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INFORMATION TECHNOLOGY / ARTIFICIAL INTELLIGENCE USE AND LABOR PRODUCTIVITY IN FIRMS*

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Abstract. This study aims to develop conceptual frameworks and propose an appropriate research methodology for analyzing the relationship between information technology (IT) and artificial intelligence (AI) use and labor productivity in firms, particularly within the context of Latvian ones. Drawing from a comprehensive literature review, it identifies key theoretical models, including the Technology Acceptance Model, Diffusion of Innovations, Resource-Based View, and Socio-Technical Systems Theory, as foundational for understanding IT/AI use in firms and its effects on productivity. The study also proposes a hybrid research methodology combining quantitative causal inference techniques (such as panel data regressions, difference-in-differences, instrumental variable regressions, and Stochastic Frontier Analysis) with qualitative approaches (including case studies, expert interviews, and content analysis) to capture both the measurable impacts and organizational dynamics of IT/AI use. Furthermore, it outlines how advanced tools like machine learning models and Bayesian networks can model complex interdependencies. The conceptual framework integrates theoretical insights with empirical indicators from Latvian official statistics, illustrating how IT/AI contributes to productivity via automation, augmentation, and labor reallocation. The study concludes by identifying limitations (such as its conceptual focus and country-specific scope) and recommends future empirical studies that apply the proposed framework across sectors and regions using firm-level data to validate and expand upon its findings.

Keywords: information technology (IT); artificial intelligence (AI); enterprises; labor productivity; conceptual framework; correlation vs. causality; research methodology.

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1. Introduction

Currently, information technology (IT) and artificial intelligence (AI) are increasingly recognized as crucial drivers of labor productivity in firms (Mura et al., 2017; Makridakis, 2017; Graetz & Michaels, 2018; Nolan,

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2020; Bonetti et al., 2022; Tugui et al., 2022; Gao & Feng, 2023). Understanding the conceptual frameworks (Ngulube et al., 2015; van der Walddt, 2020; Majeed et al., 2023; Mohammed & Ahmad, 2025) of IT/AI use in firms and their impact on labor productivity (Syverson, 2011; Zitar et al., 2023; Paudel, 2024) (or just simple correlation without any causality (Blalock, 1961; Geels, 2022; Gershman & Ullman, 2023; Little, 2023; Hussain et al., 2024) is essential for both academic research and practical implementation.

The American economist, the author of the theory of the so-called “new economic geography” P. Krugman back in the early 1990s developed the only way by which it is possible to achieve an increase in living standards in a long-term – by increasing productivity (Krugman, 1991a, 1991b, 1997). Productivity is particularly relevant for those countries and regions that are at the so-called efficiency-driven stage of their economic development, since it is at this stage that productivity (and even more efficiency) is the main driver of economic growth (Sala-i-Martin et al., 2016) (in Latvia, such regions are Latgale, Vidzeme and Zemgale (Boronenko, 2009; Zeibote, 2018)). In the modern context of fall of the labor share and the rise of superstar firms (Autor et al., 2020), labor productivity (output per worker) remains crucial for economic growth and rising living standards. However, the way productivity gains translate into wages and labor’s share of income has changed. Traditionally, higher labor productivity was expected to drive higher wages, but the rise of superstar firms suggests a decoupling of this relationship, because many of the productivity improvements in superstar firms stem from automation, IT / AI, and other labor-saving technologies. As a result, productivity growth does not necessarily translate into higher demand for labor, weakening the link between labor productivity and wage growth (Autor et al., 2020).

The Superstar Firm Hypothesis (Autor et al., 2020) suggests that aggregate productivity (driven by dominant firms) may increase, even if the average firm’s productivity stagnates. This highlights the importance of reallocation effects in productivity measurement. Techniques like work-study, automation, and quality control remain important in conceptual frameworks of productivity (Maheshwari, 2016). However, in industries dominated by superstar firms, productivity improvement is less about efficiency at the firm level and more about market structure (firms gaining market share and exercising pricing power). Some empirical insights into the role of labor productivity in modern firms performance (Yousaf, 2023) challenge the classical view that labor productivity is the most important driver of firms success. In the era of IT / AI, performance is increasingly shaped by market structure, strategic positioning, and quality management – rather than labor productivity alone, in particular, in superstar or high-quality firms (Yousaf, 2023).

Against the backdrop of unanimous acceptance of IT/AI as factors for increasing labor productivity, but ambiguity regarding the role of labor productivity itself in the economic success of firms, contemporary researchers continue to pay close attention to labor productivity along with its efficiency (Korshenkov & Ignatyev, 2020; Ali et al., 2024; Korkmaz & Korkmaz, 2024; Shamim, 2024). In particular, Korshenkov and Ignatyev (2020) distinguish labor productivity from labor efficiency. They define productivity as the ability to create as much output as possible per unit of time, whereas efficiency takes into account the amount of production factors utilized in the process (Korshenkov & Ignatyev, 2020). In turn, other modern studies (for example, Zitar et al., 2023; Korkmaz & Korkmaz, 2024) do not explicitly distinguish between labor productivity and labor efficiency in enterprises but discusses factors influencing productivity, such as human capital, technological change, and economies of scale.

In the international research space, there are suggestions that IT/AI use in firms do not directly influence labor productivity but rather modifies worker routines and interactions in firms (Zitar et al., 2023). There is an uncertainty about the magnitude of IT/AI’s impact on workforce productivity, as IT/AI-powered technologies still require human supervision in many cases. Moreover, there is no appropriate and comprehensive research methodology for studying relationship between IT/AI use and labor productivity in firms. This study aims to create conceptual frameworks of IT/AI use and labor productivity in firms, as well as to propose an appropriate research methodology for studying their relationship (correlation or causality). As a result of this study, the following research questions need to be answered: (1) What are the main theoretical backgrounds for understanding IT/AI use and labor productivity in firms? (2) Should labor productivity and labor efficiency in firms be considered distinct concepts, or can they be used interchangeably? (3) What research methodologies are best suited for studying the relationship between IT/AI use and labor productivity in firms? By addressing

these questions, the study will provide a holistic approach for understanding and analyzing the relationship between IT/AI use and labor productivity in firms, bridging conceptual insights with empirical evidence and methodological innovation.

The subject of this study is IT/AI use in relation to labor productivity in Latvian firms. To create conceptual frameworks of IT/AI use and labor productivity in firms, as well as to propose an appropriate research methodology for studying their relationship (correlation or causality) the following research methods were applied: monographic method reviewing the relevant theories and models, synthesis and logical analysis for conceptualization of IT/AI use in relation to labor productivity in firms. For empirical interpretation of conceptual frameworks of IT/AI use and labor productivity in firms, statistical indicators from the annual survey on IT/AI use in Latvian firms, which [survey] has been conducted by the Central Statistical Bureau of Latvia since 2004, were used (Central Statistical Bureau of Latvia, 2024a).

The structure of the study consists of five main sections. The literature review provides an extensive theoretical background, organized into four parts. The third section presents our original conceptual framework of IT/AI use in relation to labor productivity, integrating theoretical models and empirical indicators from Latvian statistics. The fourth section proposes a research methodology for studying the IT/AI–productivity relationship, suggesting a hybrid approach that combines quantitative causal inference methods with qualitative tools like case studies and interviews. The final section draws conclusions from the study, addresses its limitations, and offers recommendations for future empirical research.

2. Literature review

This literature review aims to explore: conceptual framework of IT/AI use in firms, conceptual framework of labor productivity, studies on impact of IT/AI use on labor productivity in firms, research methodologies used to analyze the relationship between IT/AI use and labor productivity in firms. Accordingly, this literature review is structured into several key sections:

(1) conceptual framework of IT/AI use in firms based on the following models and theories: the Technology Acceptance Model (TAM) that explains how perceived usefulness and ease of use influence technology adoption (Davis, 1986, 1989; Ma & Liu, 2004; Čižo et al., 2024), Diffusion of Innovations (DOI) Theory that examines the adoption curve of new technologies (Acemoglu et al., 2018; Cockburn et al., 2018), the Resource-Based View (RBV) arguing that IT/AI serve as strategic resources enhancing firm capabilities (Przegalinska et al., 2025; Han et al., 2025), Socio-Technical Systems (STS) Theory that highlights the interaction between technology and organizational structures (Appelbaum, 1997; Walker et al., 2008);

(2) conceptual framework of labor productivity including productivity and IT/AI relationship theories: conceptual framework and empirical interpretation of labor productivity (Maheshwari, 2016; Autor et al., 2020; Korshenkov & Ignatyev, 2020; Yousaf, 2023); Solow's Productivity Paradox that questions whether IT/AI investments translate into measurable productivity gains (Brynjolfsson et al., 2018; Capello et al., 2022), Brynjolfsson & McAfee's Second Machine Age arguing that IT/AI drive economic transformation by complementing human labor (Brynjolfsson & McAfee, 2014; Spencer, 2017), Complementarity Theory suggesting that IT/AI enhance productivity when combined with human capital and organizational changes (Biagi & Parisi, 2012; Fitri et al., 2023);

(3) studies on impact of IT/AI use on labor productivity in firms: efficiency gains – how IT/AI optimize workflows, reduce errors, and enhance decision-making (Ali et al., 2024; Shamim, 2024), automation vs. augmentation – the distinction between replacing human labor and augmenting human capabilities (Acemoglu & Restrepo, 2018; Isaza & Cepa, 2024; Paudel, 2024), challenges and risks – potential issues including workforce displacement, upskilling needs, and productivity paradoxes (Zirar et al., 2023);

(4) research methodologies used to analyze the relationship between IT/AI use and labor productivity in firms: quantitative approaches – econometric models (use of Cobb-Douglas production function with IT and AI

variables), panel data analysis (longitudinal studies examining IT/AI investments and productivity trends), productivity indices (measuring productivity changes through Total Factor Productivity (TFP) and labor productivity metrics); qualitative approaches – case studies (in-depth analysis of specific firms implementing IT / AI-driven solutions), expert interviews and surveys (gathering insights from industry professionals and researchers); hybrid approaches – mixed-methods research (combining qualitative case studies with quantitative statistical models), experimental designs (conducting controlled experiments to measure IT / AI's impact on productivity) (Bartel et al., 2007; Syverson, 2011; Bianchini et al., 2022; Rammer et al., 2022; Necula et al., 2024; Paudel, 2024).

2.1. Literature review on conceptual framework of IT/AI use in firms

The Technology Acceptance Model (TAM) (Davis, 1986, 1989; Ma & Liu, 2004; Čižo et al., 2024) is a widely used framework for understanding and empirical interpretation of IT/AI use in firms. Developed by Davis (1986, 1989), TAM is grounded in social psychology, and has been extensively tested in various organizational settings to predict user acceptance and usage behavior. TAM identifies two key determinants of technology adoption (Davis, 1986, 1989): Perceived Usefulness (PU) – the degree to which a person believes that using a system will enhance job performance, and Perceived Ease of Use (PEOU) – the extent to which a person believes that using a system will be free of effort. Davis (1989) developed validated scales for measuring PU and PEOU, with high reliability (Cronbach's alpha: .98 for PU, .94 for PEOU). Empirical studies show that PU has a stronger correlation with actual usage than PEOU (Davis, 1986, 1989; Ma & Liu, 2004). In other words, users are more likely to adopt a system if they find it useful, even if it is not particularly easy to use. A meta-analysis of 26 empirical studies (Ma & Liu, 2004) on TAM found: (1) strong support for PU's predictive power on IT/AI acceptance, (2) inconsistent effects of PEOU on actual IT/AI use, (3) the need for context-specific modifications (e.g., industry, experience level, cultural factors).

One of the most influential theories in the domain of IT/AI use in firms is the Diffusion of Innovations (DOI) Theory, which explains the adoption curve of new technologies (Acemoglu et al., 2018; Cockburn et al., 2018). IT/AI are often considered General-Purpose Technologies (GPTs) that drive technological advancements across various industries (Acemoglu et al., 2018). These technologies enhance research and development (R&D) efficiency, improve firm survival rates, and contribute to long-term economic growth. Firms differ in their innovative capacity, which determines their ability to use and benefit from IT/AI (Acemoglu et al., 2018). High-type firms with strong innovation capabilities leverage IT/AI for improved efficiency and higher productivity growth. Low-type firms struggle with IT/AI use and may become unproductive over time. Market forces ensure that only productive firms remain active. Taxing incumbent firms can facilitate the exit of low-productivity firms, allowing resources to be reallocated to more innovative, IT / AI-driven firms (Cockburn et al., 2018). The DOI theory examines how IT/AI spread within an industry. Firms use IT/AI at different rates, categorized as innovators, early adopters, majority adopters, or laggards (Acemoglu et al., 2018). To quantify IT/AI use in firms, researchers (Acemoglu et al., 2018) use the following indicators: R&D expenditure measures investment in IT / AI-driven innovation. IT / AI-related patent filings track firm-level technological advancements. The shift of skilled labor to R&D roles examines the effect of IT / AI-driven firm exits on workforce dynamics. IT / AI-induced job creation tracks employment shifts towards AI-based industries. Taxation on incumbents helps reallocate resources to IT / AI-driven firms and enhances productivity. Avoiding excessive R&D subsidies prevents the survival of non-innovative firms, maintaining market efficiency (Cockburn et al., 2018). The above studies highlight the importance of IT/AI as transformative technologies that impact firm productivity, market dynamics, and labor reallocation.

The conceptual framework for understanding and empirical measurement of IT/AI use in firms based on the Resource-Based View (RBV) (Przegalinska et al., 2025; Han et al., 2025) emphasizes that IT/AI adoption and strategic implementation are driven by an organization's internal innovation resources (IIR) and collaborative innovation networks (CIN) (Przegalinska et al., 2025). Firms with proprietary datasets, internally developed algorithms, and specialized IT/AI talent gain a competitive advantage by leveraging these resources for sustained growth. Collaborative networks further enhance IT/AI orientation by fostering knowledge exchange across technology and data domains. However, external factors such as environmental uncertainty negatively moderate this relationship by introducing risks and unpredictability, making AI resource allocation more complex. Conversely, corporate digital culture positively influences IT/AI use in firms by enhancing employees'

awareness and sensitivity to digital transformation (Han et al., 2025). The empirical measurement of IT/AI use in firms under RBV includes firm-level R&D investments in IT / AI, patent filings, IT / AI-related workforce composition, and the integration of IT / AI-driven decision-making (Przegalinska et al., 2025; Han et al., 2025). The above studies highlight that firms with strong IT/AI capabilities and collaborative innovation networks outperform competitors in terms of efficiency, product innovation, and strategic agility.

The conceptual framework for understanding and empirical measurement of IT/AI use in firms based on Socio-Technical Systems (STS) Theory (Appelbaum, 1997; Walker et al., 2008) emphasizes the integration of both social and technical components within organizations to optimize system performance. STS theory posits that firms using IT/AI in firms must ensure a balance between technological advancements and human processes to achieve sustainable efficiency (Appelbaum, 1997). The joint optimization principle of STS highlights that IT/AI should not only improve productivity but also enhance work quality and employee engagement. Empirical measurement of IT/AI use under STS theory involves assessing organizational technology adoption, employee interaction with IT/AI systems, workflow integration, and system adaptability (Walker et al., 2008). The theory underscores the importance of work design, advocating for decentralized decision-making, multi-skilled teams, and adaptive job roles that allow workers to leverage AI tools effectively (Appelbaum, 1997; Walker et al., 2008). The above studies suggest that firms using IT/AI with an STS approach see improved knowledge sharing, innovation capacity, and collaborative problem-solving, reducing resistance to AI-driven change.

2.2. Literature review on a conceptual framework of labor productivity including productivity and IT / AI relationship theories

Labor productivity is often defined as output per worker or sales per employee, reflecting a firm's efficiency in utilizing labor inputs. Recent studies (Maheshwari, 2016; Autor et al., 2020; Korshenkov & Ignatyev, 2020; Yousaf, 2023) highlight that productivity is influenced by firm-specific resources, industry concentration, and external economic conditions. The Resource-Based View (RBV) perspective emphasizes that firms with superior internal capabilities, such as investments in human capital and technology, achieve higher labor productivity (Maheshwari, 2016). The EFQM Excellence Model (Yousaf, 2023) links productivity with quality management, suggesting that firms with quality certifications tend to have different productivity dynamics compared to non-certified firms. Empirical research using firm-level panel data shows that certified firms often have lower labor productivity due to structural constraints, while non-certified firms tend to exhibit stronger performance growth (Yousaf, 2023).

Additionally, the Superstar Firm Hypothesis (Autor et al., 2020) posits that market concentration and technological advancements drive productivity growth among a few dominant firms, leading to a decline in the overall labor share of GDP. This phenomenon is observed through industry-wide shifts in sales concentration, where a small number of highly productive firms absorb a disproportionate share of economic output, reducing the relative importance of labor inputs (Autor et al., 2020). Empirical methodologies for measuring labor productivity in these studies include panel data analysis, generalized method of moments (GMM) estimation (Maheshwari, 2016), and correlation tests between firm performance indicators and labor productivity metrics. The above studies conclude that productivity is not solely a function of labor efficiency but also depends on firm strategies, technology adoption, and market structure dynamics, reinforcing the need for nuanced measurement approaches to understand labor productivity variations across industries and firm types.

The conceptual framework for understanding and empirical interpretation of labor productivity in firms based on Solow's Productivity Paradox (Brynjolfsson et al., 2018; Capello et al., 2022) focuses on the observed disconnect between technological advancements and their measurable impact on productivity growth. The above studies argue that despite rapid progress in IT/AI and digital automation, aggregate labor productivity growth remains sluggish due to four key explanations: false hopes, mismeasurement, redistribution effects, and implementation lags. The false hopes hypothesis (Brynjolfsson et al., 2018) suggests that technological optimism may be overstated, and IT / AI's real impact on productivity could be lower than anticipated. The mismeasurement explanation (Capello et al., 2022) posits that traditional economic indicators fail to capture the full productivity benefits of IT / AI, especially in industries where IT/AI contributes to quality improvements rather than direct output increases. The redistribution effect hypothesis (Capello et al., 2022) argues that IT / AI's gains are concentrated in a few superstar firms with high market power, leading to rising economic

inequality and low overall productivity spillovers. Finally, the implementation lags explanation, which is the most widely accepted (Brynjolfsson et al., 2018; Capello et al., 2022), highlights that digital innovations require substantial complementary investments, organizational restructuring, and workforce reskilling before their full productivity benefits materialize. The above studies suggest that while IT / AI-driven firms experience localized productivity gains, sector-wide and economy-wide improvements are delayed due to slow diffusion, skills mismatch, and structural rigidities.

Brynjolfsson & McAfee's Second Machine Age (Brynjolfsson & McAfee, 2014; Spencer, 2017) is centered on the transformative impact of automation, and IT/AI on economic productivity. Their framework explains how digital advancements lead to exponential improvements in labor efficiency, yet paradoxically, these gains are not evenly distributed across the economy (Brynjolfsson & McAfee, 2014). They introduce the concepts of "bounty" and "spread", where the bounty refers to the economic abundance created by digital progress, and the spread highlights the growing inequality caused by automation favoring high-skilled labor while displacing routine jobs. Labor productivity in firms is measured through Total Factor Productivity (TFP), automation adoption rates, IT / AI-enhanced decision-making, and job polarization trends (Brynjolfsson & McAfee, 2014; Spencer, 2017). They emphasize that labor productivity gains from IT/AI and robotics require complementary human skills and institutional adaptations, including education, retraining, and policy interventions. Empirical data shows that leading firms leveraging IT/AI and data analytics experience productivity surges, while others lag behind, leading to a "winner-takes-all" market structure. Measurement approaches focus on IT / AI-driven firm efficiency metrics, employment shifts towards knowledge-intensive roles, and industry-wide automation diffusion rates (Spencer, 2017). The Second Machine Age framework suggests that future labor productivity growth depends on firms' ability to integrate IT/AI alongside human intelligence, promoting policies that ensure equitable technology diffusion to prevent workforce displacement and inequality.

The conceptual framework for understanding and empirical interpretation of labor productivity in firms based on Complementarity Theory (Biagi & Parisi, 2012; Fitri et al., 2023) highlights the interdependent role of IT / AI, human capital, and organizational capital in shaping productivity outcomes. The above studies suggest that IT/AI investments alone do not yield significant productivity gains unless complemented by human capital development and organizational change (Biagi & Parisi, 2012; Fitri et al., 2023). Firms that combine digital technologies with skilled labor and adaptive management structures experience higher labor productivity growth **due to** synergistic interactions. Empirical measurement of complementarity in labor productivity relies on Total Factor Productivity (TFP) estimation, firm-level panel data on IT/AI investments, employee skill assessments, and management practice indicators (Biagi & Parisi, 2012; Fitri et al., 2023). Study on Italian manufacturing firms indicate that organizational change and human capital investment significantly enhance the impact of IT/AI on productivity, with firms that undergo structural transformation achieving higher efficiency levels than those that merely adopt new technologies (Biagi & Parisi, 2012). The evidence also supports that IT / AI-enabled decentralization of decision-making, skill-intensive job design, and flexible work arrangements further strengthen the complementarities among technology, workforce, and management (Biagi & Parisi, 2012). The above studies conclude that labor productivity growth depends not just on technological inputs but on firms' ability to integrate complementary assets, reinforcing the idea that IT / AI's productivity effects materialize only when accompanied by appropriate human and organizational capital investments.

2.3. Studies on impact of IT/AI use on labor productivity in firms

The impact of IT/AI use on labor productivity in firms is reflected in efficiency gains through multiple dimensions, including automation, decision optimization, and innovation enhancement (Ali et al., 2024; Shamim, 2024). IT/AI use improves operational efficiency (Shamim, 2024) by automating repetitive tasks, reducing human errors, and optimizing resource allocation, leading to faster workflows and reduced costs. The above studies show that firms integrating IT/AI in human resource management, production processes, and customer service achieve higher labor efficiency by reallocating human workers to more complex, value-added tasks. Empirical measurement of IT / AI-driven labor productivity includes output per worker, total factor productivity (TFP), and process efficiency improvements, with findings indicating that firms with IT / AI-enabled decision support systems exhibit greater adaptability and innovation (Ali et al., 2024). While efficiency gains are evident, the above studies also highlight challenges such as skills mismatches, resistance to

technological change, and capital investment barriers, which can delay the realization of AI-driven productivity benefits. Overall, the findings suggest that IT/AI use in firms is a key driver of labor productivity growth, provided there is complementary investment in workforce training, digital infrastructure, and strategic implementation frameworks (Ali et al., 2024; Shamim, 2024).

The impact of IT/AI use on labor productivity in firms is reflected also in studies through a complex interplay between automation, augmentation, and reallocation of labor (Acemoglu & Restrepo, 2018; Isaza & Cepa, 2024; Paudel, 2024). Automation enhances productivity by substituting human labor with IT/AI for routine and repetitive tasks, reducing costs and increasing efficiency (Acemoglu & Restrepo, 2018). However, it also introduces displacement effects, where workers previously performing automated tasks face job losses or role modifications. Augmentation, on the other hand, complements human labor by integrating IT/AI that assist rather than replace, leading to an increase in workers' capabilities, efficiency, and task complexity (Acemoglu & Restrepo, 2018; Paudel, 2024). The above studies highlight that automation can initially increase workloads as employees adapt to new technologies, reconfigure their tasks, and develop new skills. This process can cause temporary inefficiencies and even demotivation. However, once IT/AI systems and automation technologies are well-integrated, firms experience long-term productivity gains due to improved operational efficiency, error reduction, and enhanced decision-making capabilities. Augmentation, particularly in knowledge-based jobs, enables employees to leverage IT/AI for data analysis, decision support, and predictive modeling, leading to higher output per worker (Acemoglu & Restrepo, 2018; Isaza & Cepa, 2024). In general, the above studies show that IT/AI use in firms drive productivity growth by automating repetitive tasks, augmenting human decision-making, and reallocating labor towards high-value activities. However, to achieve sustainable productivity gains, firms and policymakers must carefully balance automation and augmentation while facilitating labor force transitions through training and reallocation strategies.

The impact of IT/AI use on labor productivity in firms, as reflected in the study on AI coexistence workplace (Zirar et al., 2023), is primarily viewed through the lens of worker-AI coexistence and the evolving nature of workplace interactions. AI integration in firms contributes to operational efficiency, faster decision-making, and innovation, yet the impact on labor productivity is complex and contingent on worker adaptability (Zirar et al., 2023). The above study identifies a dual effect of AI on labor: while automation reduces worker involvement in repetitive tasks, it also demands continuous upskilling and adaptation to maintain a productive human-AI relationship. AI is not merely a substitute for human labor but acts as an augmenting force, enabling workers to focus on higher-value cognitive and creative tasks. However, labor productivity gains are not uniform across all firms and industries; firms that invest in technical, human, and conceptual skill development for their employees tend to experience more sustainable productivity improvements. A key challenge to productivity growth with AI adoption is the distrust and fear of job displacement among workers (Zirar et al., 2023). The above study highlights that AI's impact on labor varies depending on skill levels: low-skilled workers face higher risks of job displacement, while high-skilled workers benefit from AI augmentation. The above study proposes that AI-driven workplaces should foster a symbiotic relationship where workers leverage AI for efficiency rather than being replaced by it. However, firms that neglect workforce training and adaptation strategies may struggle with AI implementation, leading to reduced productivity and workforce resistance.

2.4. Research methodologies used to analyze the relationship between IT/AI use and labor productivity in firms

Some reviewed studies (Bartel et al., 2007; Syverson, 2011; Bianchini et al., 2022; Rammer et al., 2022; Necula et al., 2024; Paudel, 2024) suggest several quantitative and qualitative approaches for analyzing the relationship between IT/AI use and labor productivity in firms. Quantitative approaches include econometric modeling such as panel data regressions, which incorporate firm-level data on IT/AI investments, and productivity indicators such as output per worker, innovation outputs (e.g., patents, R&D spending), and efficiency gains (Bartel et al., 2007; Bianchini et al., 2022; Necula et al., 2024). The Cobb-Douglas production function augmented with IT/AI variables is commonly used to estimate their contribution to firm productivity (Syverson, 2011; Bianchini et al., 2022). Another statistical method is difference-in-differences (DiD) estimation (Bartel et al., 2007; Necula et al., 2024), which compares firms using IT/AI with those that do not, controlling for external economic trends and firm-specific factors. This approach helps identify the causal impact (Gershman & Ullman, 2023; Little, 2023; Hussain et al., 2024) of IT/AI on labor productivity. Instrumental variable (IV) regressions are used to

address endogeneity issues, leveraging exogenous factors such as historical IT/AI infrastructure levels or government incentives for IT/AI use as instruments (Necula et al., 2024). Some studies (Syverson, 2011; Bianchini et al., 2022; Paudel, 2024) employ Stochastic Frontier Analysis (SFA) to distinguish productivity gains due to IT/AI from those arising from conventional efficiency improvements. Machine learning techniques, including random forests, support vector machines, and gradient boosting methods, are used to predict labor productivity changes and capture complex non-linear relationships between IT/AI use, workforce skills, and firm performance (Bianchini et al., 2022; Rammer et al., 2022; Necula et al., 2024). Bayesian network analysis provides insights into probabilistic dependencies between IT/AI usage, innovation, and firm-specific factors (Paudel, 2024).

Among qualitative approaches, case studies and firm-level surveys are commonly used to understand the impact of IT/AI on workplace productivity (Bartel et al., 2007; Syverson, 2011; Bianchini et al., 2022; Rammer et al., 2022; Necula et al., 2024). Researchers conduct interviews and observational studies to capture employee perceptions of IT/AI-driven changes in workflow efficiency and task augmentation (Bartel et al., 2007; Bianchini et al., 2022; Rammer et al., 2022). Content analysis of corporate reports, job postings, and policy documents helps assess how firms integrate IT/AI into their business strategies (Rammer et al., 2022). Thematic analysis of employee feedback provides insights into challenges associated with IT/AI adoption, such as skill mismatches, resistance to change, and ethical concerns (Syverson, 2011; Bianchini et al., 2022). Event studies combined with propensity score matching (PSM) are used to compare firms before and after IT/AI adoption while ensuring that firms with similar characteristics are compared to minimize selection bias (Rammer et al., 2022; Necula et al., 2024). By integrating quantitative econometric models with qualitative insights from case studies and surveys, researchers obtain a comprehensive understanding of how IT/AI use impact labor productivity in firms, identifying both measurable productivity effects and broader organizational transformations.

Summarizing, we identified the following challenges and gaps in existing research: (1) lack of a complex conceptual framework of IT/AI use in firms in relation to labor productivity, (2) measurement issues, which mean difficulties in quantifying IT / AI-driven productivity gains, (3) causal vs. correlational relationships establishing causality between IT/AI use and productivity in firms. Overall, this literature review highlights the significant role of IT/AI in shaping labor productivity while emphasizing the need for rigorous research methodologies in order to study the relationship between IT/AI use and labor productivity in firms. We hope to fill this gap by developing conceptual frameworks of IT/AI use and labor productivity in firms and the methodology for studying the relationship between them.

3. Conceptual frameworks of IT/AI use in relation to labor productivity in firms

The main ideas and guidelines for conceptual frameworks of IT/AI use in relation to labor productivity in firms, drawn from the above literature review, emphasize the theoretical foundations, methodological approaches, and empirical findings shaping this relationship. IT/AI are widely acknowledged as critical drivers of productivity, yet their effects are complex and dependent on firm-specific, industry-wide, and macroeconomic factors. The Technology Acceptance Model (TAM) explains IT/AI use based on perceived usefulness and ease of use, highlighting that productivity gains depend on how effectively firms integrate and utilize these technologies (Davis, 1986, 1989; Ma & Liu, 2004; Čižo et al., 2024). The Diffusion of Innovations (DOI) Theory underscores the adoption curve of IT / AI, identifying firms as innovators, early adopters, majority adopters, or laggards, suggesting that productivity benefits are distributed unevenly based on adoption speed and scope (Acemoglu et al., 2018; Cockburn et al., 2018). The Resource-Based View (RBV) conceptualizes IT/AI as strategic assets, meaning that firms with strong internal capabilities, such as proprietary data, specialized algorithms, and skilled labor, derive higher productivity benefits (Przegalinska et al., 2025; Han et al., 2025). The Socio-Technical Systems (STS) Theory posits that IT/AI productivity effects depend on the interplay between technology, organizational structures, and worker adaptation, advocating for human-IT/AI collaboration rather than pure automation (Appelbaum, 1997; Walker et al., 2008).

We suppose that conceptually the difference between the availability of IT/AI and its real use is important. It is stressed by van Dijk's Theory of Digital Divide (van Dijk, 2006, 2017) and the Resource-Based View (RBV) (Przegalinska et al., 2025; Han et al., 2025) rooted in Bourdieu's Theory of Social Fields (Bourdieu, 2005). Van Dijk (2006, 2017) emphasizes that mere access to IT/AI (material access) does not automatically lead to its effective use. He identifies four types of IT/AI access: (1) motivational access, which refers to interest and willingness to use IT/AI, (2) material access, which is the physical availability of devices and the Internet, (3) access skills, which encompass the necessary skills for effective IT/AI use, (4) and access use, which refers to the actual usage and application of IT/AI. This framework highlights that a lack of skills or motivation can prevent individuals from effectively using IT/AI, even if they have access to technology. The resource approach developed from Bourdieu's theory explains that individuals and firms have different "resource portfolios" and its activation/capitalization capacity, which determine how effectively they can capitalize on available technology (Komarova et al., 2022). This means that some firms may have IT/AI access but struggle to translate it into real benefits due to differences in education, social capital, and skills. Both van Dijk's Theory of Digital Divide and the Resource-Based View (RBV) stress that equal access to IT/AI does not mean equal outcomes. While infrastructure and devices may be available, their actual use (the subject of this study) depends on socioeconomic status, digital skills, and motivation of employees, as well as organizational efficiency in the field of IT/AI use. Table 1 summarizes the above theoretical background for the conceptual framework of IT/AI use in relation to labor productivity in firms providing also the empirical interpretation of the concept of IT/AI use in relation to labor productivity in firms and the empirical indicators from the official statistics of Latvia.

Table 1. Theoretical backgrounds and empirical interpretations for the conceptual framework of IT/AI use in relation to labor productivity in firms

Theoretical background for the conceptual framework	Empirical interpretation of the concept of IT/AI use in relation to labor productivity in firms	Empirical indicators from the official statistics of Latvia
Technology Acceptance Model (TAM)	IT/AI use based on perceived usefulness and ease of use; productivity gains depend on how effectively firms integrate and utilize these technologies	Firms which provide training to develop IT/AI skills of the employees Firms which employ/recruit IT specialists Firms whose employees have remote access to the firm's e-mail system, documents, applications or software
Diffusion of Innovations (DOI) Theory	Firms are identified as innovators, early adopters, majority adopters, or laggards, suggesting that productivity benefits are distributed unevenly based on adoption speed and scope	Presence of own personnel for IT functions performance in firms Firms paying for advertising on the Internet Internet connection downloading speed in firms
Resource-Based View (RBV)	Firms with strong internal capabilities, such as proprietary data, specialized algorithms, and skilled labor, derive higher productivity benefits	Employees using any type of device with Internet connection in their job regularly Use of Internet and websites in firms Use of website function in firms
Socio-Technical Systems (STS) Theory	IT/AI productivity effects depend on the interplay between technology, organizational structures, and worker adaptation, advocating for human-IT/AI collaboration rather than pure automation	Use of business software Use of social media in firms Cloud computing services purchased by firms Firms using cloud computing services Internet use in firms for interaction with public authorities IT/AI-related environmental protection measures in firms Firms that provide employees with information on IT/AI security requirements Use of Internet of Things in firms Firms that analyzed big data

Source: own elaborated based on Davis, 1986, 1989; Ma & Liu, 2004; Čižo et al., 2024; Acemoglu et al., 2018; Cockburn et al., 2018; Przegalinska et al., 2025; Han et al., 2025; Appelbaum, 1997; Walker et al., 2008; Central Statistical Bureau of Latvia, 2024b–2024t.

Table 1 presents theoretical backgrounds also empirical interpretations for the conceptual framework for understanding IT/AI use in relation to labor productivity in firms, integrating multiple theoretical perspectives with empirical interpretations and measurable indicators from official Latvian statistics. For example, the empirical indicators reflecting TAM, DOI, RBV and STS Theory include firms providing IT/AI skills training, employing IT/AI specialists, ensuring remote access to firm systems, investing in online advertising, and having

high-speed internet connections. Additionally, firms' regular use of internet-connected devices, websites, business software, social media, cloud computing services, and big data analytics further exemplify this framework. Theoretical backgrounds also empirical interpretations for the conceptual framework for understanding IT/AI use in relation to labor productivity in firms suggest that labor productivity in firms depends not only on technology adoption but also on organizational readiness, employee training, resource availability, and the balance between human and technological capabilities. The official statistics of Latvia provide empirical validation through indicators that measure IT integration in firms, workforce preparedness, IT-enabled interactions with public authorities, security measures, and environmental initiatives. By synthesizing these theories, the framework establishes that IT/AI's impact on labor productivity is multidimensional, requiring firms to align technological investments with human capital development, infrastructure, and strategic adaptation to maximize efficiency and competitive advantage.

The reviewed literature on the conceptual understanding of labor productivity in firms corresponds with the above methodological premises examining productivity measurement challenges based on the Solow Productivity Paradox, which questions why IT/AI investments do not always translate into measurable productivity gains (Brynjolfsson et al., 2018; Capello et al., 2022). Brynjolfsson & McAfee's Second Machine Age framework highlights exponential productivity growth driven by IT/AI but warns of increasing inequality and job polarization (Brynjolfsson & McAfee, 2014; Spencer, 2017). Complementarity Theory suggests that IT/AI productivity gains are maximized when combined with human capital development and organizational change, supporting evidence that firms integrating IT/AI with skilled labor and adaptive management structures outperform those relying on technology alone (Biagi & Parisi, 2012; Fitri et al., 2023). The studies reviewed emphasize that IT/AI improves labor productivity primarily through automation, augmentation, and reallocation of labor. IT/AI-driven productivity (which is often studied together with organizational efficiency in the reviewed literature) can be empirically interpreted using e-commerce indicators from official Latvian statistics:

- countries of origin of clients, from which enterprises received orders, using Internet (Central Statistical Bureau of Latvia, 2024u);
- Internet sales of goods and services (Central Statistical Bureau of Latvia, 2024v, 2024w);
- firms which have sold goods or services via Internet or other computer networks (Central Statistical Bureau of Latvia, 2024x);
- firms that issued/sent electronic or paper invoices (Central Statistical Bureau of Latvia, 2024y).

And common labor productivity (not only IT/AI-driven, but influenced by other factors) can be empirically interpreted using the indicator of total Gross Domestic Product (GDP) per person employed (Central Statistical Bureau of Latvia, 2024z).

Based on the theoretical backgrounds also empirical interpretations obtained from the reviewed literature and summarized in Table 1, we propose our own conceptual framework of IT/AI use in relation to labor productivity in firms.

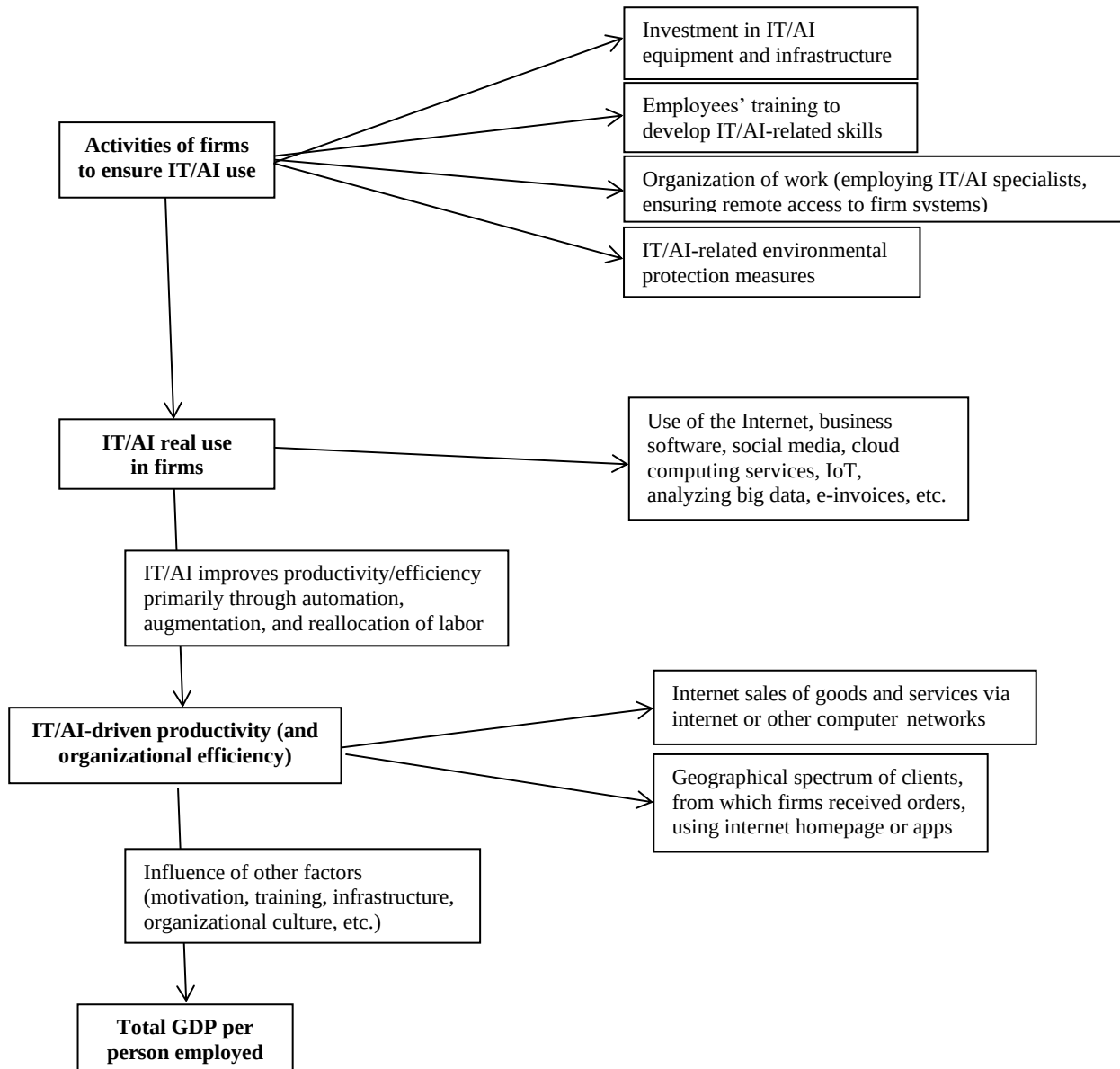


Figure 1. Conceptual framework of IT/AI use in relation to labor productivity in firms

Source: own elaborated based on the reviewed literature, Table 1 and empirical indicators provided by Latvian official statistics.

Figure 1 presents a comprehensive conceptual framework illustrating the relationship between IT/AI use and labor productivity in firms, integrating multiple theoretical models, empirical findings, and indicators from Latvian statistics. The framework is structured as a flow-like visual narrative beginning with investments in IT/AI infrastructure and employee training, highlighting the foundational role of internal firm activities. It emphasizes that real use of IT/AI technologies—including business software, social media, cloud services, IoT, and big data analytics—is central to improving productivity. The model stresses that the productivity gains from IT/AI stem from three interrelated mechanisms: automation, augmentation, and labor reallocation. Automation refers to substituting human labor in routine tasks, augmentation means enhancing human capabilities through IT/AI, and reallocation involves shifting labor toward more complex, value-added roles. The model also links IT/AI use to firms' digital business operations such as internet-based sales, issuance of electronic invoices, and international digital reach through web platforms, portraying these as outcomes of digital maturity and contributors to productivity. All these elements together feed into IT/AI-driven productivity and organizational efficiency, which in turn contribute to broader labor productivity measured through indicators like GDP per

person employed. The framework further acknowledges the influence of many other external factors on productivity, stressing that IT/AI is not a sole determinant. Conceptually, it also highlights “synergy effects” at each stage—suggesting that productivity outcomes are not just additive but result from interconnected improvements across technology, human capital, and organizational processes. In essence, Figure 1 encapsulates a systemic view where IT/AI adoption is a multi-layered process involving technological, human, and structural dimensions, all of which interact to shape firm-level productivity in a digital economy.

4. The methodology for studying relationship between IT/AI use and labor productivity in firms

Methodologically, the literature highlights quantitative and qualitative approaches for studying IT/AI and labor productivity. Econometric models, particularly panel data regressions, difference-in-differences (DiD), and instrumental variable (IV) regressions, help isolate causal effects of IT/AI use (Bartel et al., 2007; Bianchini et al., 2022; Necula et al., 2024). Stochastic Frontier Analysis (SFA) decomposes productivity into efficiency gains from IT/AI versus other factors (Syverson, 2011; Bianchini et al., 2022; Paudel, 2024). Machine learning techniques, including random forests, support vector machines, and Bayesian networks, predict labor productivity trends and uncover complex interactions (Bianchini et al., 2022; Rammer et al., 2022; Necula et al., 2024; Paudel, 2024). Qualitative methods, such as case studies, expert interviews, and content analysis, provide insights into organizational adaptation and worker experiences (Bartel et al., 2007; Syverson, 2011; Bianchini et al., 2022; Rammer et al., 2022; Necula et al., 2024). We believe that hybrid approaches, such as mixed-methods research and experimental designs, integrate statistical modeling with firm-level observations to capture both quantitative impacts and qualitative transformations.

Table 2. Research methodology for studying IT/AI use and labor productivity relationship (correlation or causality) in Latvian firms

Approaches	Methods	Data and analysis	Benefits
Quantitative (causal inference-focused) approach (to isolate causal effects , not just correlations)	Panel data regression models	Longitudinal data from the Central Statistical Bureau of Latvia (2004–present) on IT/AI use and labor productivity indicators Control for firm characteristics (size, industry, region) and macroeconomic conditions	Captures time-based trends and effects
	Difference-in-differences (DiD) estimation	Comparing productivity changes in firms before and after significant IT/AI use against firms that didn’t use	Helps establish causality by removing time-related and firm-specific biases
	Instrumental variable (IV) regression	Using instruments like prior regional IT/AI infrastructure, EU funding eligibility, or national digitalization policies to account for endogeneity	Strengthens causal claims when IT/AI use may be influenced by unobserved productivity-related factors
	Stochastic Frontier Analysis (SFA)	Decomposing total productivity into “technical efficiency” and “technological innovation” components	Useful to identify how much of productivity is driven specifically by IT/AI efficiency gains
Qualitative component (complementary)	Case studies	Deep diving into specific firms that are innovators, early adopters, majority adopters, or laggards (based on DOI theory) classified using cluster analysis	Highlight internal processes, organizational change, employee experience, and managerial practices
	Expert interviews & surveys	Sociological data from firms executives, IT managers, and employees	Assesses subjective perception of IT/AI influence on day-to-day productivity in firms
	Content & thematic analysis	Analyzing corporate reports, digitalization strategies, or internal communications	Assesses how firms perceive and manage IT/AI-related transformation
Advanced predictive/exploratory tools (optional but insightful)	Machine learning models (random forests, SVMs, gradient boosting)	A well-structured dataset containing firm-level data with both input features (predictors) and a clear target variable (output)	Can identify complex, non-linear interactions between IT/AI use and productivity outcomes
	Bayesian networks	Firm-level data structured to capture not only direct cause-effect relationships but also probabilistic dependencies between variables	Explore probabilistic dependencies among factors like training, infrastructure, remote access, and productivity

Source: own elaborated based on the reviewed literature and Figure 1.

Thus, for studying the relationship between IT/AI use and labor productivity in firms (especially to distinguish **correlation** from **causality**) the most effective approach would be a hybrid methodology that combines rigorous quantitative analysis with rich qualitative insights. For further empirical study of IT/AI use in relation to labor productivity in Latvian firms, we will use such a hybrid approach combining DiD and panel regression models (for causality), supported by firm-level case studies and interviews (for depth and context). This combination not only strengthens the empirical validity of our results but also allows us to explore the multidimensional factors (like motivation, training, infrastructure, organizational culture) that the conceptual framework in Figure 1 emphasizes.

5. Conclusions

The study set out to develop conceptual frameworks and propose an appropriate research methodology to study the relationship between IT/AI use and labor productivity in firms, particularly within the context of Latvian ones. Addressing the three core research questions, the study has yielded several key insights:

- (1) the main theoretical foundations (such as the Technology Acceptance Model (TAM), Diffusion of Innovations (DOI), Resource-Based View (RBV), and Socio-Technical Systems (STS) Theory) collectively provide a multidimensional understanding of IT/AI use in firms. These theories show that technology adoption is not solely about infrastructure or access, but deeply tied to organizational capabilities, human resources, and sociotechnical dynamics;
- (2) the study distinguishes between labor productivity and labor efficiency, arguing they are related but conceptually distinct. Labor productivity typically refers to output per worker, while efficiency considers the broader use of all production factors. However, among the key terms of this study are labor productivity and organizational efficiency, which [organizational efficiency] refers to the organization of work in firms and efficiency of business processes;
- (3) a hybrid research methodology was proposed to capture both the correlational and causal aspects of the IT/AI–productivity relationship. This includes panel data regressions, difference-in-differences estimation, instrumental variable models, and Stochastic Frontier Analysis for causal inference, complemented by qualitative methods such as case studies and expert interviews. Advanced tools like machine learning and Bayesian networks are also recommended for modeling complex relationships and probabilistic dependencies.

The conceptual framework presented in Figure 1 captures how IT/AI investments, skills development, and digital business practices interact to drive labor productivity through automation, augmentation, and labor reallocation. The framework reflects empirical realities by incorporating measurable indicators from official Latvian statistics and emphasizing synergy effects between technological, human, and organizational elements. Overall, the study provides a robust conceptual and methodological foundation for exploring the IT/AI–labor productivity nexus. Its proposed hybrid approach offers a roadmap for future research to generate both theoretically grounded and empirically validated insights in the rapidly evolving digital economy.

The study has the following limitations:

- while the study proposes comprehensive frameworks and methodologies, it remains conceptual and methodological in nature. Empirical validation of the proposed models using real-world Latvian firm data is yet to be conducted;
- the framework is rooted in data and policy conditions specific to Latvia. As such, the generalizability to other countries (especially those with different digital maturity levels) may be limited;
- the study relies on indicators from national statistics, which, although rich, may not fully capture nuanced organizational practices, employee attitudes, or informal uses of IT/AI.

For future empirical research, we are planning to conduct hybrid empirical study using panel datasets from Latvian firms, applying the proposed causal inference methods (e.g., DiD, IV models) supplementing official statistics with firm-level surveys and interviews that capture employee experiences, managerial strategies, and barriers to IT/AI use. Furthermore, we would like to apply the developed framework within specific industries (e.g., manufacturing, logistics, services) to identify and compare sectoral patterns in IT/AI use and productivity dynamics.

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