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ARTIFICIAL INTELLIGENCE IN PRODUCTION THEORY: A NEW ECONOMIC FACTOR?

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ШТУЧНИЙ ІНТЕЛЕКТ У ТЕОРІЇ ВИРОБНИЦТВА: НОВИЙ ЕКОНОМІЧНИЙ ФАКТОР?

The article examines how artificial intelligence (AI) should be represented in production theory in conditions where the traditional capital-labor dichotomy and the residual treatment of technology through total factor productivity (TFP) have become increasingly restrictive. The study systematizes four major research streams: AI as a source of productivity embedded in TFP, AI as task-automation technology, AI as a distinct production factor or "digital labor", and AI as a driver of long-run structural transformation. On this basis, the paper argues that AI should not be reduced either to ordinary capital or to labor-augmenting technology. AI is accumulated through investment like capital, but it also performs cognitive services, scales at near-zero marginal cost, learns through use, and can substitute for or complement human labor depending on task structure and organizational context. To reconcile these properties, the article proposes an integrated three-level framework. At the aggregate level, AI enters the production function as an autonomous cognitive factor. At the task level, its effects are mediated by displacement, productivity, scale, and reinstatement mechanisms. At the diffusion level, realized gains depend on data, organizational capital, sectoral exposure, and adoption lags. The paper demonstrates that this framework improves the interpretation of firm-level productivity effects, helps explain the persistence of the AI productivity paradox, and clarifies why the distributive and growth effects of AI differ across sectors and time horizons. The article concludes that the most adequate near-term representation of AI in production theory is as a distinct hybrid factor — autonomous cognitive capital-service — while transformative scenarios remain a limiting case that is analytically important but not yet a sufficient baseline for empirical modeling.

У статті досліджується, яким чином штучний інтелект (ШІ) має бути представлений у теорії виробництва в умовах, коли традиційна дихотомія "капітал-праця" та трактування технології через залишок сукупної факторної продуктивності (з англ. — total factor productivity) дедалі більше втрачають пояснювальну силу. Систематизовано чотири основні напрями досліджень: ШІ як джерело продуктивності, вбудоване в TFP; ШІ як технологія автоматизації завдань; ШІ як окремий фактор виробництва або "цифрова праця"; ШІ як чинник довгострокових структурних зрушень. На цій основі доведено, що ШІ не може бути зведений ані до звичайного капіталу, ані до технології, що лише підвищує продуктивність праці. ШІ накопичується через інвестиції под-

ібно до капіталу, але водночас надає когнітивні послуги, масштабується майже без граничних витрат, навчається в процесі використання та може як заміщати, так і доповнювати людську працю залежно від структури завдань і організаційного контексту. Для узгодження цих властивостей запропоновано інтегровану трирівневу рамку. На агрегованому рівні ШІ входить до виробничої функції як автономний когнітивний фактор. На рівні завдань його ефекти опосередковуються механізмами витіснення, продуктивності, масштабу та відновлення нових видів праці. На рівні дифузії реалізовані вигоди залежать від даних, організаційного капіталу, галузевої експозиції та лагів упровадження. Показано, що така рамка поліпшує інтерпретацію впливу ШІ на продуктивність фірм, пояснює збереження парадоксу продуктивності ШІ та дає змогу точніше зрозуміти відмінності в розподільчих і зростальних ефектах між секторами та часовими горизонтами. Зроблено висновок, що найбільш адекватним коротко— та середньостроковим представленням ШІ у теорії виробництва є окремий гібридний фактор — автономний когнітивний капітал-сервіс, тоді як трансформаційні сценарії залишаються важливим, але ще не базовим емпіричним випадком.

Key words: artificial intelligence, production theory, digital labor, total factor productivity, automation, economic growth, factor income shares.

Ключові слова: штучний інтелект, теорія виробництва, цифрова праця, сукупна факторна продуктивність, автоматизація, економічне зростання, факторні доходи.

PROBLEM STATEMENT AND ITS RELATION TO IMPORTANT SCIENTIFIC AND PRACTICAL TASKS

The rapid diffusion of artificial intelligence technologies has revealed clear limits of standard economic representations of production. In the conventional neoclassical framework, output is generated through combinations of capital and labor, while technological change is typically absorbed by total factor productivity. This architecture was analytically useful for industrial economies in which most productive capacity was embodied either in physical machinery or in human labor effort. However, it is increasingly inadequate for an economy in which productive capacity is also embodied in models, data, algorithms, cloud infrastructure, and autonomous decision systems.

The central theoretical difficulty is that AI combines attributes that economic theory traditionally distributes across different categories. AI is accumulated through investment and embedded in infrastructures, models, and software stacks, which makes it similar to capital. At the same time, it performs services previously associated with labor: classification, forecasting, recommendation, drafting, coding, and increasingly complex forms of cognitive problem-solving. Unlike ordinary capital, moreover, AI can often be replicated at very low marginal cost, improved through use, and redeployed across multiple contexts with minimal physical friction. As a result, the usual distinction between a stock input and a flow of labor services becomes blurred.

A SECOND PROBLEM CONCERNS MEASUREMENT

If AI is treated as part of the TFP residual, its contribution is not directly identified. In that case, measured productivity gains may be biased downward in the short run and conceptually misallocated in the long run. This issue is particularly visible in the divergence between strong micro-level evidence on AI-related efficiency improvements and the still modest aggregate productivity dynamics observed in many economies. The persistence of this divergence suggests that the challenge is not only statistical; it also reflects structural lags, complementary investments, and theoretical ambiguity regarding the economic status of AI.

These problems are directly connected with important scientific and practical tasks. Scientifically, the misclassification of AI distorts the interpretation of productivity, factor shares, labor demand, and long-run growth. Practically, it affects business valuation, investment decisions, competition policy, workforce strategy, and public regulation. If AI is modeled incorrectly, policy responses to labor-market adjustment, taxation, innovation incentives, and market concentration risk being built on unstable analytical foundations. Accordingly, clarifying the place of AI in production theory is now a necessary condition for an adequate interpretation of structural economic change.

ANALYSIS OF RECENT RESEARCH AND PUBLICATIONS

The contemporary literature on AI in production theory can be grouped into four major streams that are closely related but not yet theoretically unified.

The first stream continues to interpret AI primarily through the language of productivity and TFP. In this view, AI appears as a powerful but still partly hidden technological input whose effects are reflected in efficiency gains, process optimization, and innovation performance. Cao et al. (2025) show that AI adoption improves enterprise total factor productivity and that this effect is mediated by innovation capability and shaped by managerial characteristics. Lindberg (2025), using a translog production function for U.S. manufacturing, argues that AI behaves as a distinct productivity-enhancing input, although its gains remain conditioned by complementarities and diminishing returns. At the macro level, the OECD estimates that AI may add roughly 0.25—0.6 percentage points to annual TFP growth over a ten-year horizon, while emphasizing that adoption rates, sectoral exposure, and reallocation frictions are decisive for aggregate outcomes (Filippucci et al., 2024). This stream is highly valuable empirically, but its conceptual weakness is that it often leaves AI partly inside a residual category instead of resolving what kind of input AI actually is.

The second stream is task-based. Restrepo (2023) demonstrates that automation technologies operate by substituting capital for labor in a widening range of tasks, generating both a productivity effect and a displacement effect. This perspective is crucial because it explains why AI and automation reshape occupational structures and factor shares even when aggregate output rises. Aghion and Bunel (2024) adapt the task-based logic to contemporary AI and argue that the macroeconomic effect of AI depends on the share of exposed tasks, the scale of adoption, and the magnitude of productivity gains. The task approach is particularly strong in identifying heterogeneous labor effects, yet it does not on its own determine whether AI should be classified as capital, software-augmented technology, or a separate factor in the aggregate production function.

The third stream explicitly challenges the capital-labor dichotomy. Growiec (2019) proposes a hardware-software model in which production always requires both physical execution and informational instruction; in this framework, human cognition and pre-programmed software belong to the broader software factor, while physical labor and machines belong to hardware. Farach et al. (2025) develop the related concept of digital labor and argue that AI possesses distinct economic properties — scalability, intangibility, self-improvement, rapid obsolescence, and nuanced substitutability with human labor — that justify treating it as a separate production factor rather than merely an element of TFP. Gersbach et al. (2025) extend this logic further by modeling AI as self-learning capital that improves through application and interacts dynamically with applied research through spillovers and labor reallocation. This stream offers the most direct response to the classification problem, though it differs internally on whether AI should be conceptualized as software, capital, labor-like services, or a hybrid category.

The fourth stream studies structural and potentially transformative macroeconomic change. Trammell and Korinek (2023) analyze conditions under which AI could become a gross substitute for labor and thereby accelerate growth while sharply reducing the labor share. Mici et al. (2026) frame the spread of AI and automation as part of a broader transition toward technological capital-dominated production with consequences for distribution and social finance. Skare et al. (2025) reinterpret the AI productivity paradox through long-memory analysis and suggest that AI gains may arrive with substantial delays rather than being absent altogether. This stream highlights the importance of long-run growth, inequality, and institutional adaptation, but its scenarios range from cautious diffusion to transformative AI and therefore require a more explicit bridge to empirical production modeling.

Despite major progress, the literature remains fragmented. AI is alternately represented as hidden productivity, task automation, digital labor, self-learning capital, software, or transformative capital deepening. The absence of an integrated framework means that different strands often speak to different levels of analysis without a common translation mechanism between them.

PURPOSE OF THE ARTICLE

The purpose of the article is to determine the most theoretically consistent representation of artificial intelligence in production theory and to justify an integrated framework in which AI is modeled as a distinct autonomous cognitive production factor whose economic effects depend on task structure, organizational complements, and diffusion dynamics.

MAIN RESEARCH FINDINGS AND DISCUSSION

The starting point of most production theory remains the neoclassical specification in which output is represented as a function of capital, labor, and an efficiency parameter:

$$Y = A \times F(K, L) \qquad (1).$$

In the Cobb-Douglas version, the same idea is written as:

$$Y = A \times K^{\alpha} \times L^{\beta} \qquad (2).$$

The analytical attractiveness of this setup is well known: factor shares are tractable, substitution properties are transparent, and technological progress can be summarized parsimoniously by the evolution of A. Yet this very parsimony becomes restrictive once productive activity depends not only on physical capital and human effort, but also on algorithms that perform economically relevant cognitive operations.

AI challenges the standard representation in at least three ways. First, it is not merely a recipe external to production. When deployed in real organizations, AI does not simply raise the efficiency of existing inputs in a diffuse way; it performs concrete operations that can substitute for some human tasks and complement others. Second, AI is neither purely rivalrous nor purely tied to one production site. Once trained and deployed, many AI systems can be replicated across users and workflows with very low marginal cost. Third, AI quality is not static. Through retraining, feedback, and broader application, the productivity of the same system may evolve over time, which is difficult to reconcile with the treatment of technology as an exogenous and homogeneous multiplier.

These features do not imply that the capital-labor framework should be abandoned entirely. Physical capital and labor remain indispensable. Rather, they indicate that the two-factor architecture is no longer sufficient as a complete ontology of production. The key theoretical issue is therefore not whether capital and labor still matter, but whether AI can be incorporated adequately only as a shift

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parameter or whether it should enter the production function more directly.

Treating AI as part of TFP has an intuitive appeal. In many datasets, direct measures of AI are incomplete, short, or difficult to compare across firms and sectors. Researchers therefore often infer AI effects indirectly from changes in output, productivity, or profitability after adoption. This strategy has yielded important findings. Firm-level studies indicate that AI can improve productivity through automation, decision support, and innovation mechanisms, while macro scenarios suggest positive but moderate aggregate gains over medium horizons [1; 2; 3].

However, the residual approach has two limitations. The first is conceptual opacity. Once AI is folded into TFP, one cannot distinguish whether productivity gains come from algorithmic substitution for labor, better matching and coordination, improvements in quality, the exploitation of new data assets, or complementary organizational redesign. Farach et al. correctly describe TFP in this context as a black box that hides the mechanism of change rather than identifying it [4].

The second limitation is temporal. The observed divergence between promising micro evidence and weaker aggregate outcomes is not well explained by a purely residual treatment. The OECD points out that aggregate gains depend on adoption rates, sectoral exposure, input-output linkages, and reallocation frictions [2]. ?kare et al. show that AI-related TFP effects may follow a delayed and nonlinear pattern, which is consistent with a long-lag diffusion process rather than an immediate macro breakthrough [5]. In other words, when AI is captured only ex post through measured productivity, theory loses its ability to explain why effects arrive slowly, unevenly, and often conditionally.

For these reasons, TFP remains a useful empirical container, but not an adequate theoretical home for AI. It is a measurement convenience, not a satisfactory ontological classification.

The task approach is indispensable for understanding how AI changes production from within. Restrepo emphasizes that automation displaces labor from specific tasks while lowering costs and potentially increasing output; hence the core tension between the displacement effect and the productivity effect [6]. This framework explains why labor-market consequences are heterogeneous across occupations, skill groups, and industries. It also clarifies why firm-level employment outcomes cannot be read mechanically as aggregate outcomes.

For AI, the task approach remains especially relevant because many contemporary systems automate neither entire occupations nor all functions of a worker, but selected tasks embedded in broader workflows. Aghion and Bunel show that macro gains depend on the fraction of tasks exposed to AI, the magnitude of performance improvements, and the speed of adoption [7]. This is consistent with the empirical observation that AI can raise performance substantially in narrow contexts while leaving aggregate productivity statistics comparatively muted.

Yet the task perspective, while necessary, is not sufficient for the current research question. It explains where substitution and complementarity occur, but not what AI is at the aggregate level. A task model can tell us that software or machines now perform a larger share of tasks once allocated to labor. It does not, by itself, settle whether the aggregate representation should classify AI as capital, software-embedded technology, labor-equivalent services, or a separate input. Put differently, the task model is strongest at the meso level of production organization, whereas the factor-classification problem belongs to the macro and theoretical architecture of production itself.

The implication is that task-based and factor-based approaches should be treated as complementary, not competing. The task layer identifies the mechanism of reallocation; the factor layer identifies the aggregate category into which the AI service flow should enter.

The most promising theoretical advances come from the literature that places AI explicitly inside the production function. Growiec's hardware-software model provides a powerful conceptual insight: every production process requires both an executing component and an instructing component [8]. Once this distinction is made, pre-programmed software and human cognition become analytically comparable as alternative sources of instructions. This move is important because it shows that the core complementarity in digital production may run not between capital and labor as such, but between hardware and software.

Farach et al. make a related argument in the language of digital labor. Their central claim is that AI performs autonomous cognitive work and therefore deserves explicit treatment as a production factor in addition to traditional capital and human labor [4]. The strength of this view lies in the unusual economic properties it assigns to AI. Digital labor is intangible, highly scalable, partly non-rival, capable of autonomous improvement, and subject to rapid obsolescence. None of these properties fit cleanly into the textbook concept of physical capital; neither do they fit the biological and rivalrous nature of human labor.

Gersbach et al. enrich the argument by modeling AI as self-learning capital that improves through application and generates spillovers with applied research [9]. This perspective is useful because it highlights a feature often absent from traditional factor taxonomies: AI does not merely provide a service flow from a fixed stock; its productive quality can change endogenously through use, data accumulation, and feedback.

Taken together, these contributions suggest that AI should be treated as a hybrid input with three defining characteristics. First, it is investment-based: firms must spend resources to acquire, train, maintain, and deploy it. Second, it is service-delivering: it performs economically relevant cognitive operations that affect output directly. Third, it is recursively improvable: under some conditions, its quality evolves through learning and interaction. A production factor with this combination of properties cannot be represented adequately as ordinary capital alone.

On the basis of the literature reviewed above, the article proposes an integrated framework with three interconnected analytical layers.

At the aggregate layer, production should be represented not as a function of only capital and labor, but as a function of capital, labor, and effective AI services:

$$Y_t = F(K_t, L_t, G_t) \quad (3).$$

Here G_t denotes the stock of effective autonomous cognitive services generated by AI systems. The term "effective" is essential. AI does not produce value simply because a model exists. Its contribution depends on deployment quality, fit to business processes, and the availability of complementary assets. Thus, in reduced form, effective AI services can be written as:

$$G_t = \Phi(M_t, D_t, O_t) \quad (4).$$

where M_t denotes models and compute embodied in deployable AI systems, D_t denotes usable data resources, and O_t denotes complementary organizational capital, including routines, process redesign, governance, and human supervision. This second relationship does not imply that data and organizational capital must always be modeled as separate primary factors. Rather, it shows that AI performance is conditional on complementary assets and therefore should be interpreted as a realized service stock, not merely as installed software.

At the task layer, the output effect of G_t depends on the allocation of tasks between labor and AI. In some tasks AI substitutes for labor, generating displacement. In others it complements labor, raising quality, speed, or scale. The net effect therefore depends on the task composition of production, the elasticity of substitution, and the pace at which new human-intensive tasks are created. This preserves the main insight of the task literature while embedding it in a broader production-function framework.

At the diffusion layer, realized gains depend on adoption lags, sectoral exposure, regulation, organizational readiness, and general equilibrium effects. This is the layer most clearly emphasized by the OECD and by the literature on the productivity paradox [2; 5]. In practical terms, the same theoretical stock of AI may produce very different observed productivity outcomes across firms and countries because the complementary conditions of diffusion differ.

This three-level framework resolves a major part of the classification problem. AI should enter production theory as a distinct autonomous cognitive factor at the aggregate level, while its realized economic consequences must still be interpreted through task allocation and diffusion constraints. Such a framework is more informative than a pure TFP treatment, more general than a pure task model, and more empirically usable than purely transformative singularity scenarios.

Implications for productivity, labor, and long-run growth are robust. The first implication concerns productivity measurement. If AI is modeled as a distinct factor, researchers can separate direct AI services from residual TFP and thereby reduce conceptual ambiguity. This does not eliminate all measurement problems, but it improves the interpretation of empirical results. Firm-level estimates of AI's contribution can then be linked more clearly to deployment quality, task substitution, and complementary intangible investment.

The second implication concerns labor. A distinct-factor representation does not imply that labor becomes analytically secondary. On the contrary, it clarifies why labor effects are heterogeneous. Where AI performs codifiable cognitive tasks at lower cost, substitution pressures intensify. Where human judgment, tacit coordination, accountability, or relational work remain central, complementarity persists or even deepens. Restrepo's task framework remains essential here because the aggregate factor G_t does not replace the need to study task-level restructuring [6].

The third implication concerns factor shares and market structure. If AI is treated only as a technology shifter, distributional effects can be understated. Once AI enters production more directly, it becomes easier to analyze why income may shift toward owners of AI, compute infrastructure, data assets, and complementary intangible capital. This also helps explain why market concentration can increase when leading firms control the data, hardware, platforms, and organizational capabilities needed to scale AI effectively.

The fourth implication concerns long-run growth. In the medium term, the most plausible scenario remains one of positive but bounded gains shaped by diffusion frictions, sectoral heterogeneity, and complementary investment requirements [2;7]. In the longer run, however, the framework must remain compatible with more radical possibilities. Trammell and Korinek show that if AI becomes a gross substitute for labor in production and later in research, the economy may break the historical regularities of constant labor shares and stable exponential growth [10]. The integrated framework proposed here can accommodate such scenarios by interpreting them as a limiting case in which G_t becomes the dominant cognitive input across both production and innovation. But these transformative outcomes should not be treated as the default empirical benchmark for present-day modeling.

Accordingly, the most balanced conclusion is that contemporary production theory should treat AI as a distinct hybrid factor whose economic significance is already real, but whose macroeconomic consequences remain conditional rather than uniform. This position avoids the understatement inherent in pure TFP approaches and the overstatement that can arise when transformative AI scenarios are taken as an immediate empirical baseline.

CONCLUSIONS AND PROSPECTS FOR FURTHER RESEARCH

The analysis confirms that artificial intelligence cannot be represented adequately only as a residual component of total factor productivity or as an ordinary extension of physical capital. AI differs from standard capital because it delivers autonomous cognitive services, scales at very low marginal cost, and can improve through use. At the same time, it differs from human labor because it is investment-created, partly non-rival, and deployable across tasks and contexts without the biological constraints that define human work. These properties justify treating AI in production theory as a distinct hybrid factor.

At the theoretical level, the most convincing solution is not to replace existing approaches, but to connect them. The article therefore proposes a three-level framework in which AI enters the aggregate production function as effective autonomous cognitive services, while task allocation explains heterogeneous substitution and complementarity effects, and diffusion dynamics explain

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the gap between micro evidence and macro outcomes. Such a framework is better suited to contemporary production systems than a pure capital-labor-TFP scheme.

At the empirical level, this approach helps explain three stylized facts of the current AI transition: first, measurable productivity gains at the firm level; second, delayed and uneven macroeconomic gains; third, growing concern about labor shares, concentration, and the distribution of returns from intangible assets. It also clarifies that the relevant complements to AI — data, organizational capital, governance, and compute infrastructure — are not peripheral details, but central determinants of realized economic value.

Prospects for further research are threefold and include: empirical — the construction of more stable direct measures of effective AI services at the firm, sectoral, and national levels; the second is structural — the integration of task-based and factor-based estimation strategies in a single empirical design; the third is normative — the analysis of how different ownership and governance regimes for AI affect income distribution, competition, and long-run growth. Advancing these directions is necessary if production theory is to remain adequate to the economic reality shaped by artificial intelligence.

References:

1. Cao, Y., Hao, L., Kou, L., Zhou, J. and Zou, L. (2025), "Whether, How and When Do Artificial Intelligence Technologies Improve Enterprise Total Factor Productivity?", Journal of Internet Technology, vol. 26, no. 2, pp. 241—253, [Online]. https://doi.org/10.70003/160792642025032602009.

2. Filippucci, F., Gal, P. and Schief, M. (2024), "Miracle or Myth? Assessing the macroeconomic productivity gains from Artificial Intelligence", OECD Artificial Intelligence Papers, no. 29, OECD Publishing, Paris, [Online]. https://doi.org/10.1787/b524a072-en.

3. Lindberg, D.G. (2025), "Harnessing AI for smart manufacturing: insights from Industry 4.0", Discover Artificial Intelligence, vol. 5, article 111, [Online]. https://doi.org/10.1007/s44163-025-00363-0.

4. Farach, A., Cambon, A. and Spataro, J. (2025), "Evolving the Productivity Equation: Should Digital Labor Be Considered a New Factor of Production?", Papers from arXiv.org, arXiv:2505.09408, available at: https://arxiv.org/abs/2505.09408 (accessed 4 April 2026).

5. Skare, M., Porada-Rochon, M. and Veselica Celic, R. (2025), "Total factor productivity dynamics and the artificial intelligence paradox: Evidence from long-memory analysis", Journal of International Studies, vol. 18, no. 4, pp. 218—242, [Online]. https://doi.org/10.14254/2071-8330.2025/18-4/11.

6. Restrepo, P. (2023), "Automation: Theory, Evidence, and Outlook", NBER Working Paper, vol. 31910, available at: https://www.nber.org/papers/w31910 (accessed 4 April 2026).

7. Aghion, P. and Bunel, S. (2024), "AI and Growth: Where Do We Stand?", manuscript, EmergingTech Economic Research Network, Federal Reserve Bank of San Francisco, June, available at: https://www.frbsf.org/wp-content/uploads/AI-and-Growth-Aghion-Bunel.pdf (accessed 4 April 2026).

8. Growiec, J. (2019), "The Hardware-Software Model: A New Conceptual Framework of Production, R&D, and Growth with AI", SGH KAE Working Papers Series, vol. 2019/042, available at: https://cor.sgh.waw.pl/handle/20.500.12182/1120 (accessed 4 April 2026).

9. Gersbach, H., Komarov, E. and von Maydell, R. (2025), "Artificial intelligence as self-learning capital", Economic Modelling, vol. 153, article 107221, [Online]. https://doi.org/10.1016/j.econmod.2025.107221.

10. Trammell, P. and Korinek, A. (2023), "Economic Growth under Transformative AI", NBER Working Paper, vol. 31815, revised September 2025, available at: https://www.nber.org/papers/w31815 (accessed 4 April 2026).

11. Mici, V., Shehu, I., Lila, A., Hoxha, V. and Bombaj, F. (2026), "The Macroeconomic Transition of Technological Capital in the Age of Automation", Academic Journal of Interdisciplinary Studies, vol. 15, no. 1, [Online]. https://doi.org/10.36941/ajis-2026-0091.

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