introduction

Artificial intelligence (AI) has emerged as a foundational technology with the potential to enhance productivity across various production processes, foster innovation, and transform the economic structure. While expectations for its economic impact are high, the pace and extent of AI adoption vary widely by country, industry, and company, and its effects are not uniform. Some companies and economies have leveraged AI to accelerate growth, while many others have either missed the opportunity or struggled to fully benefit from it—creating what can be called an "AI divide." e.g. McKinsey & Company (2024) Why does this disparity exist, and what is needed for broader AI-driven growth? This paper addresses these questions from a theoretical perspective. The key lies in the interaction between technology investment and human capital development: effective use of AI technology requires workers who possess the skills to design, operate, manage, or collaborate with it. On the other hand, the incentive for workers to acquire such skills depends on their expectations that AI will be meaningfully adopted and lead to higher productivity and wages. This interdependence between technology and skill investments has been complicating the dynamics of AI adoption and the path to economic growth.

Endogenous growth theory emphasizes the significance of technological progress and human capital accumulation as sources of long-term economic growth. One line of research focuses on technological innovation through firms' investment in research and development (R&D) e.g., Aghion and Howitt (1992), while another highlights human capital accumulation through education and experience as a driver of growth (e.g., Lucas (1988).

Redding (1996) connects these elements, arguing that entrepreneurs' R&D investment decisions and workers' human capital investments are "strategic complements." His model shows that this complementarity can either lead an economy toward a high-growth equilibrium characterized by advanced technology and a skilled labor force or result in a "low-skill, low-quality trap," where entrepreneurs avoid investing in R&D and workers do not enhance their skills. This possibility of multiple equilibria is central to explaining why economies with similar initial conditions may follow divergent growth paths.

Recent theoretical research has increasingly incorporated AI and automation technologies into endogenous growth frameworks. Seminal works in this field focus on the distinct functional characteristics of AI. For instance, Agrawal et al. (2018) conceptualize AI primarily as a drop in the cost of prediction, analyzing how this transforms decision-making and organizational design. Acemoglu and Restrepo (2019) develop a task-based framework where AI automates existing tasks while creating new complex ones, clarifying the competing forces of displacement and reinstatement on employment. Similarly, Aghion et al. (2017) model AI's potential to drive growth through the "Baumol effect," while also discussing its non-rival nature and implications for income distribution.While these studies provide fundamental insights into the nature of AI technology, they generally abstract from the discrete barriers that prevent initial adoption. In reality, however, AI implementation often requires a lumpy, "threshold" investment—such as establishing data infrastructure, ensuring regulatory compliance, and organizational restructuring—before any marginal productivity gains can be realized. This creates a scenario where adoption is not a continuous choice but a binary one, leading to the "AI divide" observed across firms and nations.This paper complements the existing literature by focusing specifically on this adoption barrier. We argue that to understand the divergence in growth paths, it is crucial to model the strategic interaction between this investment threshold and human capital accumulation. Therefore, unlike models that focus on the prediction or task-substitution aspects of AI, we employ a simplified framework extending Redding (1996) to isolate the macroeconomic implications of the investment threshold (k).

This paper aims to extend the theoretical framework of Redding (1996) to the context of contemporary AI technology. Specifically, we model the entrepreneur's investments in AI investment as an alternative to traditional R&D investments. We focus on a key characteristic of AI technology: the 'threshold' (k) effect, which requires substantial initial investment and infrastructure before adoption becomes viable.

Within the framework of our non-overlapping generations model, we represent the process by which entrepreneurs decide to invest in AI (α), taking into account the threshold k, which leads to an increase in the level of technology (A). Workers, in turn, invest in education (ν) and accumulate human capital (h) based on their expectations of future wages. In this setting, we analyze how strategic complementarities between AI investment and human capital investment operate, and how they shape the economy's growth and equilibrium.

The main theoretical contribution of this study is the analysis the implications of the threshold effect (k)—considered unique to AI investment—using Redding's strategic complementarity framework. This allows us to provide a concrete theoretical explanation for the uneven adoption of technologies such as AI across economies and entrepreneurs, and for why "slow AI adoption" can become a self-perpetuating low-growth trap. We show that this threshold amplifies the role of expectations and demonstrates how small differences in initial conditions or parameters can lead to vastly different growth outcomes. Additionally, we compare the characteristics of high- and low-growth equilibria to explore the conditions required for AI-driven economic growth.

The structure of this paper is as follows. Section 2 describes the basic setup of the model, including workers, entrepreneurs, AI investment, and human capital accumulation, and derives the equilibrium conditions of the model. This section also shows that our model can generate both high-growth and low-growth equilibria simultaneously under specific conditions, and characterizes both types of steady-state growth equilibria. Section 3 discusses the practical relevance of the AI investment threshold and its implications. Finally, Section 4 summarizes the conclusions of this study and discusses policy implications and directions for future research.

2 The Model

This study builds on the framework proposed by Redding (1996), which examines how human capital accumulation affects firms' decisions to invest in R&D. We extend this framework to the context of AI, exploring how human capital accumulation influences

AI investment and how this interaction, shaped by an investment threshold unique to AI, affects long-run endogenous growth.

Throughout the paper, t indexes generations, while $j \in \{1, 2\}$ denotes the period within a generation.

2.1 The Basic Setup

2.1.1 Workers

We consider a standard framework of non-overlapping generations. Generations are indexed by t, and each generation comprises workers (denoted by subscript l, with a total number normalized to 1) and entrepreneurs (denoted by subscript i, also normalized to 1), both represented as continua. Each economic agent is assumed to live for two periods. Time is denoted by τ and the length of one period is set equal to one time unit.

Workers are risk-neutral, and the lifetime utility of a worker belonging to generation t is given by the following equation:

$$U_t\left(c_{1,t}, c_{2,t}\right) = c_{1,t} + \left(\frac{1}{1+\rho}\right) c_{2,t} \tag{1}$$

where $c_{j,t}$ denotes the consumption of an individual in generation t in period j, the interest rate r_t is assumed to equal the subjective discount rate ρ. $c_{j,t}$ is the amount an individual of generation t consumes in period j, and ρ is the subjective discount rate.

At birth, individuals inherit a stock of human capital from the previous generation. This intergenerational spillover of human capital follows the framework of Lucas (1988). The first-period human capital of a representative worker l in generation t is given by:

$$h_{1,t} = (1-\delta) H_{2,t-1} \tag{2}$$

where δ denotes the exogenous depreciation rate of human capital across generations and $H_{2,t-1}$ is the aggregate human capital stock in the second period of generation $t-1$.

$$H_{2,t-1} = \int_0^1 h_{2,t-1}(l)\, dl \tag{3}$$

Workers can further increase the human capital (knowledge, skills, etc.) they possess. To do so, they spend a portion of the first period of their life (the first period) in school or training (education and learning). At the beginning of life, each worker decides how much of the first period they will allocate to education. This proportion is denoted by v, where v takes a value greater than 0 and less than 1. For instance, 0.2 means that 20 percent of the first period will be spent on education. This decision of how much time to spend on education is made only once at the beginning of life and remains fixed thereafter.

After determining the time allocation to education, each worker is randomly paired with one entrepreneur. This pairing is maintained for the lifetime of the worker. The term "random" implies that the matching is determined by chance and not based on preferences or characteristics.

Once paired, production begins. Production activities occurs in both periods of life: during the first period, production it is carried out using the remaining time not allocated to education, i.e., $1-v$, and in the second period, it utilizes the entire period.

The educational production technology is modeled as follows: workers who spend a proportion v of their time in education in the first period acquire human capital for the second period according to the function:

$$h_{2,t} = \left(1 + \gamma \nu^{\theta}\right) h_{1,t} \tag{4}$$

$h_{j,t}$: Human capital in period j for individuals in generation t

δ: Rate of human capital depletion

$H_{2,t-1}$: Aggregate human capital in the previous period

γ, θ : parameters related to the productivity of education

The choice of education v should be interpreted broadly. Rather than representing formal schooling alone, v captures the overall intensity of human capital investment, including on-the-job training, reskilling, learning-by-doing, and time devoted to acquiring AI-relevant competencies. In the context of AI-driven technological change, human capital accumulation increasingly takes the form of continuous skill upgrading and adaptation to new technologies, rather than discrete schooling decisions. Modeling education as a time allocation choice is therefore a parsimonious way to capture these diverse learning activities.

It is important to distinguish between the allocation of time and the stock of human capital in the model. Education uses time rather than human capital itself. Workers devote a fraction v of their first-period time to education, which reduces the current supply of labor but increases the stock of human capital available in the second period. Entrepreneurs employ the worker's human capital stock $h_{j,t}$ in production, while education operates as a separate process that augments future human capital. Thus, there is no double counting: time devoted to education affects production only indirectly through its impact on future human capital accumulation.

2.1.2 Entrepreneurs

Each entrepreneur is assumed to produce a homogeneous final good, denoted by y, using a constant returns-to-scale production function with respect to their size:

$$y_{j,t}(i) = A_{j,t}(i)\, h_{j,t}, \tag{5}$$

where

$y_{j,t}(i)$: goods produced by entrepreneur i in period j,

$A_{j,t}(i)$: technology level of entrepreneur i in period j,

$h_{j,t}$: human capital supplied by the representative worker.

where $A_{j,t}(i)$ represents the productivity or quality of the technology employed by entrepreneur i in period j and $h_{j,t}$ denotes the human capital of the representative worker employed by entrepreneur i. The final good is chosen as the numéraire (i.e., the unit of value), and thus $p_t = 1$ for all t.

Entrepreneurs can invest a portion of their output in uncertain AI technologies to improve the quality of final goods. Specifically, the cost of AI investment in the first period is modeled as a fixed proportion α of output, which represents the investment cost. Depending on the magnitude of the AI investment, the technology level $A_{2,t}(i)$ may improve in the second period. If the AI investment is successful, the entrepreneur benefits from enhanced technology and increased production in the second period. At the end of this period, it is assumed that the outcomes of AI investments diffuse across all entrepreneurs, allowing the next generation of entrepreneurs to access the improved technological level. The rate of return on AI investment increases when the investment surpasses a defined threshold k.

$$A_{2,t}(i) = \begin{cases} A_{1,t}\big(1 + \eta\,(\alpha - k\big), & if\ \alpha \geq k, \\ A_{1,t}, & if\ \alpha < k, \end{cases} \tag{6}$$

where
α: AI investment level (fraction of production),
k: AI investment threshold,
η: efficiency parameter for AI investments.

According to a presentation by the Boston Consulting Group, the implementation and utilization of AI will entail significant costs across various domains, including human resources, infrastructure, development, and operations. It is reported that one in three companies across all markets plan to invest over $25 million in AI by 2025. Furthermore, the report projects that these costs will continue to rise as entrepreneurs increasingly seek to leverage advanced AI technologies. Investments in generative AI (Gen AI), in particular, are expected to grow by 60% over the next three years. In our model, we assume full technology propagation: by the end of the second period, all entrepreneurs will have adopted the highest level of available technology:

$$A_{1,t+1} = \max_i\{A_{2,t}(i)\}. \tag{7}$$

McKinsey & Company (2024), for example, reports that the number of people using AI has doubled within a span of just ten months. According to *The State of AI in Early 2024: Gen AI Adoption Spikes and Starts to Generate Value*, 65 percent of respondents indicated that their organizations are regularly using generative AI—nearly twice the percentage reported in the previous survey conducted ten months earlier. Moreover, this usage spans at least one business function within their organizations. Based on these developments, it is reasonable to assume that in the context of AI evolution, technological advancements propagate within the span of one generation. Thus, it is not implausible to model that all entrepreneurs will have access to the best technology available from the previous generation.

Although technological improvements diffuse fully across generations, individual entrepreneurs do not benefit from the' AI of others in their own lifetime. The private return to AI investment arises from higher productivity in the entrepreneur's second period of life, before knowledge diffusion takes place. Hence, full intergenerational technology diffusion does not eliminate private incentives to invest in AI, but instead generates a knowledge externality that shapes aggregate growth dynamics.

2.1.3 Wage Determination

Following Acemoglu (1994), workers and entrepreneurs are randomly matched one-to-one, ensuring no unemployment. The surplus generated in each match is divided between entrepreneurs and workers at shares $(1-\beta)$ and β, respectively. Accordingly, the wage per unit of human capital received by a worker employed by entrepreneur i in period j is given by:

$$w_{j,t}(i) = \beta\, A_{j,t}(i) \tag{8}$$

In period 1, all entrepreneurs operate with the same technology. When choosing how much time to allocate to human capital accumulation, workers form expectations about their second-period wages. Since matching is random over a continuum of measure 1 and each entrepreneur innovates independently with expectation μ, the expected fraction of successful innovators is μ. Therefore, the expected second-period wage is:

$$\mathbb{E}\big[w_{2,m(i)}\big] = \beta\,\mathbb{E}\big[A_{2,m(i)}\big] = \beta\big[\mu\lambda + (1-\mu)\big]A_{1,m},$$

where:
β: share of surplus accruing to workers;
μ: probability that an entrepreneur successfully innovates;
λ: factor by which technology improves upon successful innovation.

2.2 General Equilibrium

Throughout the paper, an equilibrium is defined as a self-fulfilling outcome in which agents' expectations about future technology and investment decisions are consistent with the actions they induce. As in Redding (1996), equilibria are interpreted as rational-expectations growth paths rather than static Nash equilibria played independently in each period.

Workers choose the proportion of time ν to allocate to education in order to maximize their expected lifetime earnings:

$$\max_{\nu}\ \beta\left[A_{1,t}(1-\nu)\,h_{1,t} + \frac{1}{1+\rho}\,\mathbb{E}[w_{2,t}]\,h_{2,t}\right] \tag{9}$$

with the first-order condition yielding:

$$\nu^* = \left(\frac{\theta\,\gamma\,\mathbb{E}[A_{2,t}(i)]}{(1+\rho)\,A_{1,t}}\right)^{\frac{1}{1-\theta}} = \left(\frac{\theta\,\gamma\,\big[1+\mu\,\eta\,(\alpha-k)\big]}{1+\rho}\right)^{\frac{1}{1-\theta}}. \tag{10}$$

μ: An indicator variable denoting whether an entrepreneur invests in AI (μ=1) or not (μ=0),
η: Efficiency parameter of AI investment.

The variable $\mu \in \{0,1\}$ is an indicator capturing workers' expectations regarding firm-level AI investment. Specifically, $\mu = 1$ denotes the belief that entrepreneurs will invest in AI in equilibrium, whereas $\mu = 0$ represents the belief that they will not. Importantly, μ does not represent a technological expectation. Rather, it is a coordination variable reflecting self-fulfilling expectations that are validated by firms' optimal investment choices in equilibrium.

Following Redding (1996), we abstract from explicit technological success probabilities and instead focus on expectations-driven coordination. AI investment outcomes are therefore summarized in reduced form by expected payoffs. The value functions V_R and V_0 are written as expected lifetime profits, taking as given workers' expectations and the implied expected second-period technology level. Consequently, the profitability differential $\Delta V \equiv V_R - V_0$ should be interpreted as an expected return comparison, rather than a deterministic or probabilistic realization of technological success.

Entrepreneurs decide both whether to invest in AI and the corresponding investment share α. The expected profits for entrepreneurs that choose to invest in AI can be expressed as follows:

$$V_R = (1-\beta)\left[(1-\alpha)\,(1-\nu)\,A_{1,t}\,h_{1,t} + \frac{1}{1+\rho}\,(1+\eta\,(\alpha-k))\,A_{1,t}\,(1+\gamma\,\nu^{\,\theta}\,)h_{1,t},\right] \quad (11)$$

Expected profits of entrepreneurs that do not invest in AI are as follows:

$$V_0 = (1-\beta)\left[(1-\nu)\,A_{1,t}\,h_{1,t} + \frac{1}{1+\rho}\,A_{1,t}\,(1+\gamma\,\nu^{\,\theta}\,)h_{1,t},\right]. \quad (12)$$

Entrepreneurs invest in AI when $\Delta V > 0$, where

$$\Delta V = V_R - V_0 = (1-\beta)\,A_{1,t}\,h_{1,t}\left[\left(\frac{\eta\,(1+\gamma\,\nu^{\,\theta}\,)}{1+\rho} - (1-\nu\,)\right)\alpha - \frac{\eta\,k(1+\gamma\,\nu^{\,\theta}\,)}{1+\rho}\right] \quad (13)$$

In equilibrium, workers correctly anticipate entrepreneurs' AI investment decisions and choose the optimal level of education, ν^*. Likewise, entrepreneurs correctly anticipate workers' educational investments and determine the optimal level of AI investment, α^*.

As in Redding (1996), expectations are modeled discretely: workers form beliefs about whether firms will invest, and equilibria are defined as self-consistent configurations in which these beliefs are validated by firms' optimal investment decisions.

Proposition 1 *When the efficiency of AI investment (η), the productivity parameter of education (γ), the elasticity of human capital with respect to education time (θ), and the time discount rate (ρ) lie within intermediate ranges, the model predicts the coexistence of two distinct equilibria. In a high-growth equilibrium, entrepreneurs find it profitable to invest in AI—so that $\alpha^* \geq k$ and workers respond by allocating a greater share of their time to education, yielding $\nu^* = \nu^*_{\text{high}}$. By contrast, in a low-growth equilibrium, entrepreneurs refrain from AI investment ($\alpha^* < k$), and workers choose the lower education intensity $\nu^* = \nu^*_{\text{low}}$.*

Proof.

From equation (10), the worker's optimal education choice satisfies

$$\nu^*(\mu) = \left[\frac{\theta\gamma}{1+\rho} \cdot \frac{\mathbb{E}[A_2]}{A_1} \right]^{\frac{1}{1-\theta}}, \qquad \frac{\mathbb{E}[A_2]}{A_1} = \begin{cases} 1 + \mu\,\eta(\alpha - k), & \text{if } \alpha \geq k, \\ 1, & \text{if } \alpha < k, \end{cases}$$

where $\mu \in \{0, 1\}$ denotes the expectation about AI investment. Hence ν^* is (weakly) increasing in the expected future technology level $\mathbb{E}[A_2]/A_1$, yielding two candidates $\nu^*_{\text{low}} := \nu^*(\mu = 0)$ and $\nu^*_{\text{high}} := \nu^*(\mu = 1)$ with $\nu^*_{\text{high}} > \nu^*_{\text{low}}$.

From equation (13), the profitability differential $\Delta V(\alpha; \nu)$ between investing and not investing in AI has marginal response

$$\frac{\partial \Delta V}{\partial \alpha} = (1-\beta)\, A_{1,t}\, h_{1,t} \; \underbrace{\left[\frac{\eta\big(1 + \gamma\nu^\theta\big)}{1+\rho} - (1-\nu) \right]}_{=:\, S(\nu)}.$$

Given $\bar{\alpha} \geq k$, if $S(\nu) \leq 0$ the best response is $\alpha^* = 0 (< k)$; if $S(\nu) > 0$ the best response is $\alpha^* = \bar{\alpha} (\geq k)$. Equivalently, the firm's investment expectation is $\mu^*(\nu) = \mathbf{1}\{S(\nu) > 0\}$.

Evaluate $S(\nu)$ at the two education choices from equation (10). If

$$S\big(\nu^*_{\text{low}}\big) \leq 0 \quad \text{and} \quad S\big(\nu^*_{\text{high}}\big) > 0,$$

then $(\mu, \nu) = (0, \nu^*_{\text{low}})$ is internally consistent (firms do not invest when workers choose the lower education share), yielding *a low-growth equilibrium*; and $(\mu, \nu) = (1, \nu^*_{\text{high}})$ is also internally consistent (firms invest when workers choose the higher share), yielding *a high-growth equilibrium*. Because $S(\nu)$ is increasing in ν and $\nu^*_{\text{high}} > \nu^*_{\text{low}}$, continuity implies that there exists an intermediate parameter region $(\eta, \gamma, \theta, \rho, \beta, k)$ where both inequalities hold. Hence at least two self-fulfilling equilibria exist.

2.2.1 Multiple Equilibrium Conditions

In the high-growth equilibrium ($\mu = 1$), workers anticipate firm-level AI investment and therefore choose their education share at $\nu^* = \nu^*_{\text{high}}$. Substituting this value into the expression for $\Delta V(\alpha; \nu)$ shows that the slope with respect to α is positive—barring extreme parameter configurations—so entrepreneurs find it optimal to set $\alpha^* \geq k$. This mutual consistency of expectations and choices renders the high-growth equilibrium self-fulfilling. This additional human capital further raises the profitability of AI investment, reinforcing the high-growth path.

Conversely, in the low-growth equilibrium ($\mu = 0$), workers expect no AI deployment and thus select the lower education intensity $\nu^* = \nu^*_{\text{low}}$. Under these expectations, $\Delta V(\alpha; v^*_{\text{low}})$ remains non-positive for all feasible α, so entrepreneurs optimally refrain from AI investment ($\alpha^* < k$). The resulting alignment of beliefs and actions gives rise to a self-fulfilling low-growth equilibrium.

2.2.2 Parameters and Equilibrium

For intermediate values of the parameters η, γ, θ, ρ, β and for a given threshold k, the sign of $\Delta V(\alpha;\nu)$ in (13), evaluated at the worker's high-education choice ν^*_{high}, determines whether entrepreneurs choose $\alpha^* \geq k$ (high-growth equilibrium) or $\alpha^* < k$ (low-growth equilibrium).

The AI investment share α is not intended to capture fine-grained marginal adjustments in investment intensity. Rather, it summarizes a discrete investment stance reflecting whether firms undertake sufficiently large-scale AI investment to surpass the threshold k. Given the linear structure of costs and benefits, optimal investment choices may involve corner solutions. This feature is deliberate and highlights the central role of the threshold effect, rather than the precise level of α, in shaping equilibrium outcomes.

Proposition 2 (High-Growth Equilibrium Condition) *There exists a high-growth equilibrium—characterized by $\alpha^* \geq k$ and $\nu^* = \nu^*_{\text{high}}$—if and only if:*

$$\Delta V\big(\alpha = k;\, \nu^*_{\text{high}}\big) = (1-\beta)A_{1,t}h_{1,t}\left[\Big(\frac{\eta\big(1+\gamma(\nu^*_{\text{high}})^{\theta}\big)}{1+\rho} - (1-\nu^*_{\text{high}})\Big)\alpha \right.$$
$$\left. - \frac{\eta k\big(1+\gamma(\nu^*_{\text{high}})^{\theta}\big)}{1+\rho}\right] > 0.$$

Proof.

By definition, a high-growth equilibrium requires entrepreneurs to find AI investment profitable at the worker's anticipated education time ν^*_{high}. Profitability is $\Delta V > 0$. Substituting ν^*_{high} into (13) yields the necessary and sufficient condition above: if and only if the bracketed term is positive, then

$$\Delta V > 0 \implies \alpha^* \geq k, \quad v^* = \nu^*_{\text{high}},$$

i.e. the high-growth equilibrium obtains. Conversely, if that expression is less than 0, no profitable $\alpha \geq k$ exists, and the high-growth equilibrium cannot emerge.

2.3 Steady-State Growth

As in Redding (1996), equilibria in this model are interpreted as self-consistent growth paths rather than one-period outcomes. Once expectations coordinate on either the high-growth or the low-growth equilibrium, the corresponding investment and education decisions are replicated across generations, giving rise to a stable intergenerational growth regime. Thus, the model does not generate alternating equilibria across generations; instead, each equilibrium is associated with a distinct steady-state growth path.

The output in period t is given by:

$$Y_t = A_t H_t \tag{14}$$

The per-period growth rate of output is:

$$g_Y = \frac{E[Y_{t+1}] - Y_t}{Y_t} = \frac{E[A_{t+1}H_{t+1}] - A_t H_t}{A_t H_t} \tag{15}$$

2.3.1 The High-Growth Equilibrium

Growth rate of technology:

$$g_A = \eta(\alpha^* - k) \tag{16}$$

where α^* is the optimal AI investment level in the high-growth equilibrium.
Growth rate of human capital:

$$g_H = (1 + \gamma(\nu^*)^\theta)(1 - \delta) - 1 \tag{17}$$

2.3.2 The Low-Growth Equilibrium

Growth rate of technology:

$$g_A = 0 \tag{18}$$

Growth rate of human capital:

$$g_H = (1 + \gamma(\nu_0^*)^\theta)(1 - \delta) - 1 \tag{19}$$

In the steady state under the high-growth equilibrium, the growth rate of technology equals the growth rate of human capital:

$$g_A = g_H = \eta(\alpha^* - k) = (1 + \gamma(\nu^*)^\theta)(1 - \delta) - 1 \tag{20}$$

Proposition 3 *In the high-growth steady state, both technology and human capital grow at a constant rate, given by the restated equation above:*

$$g_A = g_H = \eta(\alpha^* - k) = (1 + \gamma(\nu^*)^\theta)(1 - \delta) - 1.$$

In the low-growth steady state, technological progress stagnates ($g_A = 0$), and human capital converges to a constant level, implying zero growth ($g_H = 0$).

Proposition 4 *Let g^* denote the steady-state growth rate of output. Then, in equilibrium,*

$$g^* = \begin{cases} (1 + \gamma(\nu^*)^\theta)(1 - \delta) - 1, & \text{if } \Delta V(\alpha^*; \nu^*) > 0 \text{ (high-growth equilibrium)}, \\ 0, & \text{if } \Delta V(\alpha^*; \nu^*) \leq 0 \text{ (low-growth equilibrium)}. \end{cases}$$

Moreover, $g^* > 0$ if and only if $\Delta V(\alpha^*; \nu^*) > 0$. In the high-growth equilibrium ($\Delta V > 0$), g^* responds to parameters as follows:

$$\frac{\partial g^*}{\partial \eta} > 0, \quad \frac{\partial g^*}{\partial \gamma} > 0, \quad \frac{\partial g^*}{\partial \theta} > 0, \quad \frac{\partial g^*}{\partial \beta} > 0, \quad \frac{\partial g^*}{\partial k} < 0, \quad \frac{\partial g^*}{\partial \rho} < 0, \quad \frac{\partial g^*}{\partial \delta} < 0.$$

Equivalently, the steady-state growth rate is strictly positive and strictly increasing in $\eta, \gamma, \theta, \beta$ and strictly decreasing in k, ρ, δ if and only if $\Delta V(\alpha^*; \nu^*) > 0$. In contrast, under the low-growth equilibrium ($\Delta V \leq 0$), $g^* = 0$ regardless of parameter values.

Proposition 5 *There exists a unique high-growth equilibrium (and no low-growth equilibrium) if and only if*

$$\Delta V(\alpha = k; \nu^*_{\text{low}}) = (1-\beta)A_{1,t}h_{1,t}\left[\frac{\eta(1+\gamma(\nu^*_{\text{low}})^{\theta})}{1+\rho} - (1-\nu^*_{\text{low}})\right] > 0,$$

where ν^*_{low} is the worker's optimal education share when anticipating no AI investment ($\mu = 0$).

3 Analysis at the Thresholds: AI Investment Thresholds and Economic Equilibrium

In the model presented in this paper, the AI investment threshold k serves as a critical parameter determining whether the economy converges to a high-growth equilibrium or remains trapped in a low-growth equilibrium. This chapter focuses on analyzing the determinants of this threshold and its implications for economic equilibrium, both theoretically and in reference to real-world conditions.

3.1 High Threshold k and the Low-Growth Equilibrium

In economies facing a high AI investment threshold k, the substantial upfront costs required for AI adoption and deployment create significant barriers to technological progress. These elevated costs often stem from underdeveloped digital infrastructure—such as limited high-speed telecommunications, inadequate data centers, and insufficient high-performance computing systems—which drives up the effective value of k. At the same time, weak data ecosystems characterized by low volumes of reliable, well-maintained datasets further inflate deployment costs by reducing model performance and necessitating additional data-cleaning investments. Entrepreneurs must also navigate complex regulatory and institutional environments, where stringent data-privacy rules, elaborate licensing requirements, and slow approval processes compound compliance expenses and raise the threshold for viable AI projects. Finally, a scarcity of qualified professionals—data scientists, machine-learning engineers, and IT specialists—adds to labor and training costs, reinforcing the high-k regime. Under these combined conditions, AI investments rarely yield sufficient returns to justify their costs, dampening firms' incentives to innovate. As a result, the dynamic feedback loop between technological advancement and human-capital accumulation fails to materialize, leaving the economy trapped in a low-growth equilibrium.

3.1.1 Empirical Perspective

In many developing and emerging economies, the combination of underdeveloped infrastructure, weak data ecosystems, and regulatory shortcomings sustains a high AI investment threshold k. For instance, the World Bank (n.d.) that "access to the internet remains out of reach for most people in the continent, with only 22% reporting having access in 2017," highlighting the severe digital divide hindering AI adoption. Furthermore, analysis of International Telecommunication Union (ITU) (2024) reveals a strong correlation between low ICT scores and elevated AI investment barriers: countries with lower IDI rankings often experience limited internet penetration, poor rural connectivity, and inadequate digital skills among their populations. The 2024 Digital Development Report from the ITU further reinforces this point, noting that "internet use continues to grow, but universality remains elusive, especially in low-income economies. Access remains limited in many African countries due to infrastructure gaps, including basic necessities like electricity." Similarly, the Stanford University Human-Centered Artificial Intelligence (HAI) (2024) emphasizes that "basic infrastructure gaps such as electricity access are fundamental barriers to AI diffusion in several African and low-income nations." These empirical findings corroborate our theoretical prediction that structural deficiencies drive up the investment threshold k, thereby increasing the likelihood that such economies will remain trapped in a low-growth equilibrium.

3.2 Low Threshold k and the Low-Growth Equilibrium

While the model suggests that a low threshold k for AI investment should facilitate a transition to the high-growth equilibrium, it also reveals that the low-growth equilibrium may still persist if other key parameters limit the effective utilization of AI and hinder human capital accumulation. In such cases, even though the cost of adopting AI is not prohibitively high, the returns on AI and education investments remain insufficient to trigger sustainable growth.

3.2.1 Factors Contributing to a Low-Growth Trap Despite a Low k

Even when the financial and infrastructural barriers to AI adoption are relatively low (i.e., k is small), several impediments can still trap an economy in the low-growth equilibrium. First, low AI investment efficiency (η)—which reflects an inability to translate AI spending into productivity gains—can arise from poor technology selection, inadequate implementation processes, and weak organizational structures. McKinsey & Company (2024) report underscores this point, noting that "to create value, organizations must have all the elements in place—domain reimagining abilities, relevant skill sets (including upskilling of nontechnical colleagues), a robust operating model, and proprietary data."

Second, when educational systems fail to keep pace with technological change, both educational productivity (γ) and the elasticity of human capital formation with respect to time in education (θ) remain low. Such stagnation undermines the feedback loop between AI investment and skill acquisition, preventing the workforce from developing AI-relevant competencies. As the Organisation for Economic Co-operation and Development (OECD) (2021) Skills Outlook 2021 observes, "lifelong learning has become even more vital in the context of the COVID-19 pandemic, which accelerated structural shifts in labor markets. However, encouraging individuals to become lifelong learners remains complex, and many obstacles hinder effective adult participation in training programs."

Third, a high time-discount rate (ρ)—driven by economic uncertainty, political instability, or cultural preferences—encourages short-termism. Both entrepreneurs and individuals then underinvest in AI and education, since the benefits of these investments accrue primarily in the future.

Fourth, a low labor share of output (β) means that workers reap only a small fraction of the gains from AI-driven productivity. When workers doubt that they will benefit, their incentive to invest time and resources in acquiring new skills declines, further stalling human capital formation.

3.2.2 Empirical Evidence: Developed Economies with Low k but Low Growth

Several developed economies demonstrate that low AI adoption costs (k) alone do not guarantee technological dynamism. Take Japan: despite its strong ICT infrastructure and substantial R&D expenditures, its ranking in the IMD World Competitiveness Center (2024) slipped from twenty-seventh in 2017 to thirty-second in 2024. National authorities such as Ministry of Economy, Trade and Industry (METI) (2020) identify human capital shortages—most acute among data-science specialists—and insufficient reskilling initiatives as key constraints, reflecting low values of γ and θ. At the same time, organizational inertia and cultural barriers—manifesting in siloed departments, slow decision-making, and risk aversion—undermine effective AI deployment, depress investment efficiency (η), and exacerbate costs when data systems remain fragmented and poorly governed. Empirical studies by the OECD's Going Digital project and the World Economic Forum (WEF) (2023) show that misaligned institutions and underutilized digital capabilities frequently impede AI diffusion and productivity gains. These real-world observations align with our theoretical prediction: even when k is low, unfavorable configurations of η, γ, θ, ρ, and β can lock an economy into a low-growth equilibrium.

3.3 The High Threshold k and the High-Growth Equilibrium

Although the model typically associates a high AI investment threshold k with the likelihood of a low-growth equilibrium, it also demonstrates that a high-growth equilibrium can still be realized under such conditions—provided that other parameters are sufficiently favorable. In these cases, robust drivers of technological and human capital development offset the initial adoption costs of AI, enabling sustained economic growth.

3.3.1 Determinants of the High Growth Under High k

When the efficiency parameter η attains exceptionally high values, AI investments yield substantial returns despite their large upfront costs. Achieving such efficiency typically requires a comprehensive ecosystem that integrates a world-class R&D infrastructure, well-developed commercialization channels, and robust institutional capacity to support both adoption and scaling. Indeed, the Artificial Intelligence Index Report (2024) notes that "in 2023, the United States led with 61 notable machine-learning models, followed by China with 15 and France with 8," underscoring how an advanced innovation pipeline can sustain superior AI outcomes.

Similarly, when educational productivity (γ) and the elasticity of human capital formation with respect to education time (θ) are very high, economies can continuously supply the skilled professionals essential for AI technology design, implementation, and management. In the United States, this dynamic is driven by globally leading universities and research institutions, while in China, the large-scale expansion of both undergraduate and doctoral STEM programs has dramatically increased the flow of new talent. A 2021 analysis from the Center for Security and Emerging Technology (CSET) observes that China overtook the United States in STEM doctoral degrees conferred as early as 2007 and projects that by 2025 Chinese institutions could graduate more than 77,000 STEM PhDs compared to 40,000 in the United States.

A very low time-discount rate (ρ)—reflecting a long-term orientation in macroeconomic policy, cultural norms that value future planning, and institutional frameworks that reward patient capital—further supports sustained investment in AI, where benefits often accrue only after significant time lags.

Finally, when the labor share of output (β) is high, the gains from AI-driven productivity are more equitably shared with workers, reinforcing their incentives to pursue education and upskilling. This, in turn, strengthens the feedback loop between AI deployment and human capital formation, enabling a self-reinforcing path toward a high-growth equilibrium.

3.3.2 Empirical Examples: High Growth Despite High k

In the United States, a comprehensive AI ecosystem—spanning basic research, commercialization, and robust public–private collaboration—underpins exceptionally high investment efficiency (η) and vigorous human capital formation (γ, θ). Elite universities, a dynamic venture-capital sector, and leading technology firms such as Google, Microsoft, and OpenAI all contribute to this environment. Although regulatory complexity and high infrastructure costs (high k) present challenges, these strengths have enabled the U.S. to maintain a sustained high-growth trajectory in AI and related industries.

In China, a state-led industrial strategy has driven massive investment in AI research and development, data infrastructure, and education, resulting in rapid digitalization and a deepening STEM talent pipeline. Even when institutional and regulatory frictions elevate the effective threshold k, coordinated policy initiatives across multiple fronts—ranging from platform development to university expansion—have strengthened both η and γ, allowing China to overcome initial barriers and approach a high-growth equilibrium.

Together, these empirical cases demonstrate that favorable configurations of key parameters—particularly high η, γ, θ, and labor share β, combined with a low discount rate ρ—can offset even substantial AI investment thresholds. The experiences of the United States and China thus corroborate our theoretical prediction that the strategic alignment of technological capability and human capital policy can propel economies toward high-growth equilibria despite significant structural cost barriers.

3.3.3 Empirical Examples: High Growth Despite High k

In the United States, a comprehensive AI ecosystem—spanning basic research, commercialization, and robust public–private collaboration—underpins exceptionally high investment efficiency (η) and vigorous human capital formation (γ, θ). Elite universities, a dynamic venture-capital sector, and leading technology firms such as Google, Microsoft, and OpenAI all contribute to this environment. Although regulatory complexity and high infrastructure costs (high k) present challenges, these strengths have enabled the U.S. to maintain a sustained high-growth trajectory in AI and related industries.

In China, a state-led industrial strategy has driven massive investment in AI research and development, data infrastructure, and education, resulting in rapid digitalization and a deepening STEM talent pipeline. Even when institutional and regulatory frictions elevate the effective threshold k, coordinated policy initiatives across multiple fronts—ranging from platform development to university expansion—have strengthened both η and γ, allowing China to overcome initial barriers and approach a high-growth equilibrium.

Together, these empirical cases demonstrate that favorable configurations of key parameters—particularly high η, γ, θ, and labor share β, combined with a low discount rate ρ—can offset even substantial AI investment thresholds. The experiences of the United States and China thus corroborate our theoretical prediction that the strategic alignment of technological capability and human capital policy can propel economies toward high-growth equilibria despite significant structural cost barriers.

3.4 Estimating the AI Investment Threshold k in Real-World Economies

Accurately estimating the AI investment threshold k in real-world contexts poses significant challenges due to both its conceptual ambiguity and empirical measurement difficulties. As k encapsulates not only financial costs but also institutional, technical, and organizational barriers, direct quantification is elusive. Nonetheless, several approaches can provide indicative estimates or proxy measurements of its scale.

3.4.1 Firm-Level Surveys and Case Studies

One effective approach is to conduct firm-level surveys or in-depth case studies that collect detailed information on the factors driving the AI investment threshold k. Such research typically records each firm's initial adoption costs—including software, hardware, and integration expenses—alongside the expected time horizon before returns materialize, perceptions of implementation risk versus realized outcomes, and internal capability gaps. By synthesizing these data across a representative sample of firms and sectors, researchers can approximate the effective height of k in different contexts. For instance, the DX Trend 2024 survey finds that 47.0 percent of firms cite a "lack of understanding of the effects and risks of generative AI" as a major barrier; 41.6 percent report concerns about "belief in wrong answers"; and 40.4 percent point to "difficulty in creating usage rules." These findings illustrate how both knowledge-related deficits and organizational challenges contribute to raising the AI investment threshold.

3.4.2 Macroeconomic Data and Econometric Inference

A complementary approach examines cross-country or cross-sector macroeconomic datasets to identify how AI-related investment patterns correlate with growth outcomes. Researchers draw on measures such as AI-specific R&D expenditures and counts of patents and publications, indices of digital infrastructure (for example, the ITU's ICT Development Index), educational metrics reflecting the population's digital skill levels, and conventional growth indicators like GDP per capita and its annual growth rate of change. By applying statistical or machine-learning techniques to these variables, one can infer the extent and timing of AI adoption lags and thus derive indirect estimates of the AI investment threshold k across different economies and industries. Even among leading firms, these analyses reveal substantial upfront commitments: Accenture's 2023 announcement of a three-year, \$3 billion AI investment program underscores that real-world adoption costs remain significant, implying a nontrivial k even for market frontrunners.

3.4.3 Key Insights from Existing Evidence

The AI investment threshold k exhibits substantial heterogeneity across countries and sectors, reflecting differences in industry structure, technological maturity, and organizational readiness. In particular, human capital shortages—captured by low values of the educational productivity parameter γ and the elasticity of human capital formation θ—act as critical constraints that effectively raise both the cost and complexity of AI implementation, thereby serving as indirect components of k. Institutional uncertainty and risk perception further amplify this threshold: regulatory ambiguity, the absence of robust governance frameworks for AI, and low levels of institutional trust all contribute to firms' hesitancy and elevate the perceived k. As the DX Trend 2024 report notes, "Efforts to introduce AI technology are expanding, but there is a shortage of human resources capable of introducing and utilizing AI," underscoring the pivotal role of human capital barriers in determining k in practice. Although it remains challenging to quantify k precisely across all economies, its inherently multidimensional character requires both firm-level and economy-wide analysis. Future research should therefore pursue the construction of composite indices—encompassing infrastructure quality, human capital metrics, regulatory burdens, and organizational behaviors—to better approximate k and inform targeted policy interventions.

4 Conclusion

This paper builds on the theoretical framework of strategic complementarity—originally applied to human capital and R&D investment—to examine how investment in artificial intelligence (AI) interacts with human capital accumulation to shape long-term economic growth. Its primary contribution is the introduction of an AI investment threshold k, defined as the minimum level of infrastructure and foundational capability required for viable AI adoption. By modeling this discontinuous barrier, the framework captures the structural conditions that cause economies to diverge along distinct growth trajectories.

A core insight of the analysis is that the interplay between AI investment and human capital formation, when combined with the threshold effect, gives rise to multiple equilibria. In one scenario, firms' AI investments exceed k, triggering technological progress that raises returns to education and encourages further skill acquisition; this positive feedback loop sustains a high-growth equilibrium. In contrast, pessimistic expectations about AI returns can suppress educational incentives, preventing investments from reaching k. The resulting stagnation in both technology and human capital leads to a low-growth trap characterized by zero long-term growth.

This framework also illuminates why some economies lag despite global technological advances. In many developing countries, inadequate infrastructure and weak human capital—reflected in a high threshold k—hinder AI diffusion. Yet even in developed economies with sufficient infrastructure, low AI investment efficiency (η) or underdeveloped educational systems (γ, θ) can keep adoption below the threshold, trapping them in low-growth equilibria. Conversely, cases such as the United States and China—with strong R&D ecosystems, institutional support, and robust pipelines for skilled labor—demonstrate that favorable complementarities can overcome high thresholds and propel economies onto sustained high-growth paths.

4.1 Policy Implications

Achieving a transition from a low-growth trap to a high-growth equilibrium requires a coordinated, multi-pronged policy strategy. First, lowering the AI investment threshold k is essential. Governments should channel resources into digital infrastructure, streamline AI regulations, and provide targeted support for small and medium-sized enterprises, while also strengthening data interoperability and governance frameworks to boost returns on AI deployment. Second, fortifying human capital (γ, θ) demands a comprehensive overhaul of educational systems to equip workers with AI-era skills. This entails expanding STEM pipelines, facilitating reskilling and upskilling programs, and enhancing labor mobility across sectors so that talent can flow to where it is most needed. Third, shaping expectations through strategic coordination can foster confidence in an AI-driven growth trajectory. By articulating clear national AI strategies, promoting best practices, and synchronizing efforts among government agencies, academic institutions, and industry stakeholders, policymakers can reduce uncertainty and anchor positive investment outlooks. In addition to these core reforms, improving AI investment efficiency (η) via better implementation standards and organizational restructuring will amplify productivity gains. Finally, ensuring that the benefits of AI are broadly shared—through fair labor policies, inclusive access initiatives, and robust governance—will be crucial for securing sustainable, high-growth outcomes.

4.2 Directions for Future Research

This study adopts simplifying assumptions, such as homogeneous agents, exogenous AI efficiency (η), and perfect technology diffusion. Future extensions could explore heterogeneity across entrepreneurs and workers, endogenize AI efficiency, incorporate labor market frictions, and examine international spillovers and coordination. Such refinements would likely deepen understanding of the complex dynamics shaping the AI economy.

4.3 Final Remarks

While AI holds transformative potential for economic growth, realizing this potential hinges on our ability to lower the access threshold of AI investment while raising the level of human capability. This paper shows that achieving a high-growth future in the AI era requires not just technological readiness but also strategic investments in people, institutions, and expectations. The path forward is not automatic—it must be built deliberately through coordinated, forward-looking policy.

Statements and Declarations

Data availability. No new data were created or analysed in this study.

Code availability. Not applicable.

Funding. This research received no external funding.

Competing interests. The author declares no competing interests.

Ethics approval. Not applicable.

Consent to participate. Not applicable.

Consent for publication. Not applicable.

Authors' contributions. The author solely designed the study, performed the analysis, and wrote the manuscript.

References

Acemoglu, D.: Search in the labour market, incomplete contracts and growth. Discussion Paper 1026, Centre for Economic Policy Research (CEPR) (September 1994). Accessed August 17, 2025. https://cepr.org/publications/dp1026

Agrawal, A., Gans, J., Goldfarb, A.: Prediction Machines: The Simple Economics of Artificial Intelligence. Harvard Business Review Press, Boston, MA (2018). Accessed February 10, 2025. https://www.hbs.edu/faculty/Pages/item.aspx?num=53991

Aghion, P., Howitt, P.: A model of growth through creative destruction. Econometrica **60**(2), 323–351 (1992) https://doi.org/10.3386/w3223

Aghion, P., Jones, B.F., Jones, C.I.: Artificial intelligence and economic growth. Working Paper 23928, National Bureau of Economic Research (NBER) (June 2017). Accessed February 10, 2025. https://www.nber.org/papers/w23928

Acemoglu, D., Restrepo, P.: Artificial intelligence, automation, and work. Working Paper 24196, National Bureau of Economic Research (NBER) (February 2018). Accessed February 10, 2025. https://www.nber.org/papers/w24196

Acemoglu, D., Restrepo, P.: Automation and new tasks: How technology displaces and reinstates labor. Journal of Economic Perspectives **33**(2), 3–30 (2019). Accessed February 10, 2025

IMD World Competitiveness Center: IMD World Digital Competitiveness Ranking 2024. Web page. Accessed July 28, 2025 (2024). https://www.imd.org/centers/wcc/world-competitiveness-center/rankings/world-digital-competitiveness-ranking/

International Telecommunication Union (ITU): Measuring digital development: Facts and figures 2024. Report, International Telecommunication Union (ITU) (2024). Accessed July 28, 2025. https://www.itu.int/itu-d/reports/statistics/facts-figures-2024/

Lucas, J. Robert E.: On the mechanics of economic development. Journal of Monetary Economics **22**(1), 3–42 (1988) https://doi.org/10.1016/0304-3932(88)90168-7

McKinsey & Company: The state of AI in early 2024: Gen AI adoption spikes and starts to generate value. Survey report. Accessed July 28, 2025 (2024). https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-in-early-2024-gen-ai-adoption-spikes-and-starts-to-generate-value

Ministry of Economy, Trade and Industry (METI): Dx report 2 (chukan torimatome) [dx report 2 (interim report)]. Report, Ministry of Economy, Trade and Industry (METI) (2020). Accessed July 28, 2025. https://www.meti.go.jp/shingikai/mono_info_service/digital_transformation_kasoku/pdf/20201228_3.pdf

Organisation for Economic Co-operation and Development (OECD): OECD Skills Outlook 2021: Learning for Life. OECD Publishing, Paris (2021). Available at: https://www.oecd.org/en/publications/2021/06/oecd-skills-outlook-2021_6f4da936.html. Accessed July 28, 2025

Redding, S.: The low-skill, low-quality trap: Strategic complementarities between human capital and r&d. The Economic Journal **106**(434), 458–470 (1996) https://doi.org/10.2307/2235260

Stanford University Human-Centered Artificial Intelligence (HAI): Artificial intelligence index report 2024. Report, Stanford University, Human-Centered Artificial Intelligence (HAI) (2024). Accessed July 28, 2025. https://aiindex.stanford.edu/report/

World Economic Forum (WEF): The future of jobs report 2023. Report, World Economic Forum (2023). Accessed July 28, 2025. https://www.weforum.org/publications/the-future-of-jobs-report-2023/

World Bank: Digital Transformation for Africa. Retrieved May 4, 2025 (n.d.). https://www.worldbank.org/en/programs/all-africa-digital-transformation