

FROM THE SOLOW–SWAN MODEL TO INDUSTRY 5.0

The relationship between AI-driven knowledge management and sustainable economic growth

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ABSTRACT

The evolution of economic growth models has interpreted the role of technological progress in markedly different ways. The Solow–Swan exogenous approach treated technological progress as an external given, while endogenous growth theories identified knowledge and innovation as the internal driving forces of growth. Schumpeterian creative destruction further refined this picture by emphasizing the cyclical nature of innovation and the dynamic role of competition. Building on this trajectory of growth theory, the present study examines the economic role of artificial intelligence, with particular attention to AI-supported knowledge management. The analysis argues that artificial intelligence is not merely an automation technology but a platform that transforms the creation, organization, and utilization of knowledge, thereby affecting the internal factors of growth. The paper demonstrates how AI-based knowledge management affects productivity and labour market structure, and outlines the limitations and risks associated with its application.

The study concludes that the integration of AI and knowledge management offers a new interpretive framework for the study of economic growth, particularly within the human-centred approach of Industry 5.0, where technological progress is designed not to replace labour but to complement it.

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Keywords: artificial intelligence, knowledge management, economic growth, Industry 5.0

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1 INTRODUCTION AND BACKGROUND

The explosive development of artificial intelligence and the emergence of Industry 5.0 are fundamentally reshaping our understanding of economic growth today. The economic interpretation of the role of technological progress has gradually deepened, ranging from the neoclassical approach to Schumpeterian creative destruction. Yet despite the spectacular expansion of technological possibilities, statistical data continue to reflect the phenomenon known as the Solow paradox. This paradox indicates that the mere presence of computers and digital tools does not in itself translate into immediate productivity gains at the macro-economic level.

The current scholarly discourse reveals a gap in the detailed analysis of the transition between technological potential and actual economic performance. Particularly little attention has been paid to the question of how the transformation of organizational knowledge management might bridge this gap in the age of artificial intelligence. The present study seeks to fill precisely this theoretical gap by synthesizing neoclassical foundations with the era of generative artificial intelligence.

Our study draws on Joel Mokyr's knowledge-economy framework to examine how, alongside the abundance of information, the conversion of data into useful knowledge becomes critically important. It further reviews the challenges accompanying the development of AI, with particular attention to digital inequalities and ethical risks, and addresses the regulatory and educational conditions required for a socially sustainable application of human-machine collaboration.

The main contribution of the study lies in integrating growth theories, Mokyr's knowledge-economy framework (approach), and the field of AI-based knowledge management – areas that have thus far typically been *treated separately* in academic literature. On the basis of this synthesis, the study proposes its own conceptual framework for interpretation. This framework interprets the economic impact of generative AI through the transformation of the cost structure of access to and use of knowledge, taking into account the role of organizational adaptation, human capital, and complementary intangible investments.

1.1 Objectives and research questions

The central objective of the present study is the critical analysis and synthesis of the evolution of economic growth theories, with particular attention to the technological paradigm shift induced by artificial intelligence.

The study seeks to answer the following four interrelated research questions:

- Q1: How can the role of technological progress in economic growth be reinterpreted from the Solow model to Industry 5.0?
- Q2: Through what processes can generative AI reduce the costs of access to knowledge?
- Q3: Why is the impact of artificial intelligence not immediately reflected in macroeconomic productivity indicators, and what role do complementary intangible investments play in this regard?
- Q4: What frameworks are needed for human–machine synergy (Industry 5.0) to yield sustainable and socially just growth?

2 METHODOLOGY

The study employs the integrative literature review (ILR) methodology as defined by Torraco (2005, 2016). This approach provides an interpretive framework suited to uncovering the connections between well-established growth theory models (Solow, Romer, Schumpeter) and the technological paradigm shift currently taking shape. The methodology makes it possible to synthesize classical theoretical foundations together with the most recent professional analyses – often still at an early stage of the scholarly publication process (working papers, industry reports) – within a single, consistent logical framework.

The research focus is adapted to the specific characteristics of the macroeconomic effects of generative artificial intelligence. Because a considerable time lag can be observed between technological adoption and its manifestation in productivity indicators, the short time-series data currently available may, on their own, be misleading. For this reason, rather than relying on primary data collection, the study builds on a comparative synthesis of the relevant theoretical and empirical literature together with institutional estimates. This synthesis makes it possible to bring global tendencies and underlying economic processes into view, rather than the potential distortions of individual measurements.

In identifying sources, we employed an iterative search strategy together with a citation-network-based snowballing approach. In building the database, alongside scholarly platforms (Scopus, Google Scholar), peer-reviewed literature was given particular emphasis. Source collection is based on two complementary periods: the foundational theoretical works span the period from 1950 to 2000, while the modern impact studies cover the period from 2018 to 2026. The selection of sources was guided by their relevance to the research questions, their scholarly reliability, and the theoretical or empirical contribution they offer to the analysis.

The composition of the study’s source base and the selection process are summarized in *Table 1*:

Table 1
The source base of the research

	Specification and details
Primary databases	Academic: Scopus, Google Scholar, JSTOR, ScienceDirect. Institutional: NBER Working Papers, MIT Professional: World Economic Forum (WEF), McKinsey Global Institute, Goldman Sachs Research, IMF Publications.
Temporal coverage	Theoretical foundations: 1950–2000 (foundational works of Solow, Romer, Lucas, Mokyr, Schumpeter). Modern AI and empirical data: 2018–2026 (with particular focus on the post-2022 generative AI literature).
Keywords	Economic growth theory, Solow paradox, Total Factor Productivity (TFP), Artificial Intelligence, Generative AI, LLM, Knowledge economy, Propositional vs Prescriptive knowledge, Industry 5.0, Human-centric AI.
Source selection criteria	Relevance to the research questions; scholarly reliability; relevant theoretical or empirical contribution; economic or organizational relevance
Mode of synthesis	Thematic organization of sources along the four research questions; narrative comparison of findings, discrepancies, and uncertainties

Source: Authors’ compilation

The sources are classified into three types: peer-reviewed academic publications, institutional working papers, and industry and market reports. The cited macro-economic estimates and productivity effects derive from scenario analyses based on differing assumptions and from a synthesis of empirical findings published in the literature. These are presented not as exact forecasts, but as an interpretive framework intended to illustrate possible directions of impact and differences in order of magnitude.

3 ECONOMIC GROWTH MODELS

3.1 The Solow–Swan model

3.1.1 Key factors of the model

According to the Solow–Swan model, capital, labour, and exogenous technological progress jointly determine an economy's total output and growth. The model focuses on long-run equilibrium states, assuming that the economy operates at full employment and that capital is utilized at full capacity (Solow, 1956; Barro–Sala-i-Martin, 2004).

The model represents economic output by means of a Cobb–Douglas production function:

$$Y = A \cdot K^{\alpha} \cdot L^{1-\alpha} \quad (1)$$

which describes the fundamental structure of economic growth, where:

- **Y**: the total output of the economy.
- **K**: the capital stock, representing the physical assets involved in the production process, such as machinery, buildings, and infrastructure. These contribute to productivity growth, although, owing to the law of diminishing returns, the effect of increasing the capital stock diminishes over time. The model assumes that capital is fully utilized and does not account for idle capacity or obsolete capital assets, even though these frequently occur in the economy.
- **L**: labour, denoting the actively employed workforce. According to the model, the economy operates at full employment, meaning that the entire available labour force is drawn into the production process and there is no persistent unemployment. Although an expansion of the labour force increases output in the short run, this too fails to generate sustainable long-run growth unless accompanied by capital accumulation or technological progress.
- **A**: the exogenous level of technology, the factor that renders economic growth sustainable in the long run. The model treats technological progress as an exogenous factor – that is, it assumes that innovations and improvements result from external forces that economic agents cannot directly influence. Technological progress appears in the production function in the form of a multiplier ($A(t)$), which increases the productivity of both capital and labour without altering their relative proportions. This continuous advancement of the technological level ensures that the economy is able to overcome the constraints of diminishing returns and achieve growth in the long run.

- α : the share of capital in production, indicating the proportion in which capital contributes to output. Its value typically lies between 0 and 1, with $1-\alpha$ representing the share of labour (Barro–Sala-i-Martin, 2004).

The production function assumes that the combined growth of capital and labour is proportional to the growth of output; however, when capital or labour increases unilaterally, the law of diminishing returns applies. The effect of such unilateral growth diminishes over time, as the constraints of the factors of production impede further growth (Solow, 1956). Technological progress (A), however, is capable of offsetting these constraints, which constitutes the model's most important theoretical innovation.

3.1.2 The role of technological progress in sustaining long-term growth

The model's central proposition is that increases in capital and labour may contribute to productivity growth in the short run, but that, owing to the law of diminishing returns, these effects diminish over time. The key to sustaining long-run economic growth is therefore exogenous technological progress, which brings about a continuous improvement in the efficiency of the factors of production. According to Solow, an economy's equilibrium growth path can be sustained only if the level of technology continues to rise (Barro–Sala-i-Martin, 2004).

The model quantified the effect of technological progress through the concept of the "Solow residual", which represents the portion of productivity growth that cannot be directly attributed to increases in capital and labour. This growth component illuminates the extent to which innovation and technological progress contribute to economic development without altering the relative proportions of capital and labour. For instance, in the case of neutral technological change, the production function can simply be multiplied by an increasing factor ($A(t)$), which raises the level of output without distorting the substitution relationships between the factors of production (Solow, 1957).

Beyond this, technological progress has a substantial practical impact. It is one of the principal drivers of real wage growth and of the maintenance of economic stability, as it enables economic growth to proceed beyond the quantitative limits of the factors of production.

3.1.3 Limitations of the model

Although the Solow–Swan model constitutes an indispensable point of departure for modern macroeconomics, a number of its simplifying assumptions limit its empirical applicability.

The model's principal shortcoming lies in its treatment of the source of long-run growth. Within the neoclassical framework, technological progress appears as an exogenous variable rather than as an outcome arising from the decisions of economic agents. Because diminishing returns on capital mean that capital accumulation alone cannot generate sustainable growth, the model paradoxically explains growth by leaving its principal driver – technological progress – outside the model itself. This approach treats technology as a freely available public good, disregarding the incentives for research and development (R&D) and the partial excludability of knowledge.

From an empirical standpoint, the most contested aspect of the model concerns the speed of convergence and the explanation of international income disparities, since the standard framework predicts an unrealistically rapid catch-up between poor and rich countries. The model has also proven inaccurate with respect to international capital flows, as capital does not, contrary to expectations, flow toward poorer regions offering a higher marginal product – a phenomenon known in the literature as the Lucas paradox. Contradictions that cannot be explained by the accumulation of physical capital alone can be resolved only by broadening the concept of capital and by taking institutional factors into account, as proposed by Lucas's human capital model (Barro–Sala-i-Martin, 2004).

3.2 Endogenous growth models

In response to this fundamental shortcoming of the neoclassical models, research focus shifted from the 1980s onward, moving gradually away from exogenous factors and toward the internal decisions of economic agents and innovation (Romer, 1990). The inadequacy of the theoretical framework had already become apparent early on in the results of growth accounting. Analysing data for the United States between 1909 and 1949, Solow (1957) showed that only 12.5 percent of per capita growth could be explained by capital accumulation. The remainder was accounted for by a residual not further specified by the model, which the literature primarily identified with technological progress. Moses Abramovitz aptly termed this residual a “measure of our ignorance”, since the principal driver of growth thus remained unexplained (Abramovitz, 1956). The objective therefore became to derive technological progress endogenously, as an internal factor arising from the profit-maximizing decisions of economic agents (Barro–Sala-i-Martin, 2004).

3.2.1 Theoretical antecedents

Before the emergence of models built on deliberate research and development, the first step toward endogenizing the economic role of knowledge was taken by Kenneth Arrow. Arrow's concept broke with the assumption that technological progress should be regarded as an external given, independent of economic processes. The central element of his theory was the process of learning-by-doing. In this approach, knowledge is an unintended byproduct of investment and productive activity (Arrow, 1962).

According to Arrow, productivity growth is closely linked to cumulative gross investment, which serves as a measure of productive experience. Although individual firms invest in physical capital in pursuit of their own profit interest, with the aim of expanding capacity, this activity also generates new knowledge. This knowledge, however, does not remain confined within the walls of the firm; rather, it spreads throughout the economy through positive externalities – so-called spillover effects – thereby increasing the efficiency of all other agents (Arrow, 1962). This relationship was later incorporated by Lucas (1988) into his model of human capital accumulation, in which he distinguished between the individual, wage-enhancing effect of education and its efficiency-enhancing effect at the societal level (Lucas, 1988).

Robert Solow described Arrow's model as the ancestor – indeed, the prototype – of the new growth theories. In his assessment, this framework already represents technological progress as an internal consequence of economic processes, even though it lacks a deliberate, optimizing innovation decision (Solow, 1997). It is this passive, transitional character that distinguishes Arrow's approach from the later, first-generation endogenous models, in which agents actively allocate resources to the creation of knowledge (Romer, 1990).

3.2.2 First-generation models – Knowledge and innovation as internal drivers of growth

The approaches of Paul Romer (1990) and Robert Lucas (1988) broke with the tradition of treating technology as an external given. Their work brought about the genuine breakthrough of endogenous growth theory. In their models, technological progress is the outcome of deliberate, profit-oriented decisions made by economic agents. Lucas (1988) placed the emphasis on the accumulation of human capital, distinguishing between the individual productivity-enhancing effect of education and the positive externalities at the societal level. Romer (1990), for his part, defined knowledge as an entirely new type of economic good.

Romer's model is based on the recognition of the non-rival nature of knowledge (Romer, 1990). The use of conventional goods is limited, since a machine or an

engineer's working time can be utilized in only one place at a time. By contrast, a piece of software code or a chemical formula can be used simultaneously in an unlimited number of locations without any reduction in its value or any additional cost of reproduction (Barro–Sala-i-Martin, 2004).

This characteristic calls for a fundamental shift in our understanding of market structure. The creation of knowledge is a research and development activity involving high fixed costs, whereas its replication is cheap. However, under perfect competition, price would fall to the level of marginal cost, meaning the inventor could never recoup his investment (Dixit–Stiglitz, 1977). Firms therefore invest in innovation only if new ideas or blueprints are partially excludable. This protection is afforded to them by patent systems and trade secrets (Romer, 1990). In the technology sector, monopolistic competition therefore necessarily prevails, with excludability ensuring the monopoly rents needed to cover the fixed costs of research and generate profits (Aghion–Howitt, 1992).

In Romer's (1990) model, the production of new ideas takes place in the research sector according to the following relationship:

$$\dot{A} = \delta H_A A \quad (2)$$

In this formula, $\dot{A}$ denotes the flow of new technologies, the human capital employed in research, A the existing stock of knowledge, and research productivity. In the model, innovation is predominantly horizontal in nature. This represents an expansion of product variety, in which new goods do not displace old ones but rather complement them (Grossman–Helpman, 1991). Through specialization along the production chain, innovations increase the efficiency of final-good production (Young, 1998).

One of the most important messages of equation (2) is the cumulative nature of knowledge. The existing stock of knowledge acts as a positive externality that facilitates new research. To use Newton's famous metaphor, researchers stand on the shoulders of giants (Jones, 1995). It is this economic principle that enables increasing returns to scale for the economy as a whole. According to their theory, countries and firms that invest more heavily in research and development can achieve persistently faster growth. The growth rate is therefore endogenous, since it ultimately depends on society's patience – that is, on time preference – and on the resources flowing into the research sector (Romer, 1990; Lucas, 1988; Barro–Sala-i-Martin, 2004).

3.2.3 The empirical critique – The scale-effect problem

One of the most frequently criticized predictions of the first-generation models is the so-called scale effect. Romer's equation implies mathematically that the growth rate is directly proportional to the number of people employed in research. This relationship suggests that an economy with a larger population, or one that allocates more resources to the research sector, should grow exponentially faster (Jones, 1995). In his analysis, Charles Jones pointed to the empirical limitations of this assumption. The data showed that, while the number of scientists and engineers employed in the R&D sector in the United States increased more than fivefold between 1950 and 1990, economic growth did not follow this explosive change. The growth rate of total factor productivity (TFP) did not accelerate during this period but instead remained at a relatively constant level of around 2 percent per year (Jones, 1995; Barro–Sala-i-Martin, 2004). This was also confirmed by Jakob Madsen, analysing data from OECD countries between 1870 and 2006. He found that, although the number of researchers and R&D expenditures grew enormously on a global scale, the growth rate of GDP per capita remained surprisingly stable over the long run. According to Madsen's data, the growth rate moved within a range of roughly 1.5 to 2.5 percent per year across the countries examined for more than a century. He further pointed out that growth accounting models frequently overstate the role of capital, whereas the true source of growth lies in technological progress and human capital (Madsen, 2010).

Semi-endogenous models were developed to resolve these contradictions (Jones, 1995; Segerstrom, 1998). In these models, the so-called fishing-out effect already applies: as technology advances, readily accessible ideas become depleted, so that increasingly greater research effort is required to generate further innovations (Segerstrom, 1998). Alwyn Young (1998) likewise showed that an increase in the size of the economy often expands the number of product varieties rather than accelerating the rate of growth. Thus, long-run growth depends not on the absolute number of researchers, but on the rate at which that number grows (Young, 1998).

3.2.4 Schumpeterian models – Creative destruction and vertical innovation

The next generation of growth theories moved beyond the mere expansion of product variety. Philippe Aghion and Peter Howitt (1992) placed qualitative improvement and vertical innovation at the centre of their analysis. This approach returns to Joseph Schumpeter's original idea. According to this theory, innovation is not a peaceful process of accumulation but a constant struggle, in the course of

which new and more efficient technology necessarily displaces and devalues the old (Aghion–Howitt, 1992).

In the Schumpeterian model, every successful innovation raises the level of technology by a given magnitude relative to the previous period. It is this process that gives rise to the cycles of creative destruction. The change in the technological level is described by the following simplified relationship:

$$A_{t+1} = \gamma A_t \quad (3)$$

In this formula, the parameter denotes the magnitude of the quality improvement, and is always a number greater than one. Within this dynamic framework, the rate of economic growth is determined by two factors: the probability of innovations arriving, and the size of the quality improvement (Aghion et al., 2015).

One of the model's most important innovations is its reinterpretation of the role of competition. In the earlier models, intense competition reduced profits and, with them, the incentive to innovate. In the modern Schumpeterian models, by contrast, competition can also have a stimulating effect. Firms at the technological frontier gain an advantage through innovation, thereby escaping intense price competition and securing higher profits for themselves (Aghion et al., 2021). This market dynamic is particularly relevant to the analysis of today's digital economy. Product life cycles have shortened dramatically in recent decades, and empirical evidence confirms the acceleration of creative destruction. While the average lifespan of a large corporation stood at around 60 years in the mid-twentieth century, it has fallen to below 20 years today (Aghion et al., 2021). In the age of artificial intelligence, this process is becoming even more pronounced. New technologies go beyond the fine-tuning of existing processes, enabling even the rapid reorganization of entire business models. AI-driven automation may accelerate creative destruction, placing heightened pressure to adapt on both the labour market and the regulatory environment.

4 INDUSTRY 4.0 ECONOMIC MODELS – THE IMPACT OF AI ON PRODUCTIVITY AND LABOUR SUBSTITUTION

The evolution of economic growth theories entered a new phase with the emergence of Industry 4.0. Whereas the third industrial revolution centred on the automation of production processes, the essence of Industry 4.0 lies in the autonomy of cyber-physical systems, the Internet of Things (IoT), artificial intelligence, and the emergence of data as a new factor of production. In this model, physical capital is no longer a passive asset but may be capable of communicating with its environment and engaging in intelligent decision-making (Kovari, 2024).

This technological shift fundamentally rewrites traditional production functions. In modern AI-driven economic models, data may explicitly appear as a distinct, potential input factor on a par with capital and labour (Brynjolfsson et al., 2025). Data is thus becoming the new raw material of the digital economy, already indispensable for training, refining, and testing autonomous systems. Within the context of Industry 4.0, both the volume and quality of data have a direct impact on the performance of economic systems and on growth potential. According to the empirical study by Sun et al. (2024), decision-making based on real-time data, together with the integration of Big Data analytics, can significantly increase firms' total factor productivity while reducing marginal costs and information asymmetry in the market (Buri-Kiss, 2025).

The most critical question, however, concerns the labour market impact of these technologies. The models of Daron Acemoglu and Pascual Restrepo point out that, whereas earlier technologies (such as the steam engine or the computer) predominantly increased the marginal product of labour, advanced robotics, for example, may be capable of fully displacing human labour in routine and rule-based tasks. This process carries the risk of economic polarization: while it may reduce demand for low-skilled positions, it may simultaneously raise the value of high-value-added, creative, and problem-solving occupations. Technological progress is thus not neutral. The share of capital in national income may rise at the expense of labour, which could confront economic policy with challenges of redistribution (Acemoglu–Restrepo, 2020). Yet the data-driven infrastructure of Industry 4.0 and the automation of routine tasks were only the first step. This technological development laid the foundation for the next revolutionary leap, in which artificial intelligence no longer merely analyses data but also generates new data.

4.1 The revolution of the generative AI era

Automation technologies had for decades been a key driver of productivity growth, but the year 2022 marked a turning point in the development of artificial intelligence. OpenAI's generative large language models fundamentally changed the nature of innovation. AI has by now become a defining force even in domains previously regarded as the exclusive preserve of human creativity. This development has expanded the scope of both technological and economic opportunities. AI technologies were previously largely the preserve of large corporations, as they were the only ones with the necessary resources and expertise. For smaller businesses, the application of artificial intelligence was prohibitively costly and complex, while for private individuals it was practically inconceivable. Developments such as OpenAI's ChatGPT, however, ushered in a new era. AI tools became easy

to use, widely accessible, and affordable, revolutionizing the role of technology in the economy.

The economic impact of this technological leap is fully realized with the emergence of AI agents. These systems can function as active digital co-workers. Autonomous agent-based architectures may be capable of independently navigating corporate processes and, under human supervision, making complex decisions. This shift may reduce transaction costs and coordination burdens (Samuels, 2025). Cognitive automation thus now extends even to high-level expert tasks, which requires a fundamental reorganization of knowledge management in the interest of sustainable growth (Acemoglu, 2025; World Economic Forum, 2025). However, influencing the long-run growth trajectory can be achieved only if AI becomes a central element of knowledge management.

5 THE ROLE OF AI-AUGMENTED KNOWLEDGE MANAGEMENT

A modern understanding of knowledge management, however, requires that we move beyond a purely quantitative view of knowledge. The emergence of generative artificial intelligence not only accelerates the accumulation of information but also transforms the system through which knowledge is accessed. Joel Mokyr's economic-historical framework, which examines the structure of "useful knowledge", provides an appropriate theoretical foundation for this analysis.

5.1 Knowledge as a factor of economic growth

The endogenous models rightly point out that knowledge is a non-rival good – that is, its use does not deplete it, and its marginal social benefit in fact increases through sharing (Romer, 1990). Historical experience shows, however, that the accumulation of knowledge alone is not a sufficient condition for sustained growth. According to Mokyr (2002), the speed of technological progress is determined not by the absolute quantity of knowledge but by the quality of the connections among elements of knowledge and by the cost of accessing that knowledge. In this study, the cost of access to knowledge refers to the time and resources required to locate, interpret, validate, and apply relevant information (Mokyr, 2002, 2017).

Mokyr's model (2002) distinguishes between two closely interacting types of knowledge. Propositional knowledge (Ω -knowledge) comprises the theoretical description of natural phenomena and "what"-type knowledge. Prescriptive knowledge (λ -knowledge), by contrast, is the set of techniques, instructions, and

procedures required for practical implementation – that is, “how”-type knowledge. Economic growth becomes sustainable when the expansion of propositional knowledge is able, continuously and at low cost, to generate new prescriptive knowledge.

According to Mokyr (2017), the success of the Industrial Revolution was due not to the number of inventions but to the “Industrial Enlightenment”, which reduced the costs of access to knowledge and enabled the economic exploitation of scientific discoveries.

In the modern information society, however, knowledge management faces a distinctive paradox. Through digitalization, the propositional knowledge base (Ω) is growing exponentially. Estimates suggest that the global volume of data will reach 291 zettabytes by 2027 (Jalal et al., 2026) – an amount of information that is, in practical terms, unprocessable. John Naisbitt warned of the dangers of this phenomenon decades ago, observing that “we are drowning in information but starved for knowledge” (Naisbitt, 1982;24). This vast volume of data poses a substantial challenge to individuals and organizations alike, one that can lead to information overload. This not only reduces productivity but also complicates decision-making, causing considerable stress and a decline in quality of life (Arnold et al., 2023). From an economic perspective, this means that although the supply of knowledge is abundant, the access costs of locating and applying relevant information have risen dramatically. Owing to the limits of human cognitive capacity, it has become increasingly difficult to extract economically usable λ -knowledge from the vast Ω -set.

It is in this context that the significance of artificial intelligence can be understood, since, beyond traditional information-technology solutions, it may become one of the most effective tools for reducing the costs of access to knowledge. Large language models (LLMs) and generative algorithms are capable of synthesizing unstructured propositional knowledge on a massive scale and converting it into applicable prescriptive knowledge. In doing so, this technology also bridges the difficulties involved in transferring tacit knowledge, as it is able to render hidden patterns and relationships explicit. AI-driven knowledge management is thus an instrument of a Mokyrian digital enlightenment, one capable of ensuring that the expansion of the knowledge base translates directly into productivity growth and innovation.

5.2 The transformation of the cost structure of knowledge transfer in the age of AI

The economic impact of generative artificial intelligence is most clearly discernible in the process of knowledge transfer described by Joel Mokyr. The transition between theoretical knowledge (Ω) and practical application (λ) has traditionally been impeded by high transaction costs and informational barriers. In this domain, the primary role of AI technology is to mitigate the cognitive barriers to accessing knowledge and to reduce information-processing costs.

Table 2 sets out, according to the relevant studies, the specific tools through which AI is able to reduce the implementation barriers that constrain innovation cycles.

Table 2

The role of AI in reducing the costs of access to knowledge: The practical transformation of Joel Mokyr's knowledge types

Cost type	Traditional process (Mokyr's $\Omega \rightarrow \lambda$ barriers)	AI-driven solution	Effect on knowledge flow	Empirical evidence and source
Search and access costs	Locating relevant knowledge (Ω) is time-consuming. Innovations often arise from linking isolated domains of knowledge (silos), but recognizing these connections runs up against human cognitive limitations.	Semantic search and RAG: AI uncovers relevant propositional knowledge within minutes, based on meaning rather than keywords, and is able to reveal hidden connections across heterogeneous databases using knowledge graphs.	Relevant theoretical knowledge can become available more quickly.	In an enterprise RAG system, problem-resolution time fell from 34 minutes to 12 minutes, and top-5 relevance rose from 58% to 87% compared with keyword-based search (Baqar, 2026).
Interpretation cost	Knowledge is tacit in nature or encoded in highly specialized jargon, requiring specific human capital to understand.	LLMs are able to "translate" complex information (Ω) to the user's level of knowledge and convert it into actionable instructions (λ).	Through "knowledge democratization", even less-skilled labour becomes able to carry out complex instructions.	The use of AI was found to result in a 40 percent faster task completion time and an 18 percent improvement in quality (Noy-Zhang, 2023).
Verification and application cost	Testing a new technical solution (λ) requires physical prototypes and costly "trial-and-error" processes.	Digital twins and simulation: Proposed solutions are validated in a virtual environment. Predictive models reduce the knowledge gap.	The cost of filtering out flawed prescriptive knowledge falls; innovation cycle time shortens.	The productivity of customer-service employees using an AI assistant increased by 14%, and that of the least experienced employees by 30% (Brynjolfsson et al., 2025).

Source: Authors' compilation, based on data from the following articles: Brynjolfsson et al. (2025), Noy-Zhang (2023), Baqar (2026). In the table, Ω denotes Mokyr's theoretical/propositional knowledge, while λ denotes practical/prescriptive knowledge (instructions) required for technological application.

Generative artificial intelligence does not automatically produce a leap in productivity; rather, it may contribute to economic growth by progressively reducing the costs of access to knowledge. This reduction is thus discernible primarily in the efficiency of information processing, the shortening of learning time, and the support of decision-making, and can become measurable at the macroeconomic level only over a longer time horizon.

5.3 The adaptability of AI systems and the role of personalized knowledge management

In this domain, artificial intelligence exerts a multiplicative effect, particularly in the area of personalized knowledge management. AI systems are able to analyse real-time data, thereby providing solutions tailored to users' needs. Personalized knowledge management is of particular importance to modern organizations, as it targets the specific needs of individuals and teams. The case study of KEAS (Knowledge Enhancement and Advisory System), for example, showed that such systems reduced decision-making time by 42% and increased decision-makers' confidence by 35% (Bankole–Falaye, 2024).

AI-based systems are able to eliminate the principal obstacles to knowledge management, such as the problems of data silos and information gaps. These tools not only increase efficiency but also enable the faster and more accurate sharing of knowledge (Jarrahi et al., 2023).

AI-based knowledge management not only organizes information but also adapts dynamically to user needs. This adaptive capability enables AI to support creativity at both the individual and group level and to accelerate strategic decision-making. For example, generative AI models based on natural language processing (NLP) are able to automate the organization of knowledge and identify hidden patterns that facilitate innovation-related decisions.

AI-supported knowledge management thus not only revolutionizes the utilization of information but also plays a decisive role in enhancing creativity and productivity. Through human–AI synergy, human intuition and strategic thinking meet the rapid analytical capacities of AI, enabling more efficient organizational functioning.

6 INDUSTRY 5.0 – HUMAN-MACHINE SYNERGY AND A SUSTAINABLE LABOUR MARKET

The concept of Industry 5.0 builds on the technological achievements of Industry 4.0 but fundamentally revises its exclusive focus on efficiency (Ghobakhloo et al., 2023). The emphasis shifts from automation toward social value creation and sustainability, so that digital transformation is no longer treated as an end in itself (Buri-Kiss, 2025). This approach no longer sees the source of economic growth in the replacement of human labour and the reduction of costs, but rather in the synergistic collaboration between humans and machines (Woo, 2020).

Within this framework, the relationship between humans and artificial intelligence can be understood as a form of hybrid intelligence or co-creation, in which the two parties compensate for each other's shortcomings. Research by Daugherty and Wilson (2024) highlights that the most significant productivity gains arise in the so-called "missing middle". In this domain, humans teach machines to perform complex processes, while machines extend human capabilities through the rapid processing of data (Daugherty-Wilson, 2024). This synergy represents not substitution but augmentation, in which human creativity and ethical judgment combine with machine precision and speed (Jarrahi et al., 2023).

Concrete measurement results from critical sectors also confirm the effectiveness of this collaboration. One specific example is research published by Harvard Medical School, which found that in medical diagnostics, collaboration between human expertise and AI can achieve accuracy of up to 99%, compared with the 96% and 92% accuracy of human and machine analysis, respectively, when used independently (Woo, 2020). This result pertains to a specific, high-stakes decision-making context and therefore cannot, on its own, be generalized to the economy as a whole; it nonetheless illustrates the potential inherent in human-machine collaboration. The literature suggests that this type of partnership, by mitigating decision-making errors, may also exert an effect on performance at both the corporate and national-economy levels (Jarrahi et al., 2023).

The essence of the human-centred approach lies in using technology to enhance workers' well-being and to support their cognitive capabilities (Kaigom, 2025). Within this structure, artificial intelligence appears as a collaborative partner, actively supporting the resolution of complex problems. Advanced systems take over routine tasks, leaving creative and strategic functions in the hands of the human workforce (Kovari, 2024). In this context, human capital constitutes a dynamic source of growth and innovation (Ghobakhloo et al., 2023).

The stability of the technological foundation and long-term competitiveness are ensured by the pillar of resilience (Samuels, 2025). In the current economic environment, models optimized purely for efficiency frequently prove vulnerable to

unexpected external shocks and uncertainties, making flexible adaptation necessary (Ghobakhloo et al., 2023). Digital twins and predictive algorithms applied within the framework of Industry 5.0 may enable the real-time modification of processes and the forecasting of deviations (Kaigom, 2025). According to the literature, such a resilient structure can help ensure that the collaboration between technology and human knowledge is not only efficient but also sustainable and crisis-resistant. (Buri-Kiss, 2025).

7 CHALLENGES IN THE APPLICATION OF AI

The spread of artificial intelligence opens up not only new opportunities but also brings new types of risk to the surface. These include the deepening of digital inequalities, the need to guarantee data security, and the ethical questions associated with its application. These factors directly affect the long-term sustainability and social acceptance of AI. This chapter also highlights a further, frequently underappreciated challenge: the fact that the macro-level productivity returns to technological breakthroughs manifest themselves with a delay, and often unevenly.

7.1 The Solow paradox

Robert Solow was awarded the Nobel Prize in 1987 for his theoretical modeling and empirical analysis of technological progress in the theory of economic growth. That same year, his now-famous observation appeared in the *New York Times*: “you can see the computer age everywhere but in the productivity statistics” (Solow, 1987:36). This statement, which appears at first glance to be a contradiction, does not call into question the validity of his own theory; rather, it points to the fact that rapid technological progress does not translate into a clear, immediate increase in productivity in macroeconomic statistics. The economic effects of such progress typically differ in their timing, their structural characteristics, and the level at which they are measured (Oliner–Sichel, 2000).

The literature explains the Solow paradox through the combined effect of several closely interrelated factors. Brynjolfsson, Rock, and Syverson (2017) outline four principal explanatory factors: excessive expectations, measurement problems, redistributive and market-structure effects, and implementation and organizational lags. Together, these factors explain why, despite the rapid advancement of technological capabilities, macroeconomic productivity indicators respond only modestly. One fundamental reason lies in the time lag between technological potential and its economic application. The adoption of new technologies is a gradual process, entailing substantial learning costs and organizational restruc-

turing. Firms must not only acquire new tools but also redesign their processes, decision-making structures, and human-resource practices. In the short run, these transitional costs may even lead to a deterioration in measured productivity (Brynjolfsson et al., 2017).

The limitations of productivity measurement further reinforce the paradox. An ever-increasing share of the value generated by digital technologies and information systems takes an intangible form, for example through quality improvements, time savings, or enhanced decision support. These effects are only partially reflected in GDP and in conventional productivity indicators, particularly during the early stage of a technological transition (Oliner-Sichel, 2000).

The distribution of technological gains also plays an important role. In many cases, the benefits of new technologies manifest not as an increase in aggregate productivity but as a transformation of market structure and a concentration of income. Alongside the expansion of leading technology firms, much of the economy benefits from technological gains only to a limited extent, which weakens the macro-level statistical impact (Brynjolfsson et al., 2017). Research in this area has focused on the time required for adoption and on the role of complementary factors. New technologies are able to generate sustained productivity growth only when accompanied by adequate complementary investments. These include organizational innovation, the development of human capital, and the construction of data infrastructure. In the absence of these investments, technological potential fails to translate into economic performance (Brynjolfsson et al., 2021).

The literature frequently describes this process as a J-shaped productivity path. In the initial phase, transition costs dominate, so that measured productivity may stagnate or even decline. Later, however, once the complementary factors fall into place, technological returns emerge, and productivity indicators begin to track technological progress more clearly (Brynjolfsson et al., 2021). Empirical studies have shown that, in the United States, the acceleration of productivity in the second half of the 1990s was closely associated with investment in information and communication technology and with the associated organizational transformations (Oliner-Sichel, 2000). A similar pattern has been observed in developing economies, where the effects of ICT investment appeared in productivity indicators only following institutional and structural adaptation (Zhang et al., 2021). On the basis of historical ICT experience, it can be said that the Solow paradox is not a permanent condition but a characteristic feature of the early stage of technological transition.

The Solow paradox was originally associated with the period of diffusion of information and communication technologies, but it re-emerges today with the widespread adoption of artificial intelligence. Although AI already matches or exceeds

human performance in numerous domains, its effect at the macroeconomic level remains, for the time being, only modestly perceptible.

Estimates of the medium-term macroeconomic impact of AI diverge considerably. According to Acemoglu's analysis, AI may increase U.S. GDP by approximately 1 percent over the coming decade, while the growth in total factor productivity (TFP) remains even more modest, at between 0.53 and 0.66 percent (Acemoglu, 2025). This approach stands in sharp contrast to the scenarios formulated by market analysts. According to Goldman Sachs's forecast, artificial intelligence could raise global GDP by around 7 percent over the next ten years – that is, by approximately \$7 trillion (Goldman Sachs, 2023). McKinsey estimated the direct annual economic value-creation potential of generative AI at between \$2.6 trillion and \$4.4 trillion, and the total potential – including conventional analytics and AI applications – at between \$17.1 trillion and \$25.6 trillion (Chui et al., 2023). The divergence among these estimates illustrates clearly that a substantial gap may still exist between the technological possibilities of AI and their manifestation at the macroeconomic level.

Overall, it can be said that the Solow paradox does not deny the economic significance of technological progress; rather, it emphasizes that the effects of technological breakthroughs emerge with a delay, through structural transformations, and subject to limited measurability. This interpretive framework took shape during the era of information technologies, but it continues to provide a relevant foundation for examining the economic effects of artificial intelligence.

7.2 Digital inequalities

Regional disparities in access to, and utilization of, artificial intelligence technologies contribute substantially to the deepening of global digital inequalities. The study by Yuran Wu (2022) identifies three dimensions of the AI divide, which have direct, mutually reinforcing economic effects. Although basic disparities in internet access have narrowed globally, the access gap in AI-specific tools (hardware and software) has remained strongly income-dependent, which, owing to the uneven distribution of infrastructure, widens productivity differences across sectors (Acemoglu, 2025). The capacity gap is further deepened by the complexity of the technology and by the lack of requisite skills, which disproportionately disadvantages marginalized groups and lower-income regions (Wu, 2022). The WEF (2025) has defined this as a shift in technological literacy and skills supply. This process impedes the returns on the human-capital investments needed to exploit the technology, thereby slowing the upward-sloping phase of the productivity J-curve (Brynjolfsson et al., 2021). Finally, the gap in performance leads to increased

market concentration and the dominance of “superstar firms”, as actors capable of converting technological advantages into profit draw growth resources away from those falling behind (Aghion et al., 2021), entrenching digital inequalities.

This theoretical framework is corroborated by macroeconomic empirical data from Azhar et al. (2025), who point to the decisive role of structural readiness. Their study of OECD countries sheds light on the phenomenon of the Solow paradox within the context of AI. Their results show that, while AI investments in high-income economies generate significant GDP growth following the adoption period, this positive effect cannot be clearly demonstrated statistically in lower-income countries. This is because developing regions frequently lack adequate absorptive capacity. Owing to weaker digital infrastructure, lower reserves of human capital, and insufficient R&D expenditure, these countries find it more difficult to convert new technology into productivity gains (Azhar et al., 2025).

The social benefits arising from technological advantages, together with actual economic growth, are thus concentrated primarily in more developed regions. This process further widens the gap between economically advanced and developing regions (Azhar et al., 2025; Wu, 2022). The report of the World Economic Forum (2025) confirms this tendency as well: 60 percent of employers regard the broadening of digital access as the most critical business transformation factor, while identifying the labour-market skills gap as the principal obstacle to transformation. Wu (2022) emphasizes that, in order to reduce inequalities, it is essential to develop digital infrastructure and to provide broad-based education in digital competencies, particularly in marginalized regions.

7.3 Data protection and information security

The development of artificial intelligence requires the processing of enormous volumes of data, which poses serious challenges for data protection and information security. Given the exponential growth in data volume, encryption, authentication protocols, and the anonymization and transparent regulation of data have become critically important. The data processed by AI may include personal or sensitive information, unauthorized access to or unintended disclosure of which can pose risks at both the individual and organizational levels.

In addition, the literature has identified new types of vulnerability, such as data and model poisoning, unauthorized information extraction, and the leakage of user data (Yao et al., 2024; Das et al., 2025). The sustainable exploitation of the economic and organizational benefits of AI therefore requires appropriate data governance, access control, and continuous information-security controls.

7.4 The ethical dimensions of AI

While generative AI has opened up unprecedented opportunities, it has also brought serious ethical and social questions to the surface. “Deepfake” technology, through manipulated video and audio recordings, can not only violate personal rights but also cause political destabilization and social distrust.

According to Caldwell (2023), algorithmic bias poses a serious social risk, as AI models frequently reproduce – or even amplify – the biases embedded in their training data, thereby further deepening existing social inequalities. The lack of transparency in data usage and in AI systems likewise raises significant concerns. The decision-making processes of so-called “black box” systems are often incomprehensible to users, which constitutes a substantial obstacle to building trust in the technology. The question of accountability is particularly pressing, since the complexity and autonomy of AI decision-making architectures make it difficult to determine who can be held responsible for any unintended consequences (Jarrahi et al., 2023; Daugherty–Wilson, 2024).

7.5 The need for regulatory and educational measures

The sustainable and socially acceptable governance of digital transformation requires coordinated regulatory and educational measures aimed at managing the technological, data-security, ethical, and social risks outlined above. A central element of this framework is the European Union’s Artificial Intelligence Act, which establishes harmonized rules for the placing on the market, putting into service, and use of AI systems within the EU. Through its risk-based approach, the regulation aims to ensure a high level of protection for fundamental rights, safety, and health, while creating conditions for the economic exploitation of trustworthy, human-centred AI systems. As opposed to technological solutions optimized purely for efficiency, the regulatory logic prioritizes the institutionalization of resilience, transparency, and human oversight, particularly in the case of high-risk applications (Regulation (EU) 2024/1689, 2024). If, however, such regulatory constraints apply exclusively within the European Union, there is a risk that technological innovation and the economic exploitation of AI-based solutions will slow down. This could result in a relative competitive disadvantage vis-à-vis regions operating under more flexible regulatory environments, such as the United States or China.

The regulatory environment alone, however, is not sufficient for the successful and responsible integration of artificial intelligence. Education and retraining play a key role in enabling the workforce to adapt to the new competency require-

ments generated by AI and to meet the operational and ethical expectations set by regulation. The early, school-level development of the basic digital skills needed to understand AI-based systems contributes, in the long run, to mitigating technological inequalities. In higher education and vocational training, meanwhile, the acquisition of specialized knowledge enables economic agents to apply the technology in a manner that is both compliant with regulation and competitive. The coordinated functioning of these three domains creates the conditions under which artificial intelligence can simultaneously contribute to productivity growth and to long-term sustainable economic development.

8 THE RELEVANCE OF AI TO GROWTH AND FINANCE IN HUNGARY

The relevance of AI-based knowledge management to Hungary is also indicated by the gap between corporate AI adoption and digital readiness. According to European Commission data, in 2025, 10.4 percent of Hungarian enterprises made use of AI technology, compared with an EU average of 20.0 percent. The share of Hungarian SMEs with at least a basic level of digital intensity reached 59.8 percent, compared with 71.4 percent for the EU (European Commission, 2026). These two indicators suggest that, alongside technological infrastructure, digital skills, organizational adaptation, and the ability to utilize knowledge may also influence the economic exploitation of AI.

In the financial sector, the integration of AI is at a more advanced stage. According to the 2025 FinTech and Digitalization Report of the National Bank of Hungary (MNB), the domestic banking sector's digital development index rose from 66 to 69 points in 2024. The availability of employee training related to AI and process automation doubled within a single year, while the application of AI appeared at nearly every domestic credit institution, although for the time being typically still at an experimental stage, primarily in support of product-sales processes (MNB, 2025).

9 RESULTS OF THE LITERATURE REVIEW

Based on the review of the literature, answers of varying degrees of certainty can be given to the four research questions. With respect to the first research question, the evolution of growth theory has progressed from the exogenous treatment of technology to the recognition of the endogenous role of knowledge, human capital, and innovation. However, certain predictions of the endogenous models – in

particular the scale effects – have not received unambiguous empirical confirmation (Jones, 1995).

The findings relating to the second research question indicate that generative AI may reduce the time required for search, processing, and application in certain knowledge-intensive tasks (Noy–Zhang, 2023; Brynjolfsson et al., 2025). These effects, however, are task- and user-dependent, and therefore do not imply a general reduction in the total cost of access to knowledge.

With respect to the third research question, the literature emphasizes the role of organizational adaptation and complementary intangible investments in the emergence of productivity effects (Brynjolfsson et al., 2021). Estimates of the magnitude and time path of AI’s macroeconomic impact, however, diverge considerably.

For the fourth research question, the Industry 5.0 literature prioritizes human-centred approach, sustainability, and resilience. Complementarity between humans and AI cannot, however, be regarded as automatic, since the technology may have a complementary effect in some tasks and a substituting effect in others. The long-term economic and social consequences of this collaboration therefore require further empirical investigation.

10 LIMITATIONS OF THE STUDY AND DIRECTIONS FOR FURTHER RESEARCH

This study has three limitations. The first concerns the nature of the data: since the analysis is based on secondary sources and does not involve primary data collection, the relationships formulated should be understood as interpretive proposals rather than empirically tested claims. The second limitation concerns the composition of the source base: a substantial portion of the literature on the economic effects of generative artificial intelligence has not yet undergone a complete peer-review process, and the estimates produced by market research firms are not methodologically equivalent to academic findings. The third limiting factor is the shortness of the observation period: generative models have been widely available only since 2022, which – particularly in light of the adaptation lags indicated by the J-curve literature – is still too short a period for the reliable measurement of productivity effects.

These limitations give rise to three directions for future research. The first concerns the company-level operationalization and measurement of the four components of access cost. The second is an investigation of domestic small and medium-sized enterprises, testing the relationship between absorptive capacity and knowledge-management practice. The third is a case study on the financial sector,

which would examine the productivity gains resulting from the formalisation of knowledge management driven by regulatory compliance.

11 SUMMARY

Linking economic growth with AI-driven knowledge management offers a new interpretive framework for analysing long-run productivity processes. The study shows that, in the digital era, closer integration between macroeconomic processes and organizational-level knowledge management has become indispensable. In the age of artificial intelligence, the dynamics of economic growth are increasingly determined – alongside the accumulation of physical capital – by the efficiency with which organizations are able to convert available information into usable knowledge.

This approach places the development of the neoclassical and endogenous models within a new framework. Whilst economic thought has historically viewed technological progress first as an external factor and then as a driver of innovation, in today's economic environment technological development is increasingly becoming an element that can be shaped through internal, organisational knowledge management processes. The paper shows that generative artificial intelligence becomes a macroeconomic factor through the substantive reduction of the knowledge-access costs defined by Joel Mokyr. This is because the technology is capable of converting accumulated, unstructured theoretical knowledge (Ω) into practical applications (λ) with minimal effort, thereby contributing to our understanding of the relationship between innovation and productivity.

One possible explanation for the Solow paradox observed in macroeconomic data can be sought in the time lag between technological adoption and company-level adaptation. The theory of the productivity J-curve suggests that technological investment is a necessary but not, on its own, sufficient condition. The realization of the growth surplus depends, alongside technological adoption, on complementary intangible investments – primarily the transformation of organizational processes and the development of human capital.

In conclusion, based on the Industry 5.0 approach, it can be assumed that long-term economic stability is built on the collaboration between human and machine capabilities. This complementary form of collaboration can help ensure that the growth of the knowledge-based economy remains socially acceptable, provided that regulatory and educational systems are able to address the challenges arising from the digital transition.

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