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The Role of AI-Driven Automation Exposure in Shaping the Productivity Effects of European Intangible Capital Investments

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ABSTRACT:

This thesis researches the role of artificial intelligence-driven automation exposure in impacting the productivity effects of intangible capital investments in different European sectors. AI, recognized as general-purpose technology, has the potential to augment knowledge-intensive work while displacing routine tasks. The central research question is how sectoral differences in AI-driven automation potential influence the productivity returns from intangible capital.

Using GLOBALINTO innovation survey, this study develops sector-specific investment multipliers based on predicted occupational shifts caused by AI-driven automation. These multipliers are applied to intangible variables to account for AI-impacted changes in nature of work. The analysis distinguishes between innovative (IC) and non-innovative (NOIC) occupations and models how AI alters their proportions, with the assumption that only a small portion of displaced NOIC workers can be translated into IC roles.

Regression results show that organizational capital is consistently and positively associated with labor productivity, while AI exposure does not amplify this effect. R&D employment is negatively associated with productivity in short term, but the effect is slightly mitigated when AI exposure is considered, suggesting potential long-run complementarities. ICT investments do not show direct productivity gains but are strongly linked to innovation activity. These results highlight that intangible asset: organizational capital, ICT, and R&D function not in isolation, but synergistically. Their combined presence supports firm’s ability to adapt to AI-driven change. Moreover, AI increases the scaling effect of intangible assets by expanding intangibles and further increasing their collective impact on productivity and innovation.

The thesis contributes to the literature by linking AI’s transformative potential with the productivity of intangible capital, emphasizing the need for sector-specific and task-level understanding. Limitations include the cross-sectional nature of the data, simplified assumptions in multiplier construction, and the challenge of fully capturing dynamic restructuring processes. Future research could build on this work by employing time-series data, firm-level AI adoption metrics, and improved measures of organizational transformation.

Keywords: Artificial intelligence, intangible investments, productivity, automation, R&D, ICT, digitalization

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1 Introduction

The accelerating development and adoption of artificial intelligence (AI) technologies is changing modern economies. As AI-driven automation transforms the nature of work and the organization of production, it also changes the role of intangible capital as a crucial input for firm productivity. Unlike previous industrial waves that primarily relied on physical capital and labor, the current technological shift is increasingly dependent on intangible assets such as research and development (R&D), information and communication systems (ICT), and organizational capital (OC) (Hazan et al. 2024; Calvino & Fontanelli, 2023). However, the interaction between these intangible investments and AI driven automation is empirically unexplored territory.

In this thesis AI is classified as general-purpose technology (GPT), meaning that it has potential to generate broad and impactful effects across industries (Bresnahan and Trajtenberg, 1995). These gains tend to be delayed and dependent on complementary inputs Brynjolfsson, et al., (2017). Recent literature suggests that such complements are intangible in nature (Damioli et al., 2021). R&D drives innovation, ICT provides technical infrastructure for deploying AI systems, and organizational capital enables firms to restructure workflows, retrain staff, and absorb new technologies. These factors collectively determine whether AI leads to productivity improvements or stalls in implementation. At the same time, automation induced by AI disproportionately affects occupations, meaning that the impact of AI is not uniform across sectors.

This thesis aims to explore the intersection of automation exposure and intangible capital investment. More specifically, it investigates how firms operating in sectors with different levels of AI driven automation potential invest into intangibles, and whether those investments contribute to labor productivity. The study applies AI automation forecasts to firm-level intangible investment data, allowing empirical tests of whether intangible capital is productive depending on the degree of automation exposure. The analysis contributes to the research of AI as GPT and the role of intangibles in technology adoption.

1.1 Background

The AI-driven technological change is changing production, labor and value creation. AI has changed from theory to a practical tool which can be implemented to a wide range of tasks, from customer service and logistics to finance and manufacturing. Unlike earlier waves of technological advancement, such as the machines replacing physical labor or the spread of information and communication technologies, AI does not only automate physical tasks (Hazan et al. 2024). Instead, it targets a broader range of activities, including cognitive and decision-making tasks traditionally associated with knowledge-intensive work. This has raised both expectations and uncertainties about AI's economic implications, especially regarding its impact on labor markets and productivity.

At the same time, a long-term structural shift has been underway in how firms generate value. Intangible capital, including R&D, ICT and OC have become increasingly important in terms of competitive advantage. According to Corrado, Hulten, and Sichel (2009), intangible investments have exceeded tangible capital formation in many advanced economies. This change towards knowledge-based assets means that a firm's performance is shaped less by machinery and more by intellectual and organizational capabilities. The connection between this change and emerging technologies like AI present an important but still unexplored area for empirical research.

Even though AI as general-purpose technology is expected to change the structure of work, according to Brynjolfsson et al. (2017), the productivity benefits of AI do not become a reality on their own. They often require large-scale complementary investments, changes in work process, and time for firms to learn how to use them effectively. For AI, these complements are largely intangible. R&D enables the creation and adaptation of AI tools, ICT provides the digital infrastructure needed to implement them, and OC supports restructuring, learning, and task reallocation. This has led to understanding that the benefits of AI are unevenly distributed, across firms and sectors, depending on their readiness to absorb and apply the technology.

There remains limited empirical research on how AI-driven automation exposure links with productivity of intangible investment at firm or sector level. Most existing studies examine either AI or intangibles in isolation, without fully accounting for how these interact. This thesis aims to understand how firms operating in different sectors with different AI-driven automation potential experience benefit from intangible capital investments.

1.2 Research Questions

This thesis aims to examine how sector-level AI-driven automation exposure interacts with different forms of intangible capital to affect firm productivity. Given that artificial intelligence functions as a general-purpose technology, its productivity effects depend not only on technological maturity but also on the presence of complementary intangible assets. Building on theoretical foundations, hypothesis is developed to explore how specific types of intangible capital impact the productivity of AI.

(H1) Firms that have better organizational capabilities in AI impacted sectors achieve greater productivity gains than firms with lower organizational capital investment.

This hypothesis is built on the concept of absorptive capacity introduced by Cohen and Levinthal (1990), which extends from R&D to how organizational structures and internal learning systems enable firms to integrate and apply new technologies effectively. As discussed by Brynjolfsson et al. (2017), AI-impacted productivity gains often require extensive organizational transformation, like changes in workflows and retraining of employees. Therefore, firms with greater investments in organizational capital may be better positioned to adapt and benefit from AI.

(H2) Firms with better R&D and innovative capabilities experience greater productivity gains from AI-related automation exposure than firms with lower R&D investment.

According to Bresnahan and Trajtenberg (1995), general-purpose technologies like AI produce their largest economic impact through innovation complementarities, such as in ability to enhance productivity of R&D. R&D investments allow firms to not only develop new technologies but also adjust and integrate AI into specific operational tasks, thereby increasing its effectiveness and long-term value. This hypothesis tests whether R&D functions as a complement and amplifies the productivity benefits of AI.

(H3) Firms with stronger ICT infrastructure benefit more from AI-related automation exposure in terms of productivity than firms with weaker ICT infrastructure.

AI can be conceptualized as a form of intangible capital as it involves significant investments in software, data, and algorithms. Additionally, AI requires powerful hardware and extensive software and data to be utilized properly (Corrado, Haskel and, Jona-Lasinio, 2021) Moreover, Calvino and Fontanelli (2023) show that firms developing AI in-house only gain significant productivity advantages if they possess strong digital infrastructure. This supports the idea that firms with better ICT readiness are more likely to convert AI exposure into productivity gains.

1.3 Structure of the Thesis

This thesis is divided into six main chapters. The first chapter introduces the background and motivation of the research, presents the research questions and hypotheses, and outlines the objectives and structure of the study. The second chapter reviews the role of intangible capital in economic growth. It defines the main categories of intangible capital and explores their theoretical foundations and importance in driving productivity, particularly in the context of digital transformation and artificial intelligence. The third chapter focuses on the effects of automation and AI on employment and the structure of work. It reviews key literature on automation-related displacement and job creation, discusses skill-biased technological change, and explains how AI impacts different occupational groups. The fourth chapter introduces AI as general-purpose technology, discussing how its transformative effects are often delayed due to the need for complementary intangible investments. It also examines the importance of absorptive capacity, organizational readiness, and evolving skill requirements in determining how firms benefit from AI. Sectoral and firm-size differences in AI adoption are also explored.

The fifth chapter presents the empirical section of the thesis. It explains the methodology used to estimate AI-driven automation exposure across sectors by linking occupational automation potentials to sectoral level. The chapter details how AI impacts were translated into investment multipliers for different intangible capital categories and presents descriptive statistics and regression results to understand the relationship between AI exposure, intangible investment, and firm productivity. The sixth and final chapter summarizes the main findings of the study, discusses the limitations of the analysis, and provides conclusions. It reflects on the theoretical and empirical implications of the research and offers suggestions for future studies on the impact of AI, intangible capital, and productivity.

2 Intangible Capital and Economic Growth

In recent decades, intangible capital has become central driver of innovation adaptation and long-term growth. Unlike tangible assets, intangible investments are more difficult to measure, harder to finance, and are often underrepresented in national accounts. Yet they play a crucial role in enabling firms to benefit from emerging technologies, like artificial intelligence. As AI becomes increasingly embedded in business operations, understanding the nature, classification, and economic significance of intangible capital is important. This chapter outlines the theoretical foundations, historical evolution, and structural characteristics of intangible capital, with a focus on how these assets shape productivity and AI-driven automation change.

2.1 Definition and Capitalization Criteria

In economic research, intangible capital typically refers to non-physical assets that generate future benefits for firms but are not recorded as conventional fixed capital in official statistics. According to Corrado, Hulten, and Sichel (2005, pp. 11-12), these assets involve expenditures that reduce current consumption or output but are intended to increase an organization’s productivity, revenue, or market prospects in future periods. This aligns with the principle of deferred consumption, giving up resources today to benefit from increased productivity tomorrow. Intangible investments fit the definition of capital in broader, intertemporal model of economic growth (Corrado et al., 2005, pp. 19-20).

More concretely, Corrado, Hulten, and Sichel (2005) group intangible capital into three broad categories. Firstly, computerized information (ICT), this category includes the knowledge in computer software and databases. Although business software is now largely recognized as investment by national accounts, Corrado et al. emphasize that own-account software development carried out internally by firms must also be treated consistently with purchased software to avoid underestimating capital formation. The second category is innovative property, this includes scientific research and development (R&D), mineral exploration, new designs and product blueprints, as well as creative efforts leading to copyrights or licenses (pp. 20-21). Traditionally national income accounts until 2014 have labelled this activity as “intermediate consumption” instead of long-lived investment. Yet, to the extent that R&D yields assets with multi-year returns such as patents or new product lines, they behave similarly to physical capital. (p. 12). As of 2014, survey data of R&D and ICT have been used to evaluate these at aggregated level and included recursively in the national accounting. The last category is economic competencies, which have not been integrated in the system of national accounting, in any of the developed countries. Economic competencies are the firm-specific human and structural resources that enhance productivity over time. Examples include employee training programs, organizational re-engineering, proxied by management labor costs spending, and brand-building, that includes marketing (Corrado et al., 2005, pp. 20-21). Often such costs arise as operating expenses like wages for managerial staff, consulting fees, advertising budgets, rather than explicit “capital” items. However, if their benefits extend beyond the current accounting period, they represent intangible capital creation (pp. 23-24).

From a theoretical perspective, treating this expenditure as capital aligns with an intertemporal growth model, where firms go without immediate output to make internal investments (Corrado et al., 2005, pp. 11-13). National accounts currently include only small subsets of these activities, mainly software and certain R&D categories as they most clearly meet the accounting criteria, and other intangibles like brand building or firm-specific employee training, and organizational transformation are not systematically tracked by data collectors, leading to potentially large underestimates of both gross domestic product and overall investment (Corrado et al., 2005 p. 20-23). In summary, intangible capital comprises a wide range of knowledge-creating expenditures whose benefits are realized over multiple years, which have often been overlooked in standard accounting practice.

Recent extensions of this framework have emphasized that emerging technologies like artificial intelligence also meet the definition of intangible capital. Corrado, Haskel and, Jona-Lasinio (2021) argue that AI can be conceptualized and measured as a form of intangible capital, particularly involving software, data, and databases (p. 436). These intangible assets are often missing or underestimated in official national accounts and simultaneously they have significant impact on how AI contributes to productivity growth. AI typically requires powerful hardware but also extensive software and data while data is rarely captured in standard productivity metrics (pp. 436-438). Authors suggest that data analytics and algorithm development should be treated like long-term capital assets, meaning that expenditures on AI should be recorded as investment rather than expense (pp. 439-442).

2.1 Historical Trends and Economic Significance

Haskel and Westlake (2018, pp. 1-14) describe how, over recent decades, the nature of capital in developed economies has fundamentally evolved from traditionally business interesting merely in tangible goods, like factories, trucks and store furnishings. The last quarter of the twentieth century brought an increasing emphasis on investment in intangible areas like design, brand equity, training, process engineering, and other knowledge-rich activities. These intangible expenditures go underrepresented in national accounting data and on corporate balance sheets (p. 15-17), leading to misperceptions about the real level of capital information.

With data from primarily the United States and United Kingdom, Haskel and Westlake (2018) show that spending on intangible assets has steadily grown relative to tangible spending. By the mid-to-late 1990’s, in both economies, the overall investment in intangibles outpaced physical infrastructure and equipment (pp. 23-29). This transition can be explained by factors such as intensifying global competition where a premium is charged for innovation and brand power, rising information technology capabilities, and the growing importance of service-oriented industries that lean heavily on nonphysical assets. The authors emphasize that capital accumulation drives productivity and growth.

If national statistics fail to measure intangible outlays accurately, analysts end up with incomplete investment data and sometimes underestimate economic output Haskel and Westlake (2018, pp. 30-35). Consequently, older tools for economic policy, which assume the importance of physical plant and equipment, become less reliable in diagnosing modern issues, like lagging productivity or unexplained gaps in corporate valuation. Historically, only a few nonphysical assets like purchased software were recognized as capital in official GDP statistics (Haskel & Westlake 2018, pp. 40). Haskel & Westlake trace the evolution of statistical treatments from early efforts that simply saw intangible expenditures as “intermediate costs” to more recent research frameworks that redefine certain intangibles like internally produced software or R&D as long-lived assets (pp. 36-40).

Corrado, Hulten and Sichel (2009) show that intangible capital accounted for larger portion of capital formation that tangibles in the U.S. economy. Their estimates suggest that by the early 2000s, intangible investment reached over $1 trillion annually, with total business intangible capital stock exceeding $3 trillion. The capitalization of these assets changes the understanding of economic growth (Corrado et al., 2009, pp. 661-676). Corrado, Hulten, and Sichel (2009) include computerized information as a factor of production in macroeconomic growth models. They show that treating software and digital systems as capital rather than intermediate inputs leads to a significantly higher estimate of labor productivity growth, mostly through capital deepening. It is worth noting that computerized information was among the fastest growing intangible categories between 1995 to 2003. (Corrado et al., 2009, pp. 676, 681). These developments highlight the rising strategic importance of intangible capital and its rapid growth-phase until the financial crises in 2008 and provide historical context for this thesis and how such assets interact with AI-driven automation.

2.2 Risks, Financing, and Replicability

Digital or knowledge-embedded assets can be replicated widely at minimal additional cost. Once company has built a strong software platform or brand identity, it can serve millions of customers with relatively modest expansion of physical infrastructure. Digital data, software, and other intangible goods can be replicated at near-zero marginal cost, allowing successful innovators to reach large markets quickly. This helps explain "winner-takes-all" outcomes: once you create a valuable intangible asset, you can reuse it, like for example algorithm, brand, or design without depleting it (Haskel & Westlake 2018, pp. 65-68). Because usage of ideas by one party does not prevent usage by another, investments in intangibles may leak into the broader industry or society (Haskel & Westlake 2018, pp. 72-79). Competitors can sometimes reverse engineer a newly developed service process or software interface, letting them benefit from the originator's R&D. Spillovers mean that the social return on intangible investment can exceed the private return, or what the original investor captures. This helps explain why intangible underinvestment might persist in the absence of intellectual property protections or government support. New ideas and specialized knowledge often gain significantly more value when combined with other intangible assets (Haskel & Westlake 2018, pp. 80-83). For instance, a new software system might be of limited benefit until paired with an organizational redesign or rebranding that unlocks synergy. However, these combinational effects are difficult to predict or plan. Breakthroughs often emerge from unexpected combination of areas of expertise or from flexible management structures that harness new technologies.

It is also worth noting that intangible investments often involve costs that cannot be recovered by selling the underlying assets. For instance, spending on training employees or developing an internal organizational process rarely has much resale value to another firm. A firm that invests heavily in organizational reshaping will find it difficult to recoup those funds. This is unlike purchasing machinery, which can still be sold on a secondary market (Haskel & Westlake 2018, pp. 68-70). As a result, intangible investment often appears riskier for lenders, as there is little collateral for them to seize, making debt financing more challenging and prompting intangible-intensive businesses to seek equity, venture capital, or retain earnings.

3 Automation and Job Displacement

The rise of AI and automation technologies has sparked interest in their impact on labor markets, tasks structures, and productivity. This chapter reviews relevant theories and frameworks explaining how automation affects job displacement, wage dynamics, and the composition of work. Automation potential describes the share of job tasks that can feasibly be performed by machines or software using currently demonstrated technologies. Rather than assuming entire occupations vanish, researchers assess specific tasks and judge whether they can be automated to an acceptable performance level. According to Future That Works by McKinsey Institute (Manyika et al., 2017), under 5% of occupations can be fully automated, yet around 60% have at least 30% of similar activities that could be performed by machines. Tasks with repetitive and predictable components like data collection or basic physical operations are generally more automatable than those demanding creativity, interpersonal empathy, or complex decision-making.

A study by Acemoglu and Restrepo, (2018) presents a framework where automation replaces human labor, but new tasks emerge where labor has comparative advantages, as humans can adapt, learn and specialize in more complex and new tasks that machines struggle to handle. They propose a model where automation reduces employment and the labor share of income when capital replaces previously labor-intensive tasks. However, the introduction of new tasks counteracts this effect by increasing labor demand and wages. The equilibrium between new tasks and automation is crucial for understanding the employment dynamics in an era of rapid AI advancement (Acemoglu & Restrepo, 2018, p. 1489).

Acemoglu & Restrepo (2018) argue that when automation goes too far ahead of new task creation, market forces naturally slow down automation while encouraging the development of new tasks (Acemoglu & Restrepo, 2018, p. 1491). This mechanism ensures that economic growth remains balanced over time rather than leading to excessive labor displacement. Grossman et al. (2016) build on this concept by discussing the Balanced Growth Path (BGP), which describes an economic state in which macroeconomic variables like output, capital, and consumption grow at a constant rate, while maintaining stable income shares between labor and capital. This idea is rooted in the Kaldor facts, which highlight the long-run stability of capital-output ratios and the division of income between labor and capital (Grossman et al., 2016, p. 1). However, in this study they also emphasize that traditional models must be adjusted to account for declining capital costs, which have made automation more accessible and widespread. Additionally, their framework emphasizes the crucial role of education and skill development in maintaining a stable labor-capital balance.

3.1 Concerns Related to Automation

Technological progress has historically been open to different opinions regarding the future prosperity and anxiety over labor-market disruptions, this is particularly evident since the industrial revolution. Mokyr, Vickers, and Ziebarth (2015) emphasize that while technology is widely credited for driving economic growth, it has also sparked fear. This fear often surfaces most strongly during periods of slower economic growth when concerns over labor displacement and inequality intensify. A central debate around technological innovations’ impact on jobs is if they primarily create or destroy jobs in the long run (p. 31-32). History has shown that when new technologies offer more cost-and time-efficient solutions, they often displace workers performing those tasks. However, this displacement has historically been accompanied by rising demand for new complementary roles. For example, nineteenth-century Britain, when factories took over, among these jobs were mechanics to fix the new machines, and the factories where machines operated needed supervisors. As the operation scaled up, the operations needed accountants to manage the enterprise operating on a much larger scale. On top of this the technological leaps in production also sparked interest in product innovation, and thus a completely new sector for the economy has developed. Prior to these jobs emerging, economists completely missed this outcome in the discussions, and the discussion was mostly focused on machines replacing humans (Mokyr et al. 2015, pp.

36). Early factory labor featured harsh conditions, strict timekeeping, and erosion of independence. Over time, safety regulations, organized labor, and broader social reforms to help address some of these challenges. Nonetheless, the tension between technological advancement and the desire for meaningful, less routinized work persists in modern discussion of mechanization, artificial intelligence, and robotics (Mokyr, et al. 2015, pp. 38-39).

There is also a concern that a “technological horizon” might be imminent, after which further innovation will stall. Nineteenth-century economists who foresaw a “stationary state” in which growth would reach a “stationary state” argue that “low-hanging fruit” of discovery has been exhausted, each era grapples with the possibility that continuing leaps in productivity could slow (Mokyr, et al. 2015, pp. 40-42). Yet Mokyr, Vickers, and Ziebarth (2015) remain broadly optimistic that persistent competition and the ever-expanding research from powerful data analysis to genetic engineering will sustain innovation (pp. 47-49) They caution, however, that even if widespread “technological unemployment” is unlikely to happen, the transition can be painful in specific professions. Policies that mitigate short-term hardships, support reskilling, and ensure broad access to the benefits of each new wave of technology therefore remain essential (pp. 47-49). These dynamics help explain why the effects of adoption of AI may be uneven across firms and sectors.

3.2 Challenges of Automation Adoption

Industry analysis suggests that while technical automation potential may be high for numerous tasks, actual adoption of robotics and AI in the workplace can take decades. The timeline depends on five interrelated factors, firstly the technical feasibility. A core requirement is that existing technologies reach a dependable performance level for specific work tasks. Each occupational activity typically involves multiple capabilities, like information retrieval, gross motor movement, or advanced reasoning, and machines must integrate these capabilities effectively. For instance, a system that handles sensory perception and mobility simultaneously must be carefully engineered to ensure reliability. Current limitations in areas like natural language understanding and socio-emotional sensing can slow progress for certain types of jobs (Manyika et al., 2017, pp. 10).

The second factor is cost of development and solution deployment. Even if a task can technically be automated, the investment in creating, customizing, and maintaining an automation solution may be more expensive than paying a human to do the same work. Hardware-based automation like robotics involves significant capital commitment and ongoing maintenance. On the other hand, software-driven tools have lower marginal costs but still require initial engineering and possible data-model training. Over time, technology costs typically decline. As they do, automated solutions can outcompete human labor in more tasks (Manyika et al., 2017, pp. 10).

The third factor is labor market dynamics. The availability, wage levels, and skills of human workers strongly shape whether automation is adopted. In high-wage regions, implementing automated machinery may make economic sense more quickly. However, abundant low-cost labor can delay automation, since the financial benefit may be smaller. For example, deciding to automate kitchen tasks in a restaurant at 11$/hour wages needs careful cost-benefit analysis. In addition, if no job displacement occurs, re-employment pathways and retaining capacity influence how rapidly the workforce adapts (Manyika et al., 2017, pp. 10).

The fourth factor is economic benefits. While labor cost savings are typically motivating factors, automation can yield broader performance improvements. Examples include higher production cycles, fewer errors, improved safety, and overall quality gains. In some scenarios, these non-labor benefits outweigh wage reductions. For instance, automating control rooms in energy facilities might improve operational reliability to the point that it lessens any direct labor saving. Similarly, autonomous vehicles could enhance road safety and fuel efficiency, which adds economic value beyond labor substitution (Manyika et al., 2017, pp. 10-11).

The fifth and last factor is regulatory and social acceptance. Even when the business case for automation is strong, adoption may be slowed by regulations, liability concerns, or societal perceptions. For activities tied to public safety like self-driving cars or robotic surgery, thorough testing and compliance process can extend timeframes. Social or ethical unease about machines replacing certain human functions may also influence policymaking and consumer acceptance, this affecting the speed of deployment (Manyika et al., 2017, pp. 11). Understanding these adoption constraints is important for interpreting differences in automation exposure and investment responsiveness.

3.3 Labor Market Polarization

According to Future That Works by McKinsey Institute intangible capital is closely connected to workforce skills and competencies, which play a critical role in adapting to and leveraging technological advancements like automation. The relationship between technological change, workforce skills, and productivity is framed within the concept of skill-biased technological change (SBTC). SBTC refers to technological innovations that disproportionately increase the productivity of highly skilled workers relative to less skilled counterparts. This dynamic contributes to job polarization, characterized by a decline in routine middle-skill jobs and relative increase in the number of both high-skill, highly compensated roles and low-skill, lower compensated jobs that are less easily automated. (Manyika et al., 2017, pp. 2).

Automation primarily affects routine tasks, which can be either manual, like assembly line work or machine operation or routine tasks that can be cognitive like clerical work and bookkeeping, these tasks are rule-based and predictable, making them easier to automate through robotics, and software. (Autor, 2015, p. 11). In contrast, non-routine tasks, which require problem-solving capabilities, intuition, creativity and persuasion are more resistant to automation (Autor, 2015, p. 12). Even if automation does not reduce the overall labor quantity, it may greatly affect the qualities of jobs available. This explains why some sectors see job displacement while others experience growth. The impact of automation on the labor market has led to job polarization, where middle-skill jobs decline while low-and high-skill jobs grow. Middle-skill occupations like manufacturing jobs, office administration, and clerical work are shrinking as automation replaces workers, low-skill jobs like food service, caregiving, and janitorial work remain in demand as they require human dexterity and social interaction, which is difficult to automate. High-skill and cognitive jobs, like management, law, medicine, and technology are also growing, as they rely on abstract thinking, decision-making, and problem solving, which are complemented by automation rather than replaced by automation (Autor, 2015, p. 9-12). Similar fears of job displacement existed in previous industrial revolutions, yet new industries eventually created more employment opportunities (Autor, 2015, p. 5-6). Unlike previous waves of automation, AI increasingly affects not only manual routine tasks, but also cognitive tasks, further intensifying labor market polarization.

4 Artificial Intelligence as a General-Purpose Technology

Bresnahan and Trajtenberg (1995) argue that most general-purpose technologies (GPTs) function primarily as enabling technologies, which create the potential for widespread transformation across industries rather than offering immediate productivity gains. A central part of this transformation is what the authors refer to as innovation complementarities, the idea that innovation in a GPT increases the productivity of R&D in downstream sectors. In other words, firms can achieve greater productivity or develop new capabilities when they integrate the GPT into their own innovation process (p. 84-85). For example, productivity improvements after the introduction of electric motors were not only due to energy efficiency. Instead, electric power allowed factories to be redesigned more flexibly and efficiently. A demonstration of how a GPT reshapes organizational and physical structures when paired with complementary innovation (p. 84). In return this relationship creates a positive feedback loop, as downstream sectors adapt and innovate around the GPT, they increase demand for further improvements in the GPT itself. Advancements in the GPT simulate further innovation in the user sectors. This mechanism helps spread the GPT's influence across the economy and magnifies its long-term impact (pp. 84-85). However, these complementarities also create coordination challenges. Because the innovation efforts are distributed across many actors and sectors, decentralized market systems may suffer from underinvestment in both GPT and its applications, the authors refer to this "too little, too late" problem (pp. 85-86). In context of AI, the productivity effects are not delayed due to technological immaturity alone, but because organizations need time and capacity to develop the necessary complements such as new skills, workflows, and infrastructures. Additionally, according to European Investment Bank (2022) firms that implement advanced digital technologies, like AI, were significantly more resilient during COVID-19 crisis. These firms were less likely to experience large sales declines and more likely to seize the crisis as an opportunity to accelerate their digitalization processes (EIB, 2022, pp 1-2, 19)

To summarize, AI shares the defining characteristics of general-purpose technology, AI's wide applicability, transformative potential, and dependency on complementary assets.

However, its productivity benefits are linked to firms' ability to adapt through intangible capital, skill development, and restructuring of workflow. These dynamics explain why AI's adoption and impact vary by sector and firm size.

4.1 AI's Unique Features

According to Agrawal, Grans, and Goldfarb (2022), AI should be understood not as general intelligence, but as a technology that drastically lowers the cost of prediction, which is a fundamental input in many economic activities. They argue that this drop in cost is economically significant because predictions are widely used across industries, like forecasting demand and enabling autonomous vehicles on the roads where the environment is more unpredictable (pp. 3-4, 12-14). Like previous general-purpose technologies like electricity, AI has broad applications across sectors and the potential to transform decision-making. The authors emphasize that earlier technologies also had disruptive potential once they became cheaper and more accessible, like for example computing made arithmetic cheap (pp. 10-12). In the same way AI makes prediction cheap and abundant, enabling new uses and making previously unviable applications practical (p. 14). However, the full economic effects of AI will not be immediate. Firms need time to redesign workflows to benefit from electricity or digital infrastructure, AI also requires complementary changes, like data systems, retrained workers, and new decision-making processes to generate value (p. 16-19). Until these changes are applied, productivity gains from AI may remain limited or delayed.

Brynjolfsson, Rock, and Syverson identify a seeming contradiction. On one side, advances in artificial intelligence, especially in machine learning, are accelerating, with many experts praising AI as the next big general-purpose technology (GPT). On the other hand, aggregate productivity growth in many advanced economies has slowed since the mid-2000's. The authors label this disconnect the modern productivity paradox (Brynjolfsson, et al., 2017, pp. 1-3). Brynjolfsson, et al., (2017) propose four explanations for the gap between optimistic forecasts and lacklustre productivity growth. Firstly, false hopes, the expectations surrounding AI are overhyped. The authors cite past examples like nuclear power, once considered revolutionary yet failing to meet great predictions. Another reason for mismeasurement is the possibility that GDP and productivity metrics fail to capture the value of new technologies. Many modern digital services, such as social networks or online media, generate substantial consumer surplus yet have a small direct effect on measured output. The third reason proposed is concentrated distribution. Gains from AI could accumulate disproportionately to a few firms or individuals via, for example automated financial trading or online advertising without boosting average productivity or wages. AI based innovations can create "winner-takes-all" outcomes where only handful of companies reap most of the benefits. The fourth and last explanation is implementation and restructuring lags. The explanation they judge most likely is time lags in developing, adopting, and fine-tuning transformative technologies. While AI appears highly promising, its broader productivity effects won't show up until firms have made complementary investments in new skills, processes, and intangible assets (p. 7-10).

4.2 Delayed Productivity Effects, The J-Curve

Brynjolfsson, et al., (2017) emphasize that short-term difficulties, lack of measured productivity growth, distributional concerns, intangible capital challenges are not necessarily evidence that new technologies are worthless. Instead, they warn that capturing AI's benefits requires sizable complementary investments in intangible assets and organizational transformation. Potentially improved metrics that reflect intangible investments and consumer surplus and longer horizons for productivity payoffs, as the economy experiences a multi-year restructuring process. In conclusion they see AI as a potentially major driver of future productivity growth, despite the current apparent mismatch between exciting technological advances and weak official productivity statistics (p. 33-35).

Brynjolfsson, et al., (2017) highlight how traditional growth accounting may understate AI's contribution. Much of AI's value is tied up in data sets, algorithms, and intangible forms of “capital” that do not show up neatly on firm balance sheets or in national accounts. Early, rapid investments in such intangible assets can reduce the measured productivity because the costs appear immediately, but the benefits are only observable later. Eventually, once intangible investments diminish and technologies mature, official metrics may overstate productivity gains. They call this the “J-curve” phenomenon: short-run productivity lags followed by sharp gains (p. 28-33)

A major claim is that the slow productivity growth we observe today can coexist with an optimistic future. Brynjolfsson, et al., (2017) note parallels with past “big waves” of electrification or computerization, where measured productivity only surged decades after the foundational invention (p. 11-12). They highlighted two delays, firstly companies must build the capital stock, or in other words buy or develop enough AI-related systems to meaningfully affect total output. Secondly there is a need for intangible compliments. The full impact of AI depends on organizational change, new “hybrid” jobs, employee retraining, data platform setups, and complementary innovations. All these intangible investments take time, cost money, and often depress measured productivity in the short run. Eventually, once these complements are in place, gains appear and can even create a “J-curve” effect in productivity (p. 29-33).

4.2.1 Technological Diffusion

Technological diffusion is the process by which new innovations spread across firms and sectors. Instead of these technologies being simultaneously adopted, they are adopted gradually as firms weigh potential benefits against uncertain and often irreversible costs Adoption decisions are not only about whether a to use new technology or not, but when to adopt it. Firms often delay adoption due to uncertainty about the future returns and postpone costly and irreversible investments until benefits clearly exceed costs (Hall & Khan, 2003, pp. 1-2).

Firms’ likelihood to adopt also depends on their internal characteristics. According to Hall and Khan (2003), larger firms with greater market power are generally better positioned to adopt new technologies because they can spread fixed costs, manage risks more effectively, and access complementary assets such as skilled labor and advanced capital equipment (pp. 9-10) Importantly, Organizational capabilities, like management quality and the ability to reconfigure workflows, impact the adoption rates significantly. Additionally technological capacity plays an important role in technological diffusion as the new technology is conceptualized firms need sufficient technological capabilities to utilize them in a commercially viable manner. If the technology is too advanced compared to the skill level of workers, it will take longer for the technology to be implemented (p. 4). Additionally in industries where customer relationships are uncertain or product demand is unstable, adoption may also be delayed. Stable customer relationships or long-term contracts can incentivize investment in new technologies by reducing uncertainty and increasing the likelihood of recouping sunk costs (Hall & Khan, 2003, pp. 5-6).

While Hall and Khan (2003) explain why technology adoption at the firm level can be slow and uneven, Comin and Mestieri (2018) provide a macroeconomic perspective on the same issue. They show that although the time lag between invention and adoption has decreased globally, especially in poorer countries, the intensity of use or how deeply the technologies are embedded in production has diverged significantly between rich and poor countries. In their analysis of 25 major technologies across 139 countries over two centuries, they find that poorer counties tend to adopt technologies at lower scales, leading to weaker productivity gains (pp. 137-140).

4.3 Elasticity and Job Impact

The impact of artificial intelligence on employment is not determined solely by the degree of automation or technological capability, but also by how demand for products and services respond to those advances. Bessen (2018) argues that employment outcomes from automation depend on demand elasticity, as in how consumers respond to lower costs or improved quality by purchasing more (p. 2-3). If demand increases sufficiently as AI reduces production costs or enhances production quality, overall employment may rise, even if individual tasks become automated (Bessen, 2018, p. 3). Bessen (2018) introduces an inverted U-shaped model to describe the relationship between automation and employment. In early stages of automation, demand is often elastic and leads to employment growth but eventually reduces employment demand as demand becomes inelastic and saturated (pp. 4-7). This model explains how employment in the manufacturing sectors first rises and then falls, despite the continuous improvements in productivity (p. 7). Bessen also emphasizes that most automation is partial. AI and other technologies typically augment human workers rather than fully replace them. This suggests that employment effects will depend on whether AI complements human tasks in ways that it introduces new demand (pp. 15-17).

4.4 Complementarity Between AI and Intangible Capital

A study by Damioli, Van Roy, and Vertsey (2021) provides empirical evidence showing that firms investing in AI through patenting activities see positive and significant effect on labor productivity, especially when those firms are in service sectors or are small and medium-sized enterprises (SMEs) (p. 14). This outcome suggests that AI alone does not automatically lead to higher productivity. Instead, its benefits are conditional on the firm’s ability to reorganize workflows, apply the technology effectively, and integrate it into their operations. These are all areas that depend heavily on intangible investments like data quality, human capital, and new decision-making structures. The authors conclude that the productivity-enhancing potential of AI is more visible among more agile firms, those that can quickly adapt and implement AI in ways suited to their business model (pp. 15-16).

Similarly, Calvino and Fontanelli (2023) provide compelling firm-level evidence from French enterprises that shows the importance of complementary intangible assets in realizing productivity gains from AI adoption. Their study distinguishes between firms that purchase AI technologies and those that develop AI internally. The authors find that AI users tend to be more productive than non-users, but this difference is largely explained by pre-existing characteristics. Firms that adopt AI are already more productive before implementation (p. 2-3). In particular, the productivity premium among AI purchasers disappears once observable firm characteristics are controlled for, suggesting no significant causal impact from just buying AI systems (pp. 17).

However, a different pattern emerges for firms that develop AI-solutions in-house. These developers exhibit a significantly larger and more persistent productivity advantage, even after accounting for selection effects. The productivity gains in this group are not automatic but strongly associated with the presence of complementary capabilities, like digital infrastructure and organizational capital. This finding reinforces the view that the successful integration of AI into the business process requires absorptive capacity, the ability to integrate and use new technologies through aligned organizational practices and workforce skills (Calvino & Fontanelli, 2023, pp. 22-25). In short, AI's productivity impact is conditional on firms' intangible capital foundation, especially in terms of internal capabilities to adapt, implement and customize digital innovations effectively.

European Investment Bank (2022) report shows that digital adopters invest significantly more in intangible capital, especially software, data R&D, and employee training. These firms also demonstrate higher total factor productivity (TFP), and are more likely to export, and charge higher prices due to enhanced market power and product differentiation. Additionally, digital firms are more innovative. They are significantly more likely to introduce new products and processes and report a higher share of investment allocated to innovative activities compared to their non-digital counterparts (p. 23-25).

4.4.1 Organizational and Human Capital as Enablers

The adoption of artificial intelligence and automation technologies is not only a technological shift, but one that demands changes in organizational structures, workforce capabilities and strategic priorities. The economic impact of AI is not only the technology itself but how firms restructure their operations, scale through intangible assets, and adapt their workforce skill base to fit new demands (McKinsey 2018, pp. 1-2). Almost 20 percent of companies state that their leadership lacks sufficient knowledge to guide automation strategies, and one-third are concerned that skill shortages will limit their ability to adopt AI successfully (McKinsey 2018, p. 1). This reflects the need for organizational learning and management adaptation to unlock the value of AI technologies.

Cohen and Levinthal (1990) introduce the concept of absorptive capacity, which they define as an organization's ability to recognize the value of external information, assimilate it, and apply it commercially (p. 128). This capacity is crucial to firm's innovative performance. The premise is that absorptive capacity depends critically on the existing stock of related knowledge (pp. 128-129). The authors argue that learning is cumulative, individuals and organizations learn more effectively when they already possess relevant background knowledge and problem-solving skills. Although an organization's absorptive capacity builds on the expertise of its individual members, it also requires robust internal structures for integrating and sharing new knowledge. Certain individuals or "gatekeepers" play a special role in gathering external knowledge and then translating or sharing it with other internal groups. These individuals can be essential for connecting diverse knowledge sets within organization, but too much specialization in a specific domain can prevent others from understanding new information (pp. 131-133). The development of absorptive capacity is history-dependant, a firm that fails to invest in learning in each knowledge domain may find it increasingly costly and less likely to enter domain later, even when new opportunities arise (pp. 135-137).

Chen et al. (2021) examine how investments in intangible capital, specifically human capital and organizational capital influence the productivity impact of industrial robots. The panel data consists of 18 European union countries between 1995 and 2015, and the study underscores that intangible capital significantly complements robots and shaping how effectively automation translates into productivity gains (pp. 1-2). Previous research has shown that robot adoption often enhances output per worker, however, Chen et al. argue that these gains can be uneven or slower to appear when organizations lack supportive intangible assets, especially the workforce skills and structural or managerial readiness to leverage new technologies (pp. 2-4). The study finds that investments into organizational capital in short term tend to boost robot's productivity impact immediately. Better organizational alignment allows robotics to be integrated faster and more flexibly. Long-term impact paradoxically hinders over time as old organizational capital becomes incompatible with the new installation of robots. Human capital on the other hand shows diminished returns in short-term from robotic adoption, but in the long-term the impact is greater because of the learning curves (pp. 26-29).

Organizational capital plays a significant role in how firms adapt to and benefit from automation and technological advances. Bloom, Sadun and Van Reenen (2012) highlight organizational capital as surrounding intangible resource embedded with a company's structure, like culture and management practices. These intangible resources include effective organizational procedures, effective task allocation, internal communication systems, managerial experience, and adaptive corporate culture (pp. 1667-1668). Such intangible capital becomes particularly valuable in context of technological disruption and automation, as firms mush reconfigure their internal structures to harness the benefits of modern technologies effectively. Bloom, Sadun, and Van Reenen argue that one critical dimension of organizational capital is the level of social capital, especially the trust that senior executives place in subordinate managers. Trust facilitates decentralized decision-making withing firms, enhancing organizational efficiency and adaptability (pp. 1668-1671). Decentralization, defined as the delegation of decision-making authority from corporate headquarters to local plant managers, is crucial when firms grow, or complexity increases. It reduces the cognitive load on senior executives by allowing them to delegate routine or specialized tasks down the management hierarchy.

Training represents an essential intangible investment enabling workers and firms to adapt to automation-induced task restructuring. OECD findings indicate that a complex relationship between the risk of automation and training provision. Workers in partially automatable jobs often receive substantial training to transition into new roles within the same organization. On the other hand, employees in jobs deemed fully automatable typically receive much less training, suggesting that firms are reluctant to invest in skills for jobs they anticipate will disappear entirely. Statistical analysis revealed that individuals occupying highly automatable jobs are significantly less likely to have participated in any job-related training in the preceding year. Specifically, workers in fully automatable roles were about four times less likely to receive training compared to those roles with minimal automation risk. This reduced investment in training highlights firm's strategic decision-making regarding intangible capital investment in human resources based on anticipated automation outcomes (OECD, 2018, pp. 104-107).

4.4.2 Evolving Skill Requirements

McKinsey highlights that digital literacy will no longer be specific to IT departments, instead functions like supply chain, procurement, HR, and customer service will increasingly require staff to use digital tools and interpret data-driven recommendations (MGI, 2018, p. 17) The greatest impact of AI and automation is expected to emerge through changes in the demand for workforce skills. McKinsey forecasts that the need for technological skills will increase by 50 percent by 2030. This is driven by a sharp increase in demand for advanced IT and programming skills, which is expected to increase by 90 percent between 2016 and 2030 (MGI, 2018, pp. 1, 8). In addition to technical expertise, demand for social and emotional skills, like leadership and managing is expected to rise by 24 percent (MGI, 2018). Higher cognitive skills are also expected to become increasingly valuable, as MGI projects the share of higher cognitive share across occupations to increase from 55 percent in 2016 to 61 percent in 2030, these skills include advanced literacy and writing, quantitative and statistical skills, critical thinking and decision making and creativity. Conversely the report predicts a decline in time spent on basic cognitive skills, like basic data processing and literacy, with approximately 15 percent reduction by 2030. Similarly, manual and physical skills are expected to decrease by 14 percent, particularly in sectors such as manufacturing and finance (MGI, 2018, pp. 1, 12). These shifts are not evenly distributed across sectors. For example, healthcare is expected to see the most increased demand for both social-emotional and fine motor skills, while banking and insurance will experience the strongest declining needs for basic cognitive skills. A growing mismatch between workforce capabilities and employer needs is already apparent. Over 30% of workers in OECD countries report that their current job does not fully utilize their skills, while several countries report shortages in areas such specialized information technology workers and data scientists (MGI, 2018, pp. 3-4).

4.4.3 Retrain and Redeploy

To address growing skill mismatches brought by AI, companies must adopt active strategies for retraining and redeploying workers. Retraining encompasses several approaches: upgrading the skills of current employees, teaching them entirely new competencies, or hiring new talent specifically with the goal of training them in job-specific capabilities. This kind of investment preserves valuable in-house knowledge and organizational culture while aligning employee skills with future business needs. Companies often prioritize retraining for strategically important skills, like programming, advanced literacy, and critical thinking, while preferring to recruit externally for more routine tasks (MGI, 2018, pp. 50-53).

Simultaneously, redeployment allows companies to make better use of their existing workforce by reallocating employees to roles where their skills can be applied more effectively. This may involve breaking down and reconfiguring job tasks, moving employees laterally across departments, or shifting them entirely into a new function.

One example involves the German postal service, which expanded the role of mail carriers to include welfare checks on elderly residents, an initiative that combines service innovation with social value. In a McKinsey survey, 55% of large firms reported that they were more likely to move people into new roles than let them go, highlighting the importance of redeployment as part of broader workforce strategy (MGI, 2018, pp. 50-53).

4.5 Sectoral and Firm Size Differences in AI Adoption

OECD (2018) report emphasizes that AI-driven automation potential significantly differs across occupations and industries. For instance, occupations related to teaching and healthcare exhibit lower automatability, whereas tasks with lower-skilled occupations such as manual labor, machine operation, or administrative roles face a higher risk of automation. Additionally, tasks involving social intelligence, perception, and physical manipulation present different automatability levels, further reinforcing that automation targets specific task characteristics rather than entire occupational categories uniformly (OECD, 2018, pp. 61, 104).

Research on intangible capital consistently highlights that the intensity and the structure of intangible investment differ significantly across sectors, affecting their respective labor productivity growth rates. Roth (2022, p. 15) emphasizes that industries differ substantially in both their overall intangible investment intensity and the specific types of intangible capital they prioritize. According to the empirical results of Roth’s econometric analyses, intangible capital per worker is notably significant at both aggregate and sectoral levels, accounting for approximately half of the labor productivity growth (Roth, 2022, p. 18). In the manufacturing sector, investments in intangible assets are dominated by R&D activities, reflecting the sector’s dependence on innovative property to maintain competitiveness. Manufacturing firms typically prioritize R&D investments significantly more than other intangible types, due to their reliance on continuous technological advancements for product development and process efficiency

(Roth, 2022, pp. 15-16). Although, the market services sector, including finance, business services, and information and communication, show a different intangible capital composition. Those sectors primarily invest in non-R&D intangible assets, particularly organizational capital and software investments. These intangible assets support productivity by enhancing firm's ability to organize, adapt and effectively integrate digital technologies within their operations (Roth, 2022, pp. 16-17). On the other hand, sectors like wholesale and retail, or broader distributive services prioritize intangible investments related to economic competencies, notably organizational capital, training, and software, emphasizing process efficiency, customer relationship management, and internal knowledge development (Roth, 2022, pp. 15-16).

Organizational capital specifically emerges as a critical driver of productivity growth within the service sectors alongside with software investments. It has been demonstrated that investments in organizational structures, process and management practices significantly enhance labor productivity. This occurs through improved operational efficiency, higher flexibility, and better integration of technological innovations into the firm's operational processes. The study finds organizational capital has particularly strong productivity impacts in business services, suggesting that managerial and organizational innovations are crucial for leveraging potential for intangible assets in services (Roth, 2022, p. 20).

The adoption of AI technologies across European enterprises is uneven and strongly influenced by both sector and firm size. According to Eurostat (2024), only 13,48% of EU companies with at least 10 employees reported using AI in 2024, having increased by 5,45 percentage points compared to 2023. However, there are substantial disparities. Among large enterprises, 41,17% had adopted AI, compared to 20,97% of medium-sized and 11,21% of small enterprises. These differences suggest that economics of scale, implementation complexity, and investment capability are key enablers for AI adoption (Eurostat, 2024, p. 1-2) Significant differences also exist across sectors. AI use was most widespread in the information and communication sector, where almost 50% of enterprises reported using AI. The professional, scientific, and technical activities sector followed with a 30,53% adoption rate. All other sectors remained below 16% with manufacturing using little over 10% (Eurostat, 2024, p. 4)

5 Research Methodology, Data and Empirical Analysis

This thesis investigates how AI-impacted automation affects the structure of labor and what is the following implication for intangible capital investments and productivity across business activities. The analysis relies on combining occupational-level automation potential estimates with business activity-level employment data to simulate future shifts in task content and to calculate automation-adjusted investment multipliers for different intangible capital categories. Further these shifts are analysed at a sectoral level to calculate AI-driven intangible multipliers to analyse the productivity of different intangible categories.

The methodological foundation is built on the assumption that AI has different effects on occupations, as it tends to augment knowledge-intensive roles (IC-work) and more readily displace routine, non-innovative occupations (NOIC work). This division into two types of work helps organize the analysis and is used to calculate adjusted investment levels, which are then tested in productivity analysis. STATA IC 16.1 and Excel were used to conduct this analysis.

5.1 Data

The automation exposure data is derived from McKinsey Global Institutes Midpoint Automation Estimates by 2030 (Hazan et al. 2024), which provides estimates of AI-driven automation by occupation in worked hours, see Table A.1 in the Appendix. This thesis focuses on the non-generative AI-driven automation estimations. These occupational-level estimates are mapped to Eurostat (2025) labor force statistics, specifically the business activity (NACE Rev. 2 letter-level) distribution of occupational shares. This allows the estimation of automation potential across each business activity by weighing occupational shares with their respective AI-driven automation estimations. Occupations are then grouped into two broad categories, IC and NOIC. Further, this business activity applied AI-driven automation estimates are split into sectors.

Table 1. Innovative and non-innovative occupations based on ISCO08 classification

Eurostat ISCO-08 Group	Matched McKinsey Category	IC/NOIC Classification
Managers	Managers	IC
Professionals	STEM professionals	IC
Technicians and associate professionals	STEM professionals	IC
Clerical support workers	Office support	NOIC
Service and sales workers	Customer service and sales	NOIC
Skilled agricultural, forestry and fishery workers	Agriculture	NOIC
Craft and related trades workers	Builders	NOIC
Plant and machine operators, assemblers	Production work	NOIC
Elementary occupations	Food services	NOIC

Table 1 categorization enables the splitting of AI-driven automation exposure into IC- and NOIC- work, which is consistent with theoretical assumption that AI complements cognitive, abstract tasks while substituting routine labor.

The EU Horizon 2020 project GLOBALINTO aims to study intangible investments and growth across Europe. The multipliers are evaluated from Piekkola H. (2024, Table 6.2) which shows the constructed intangible investment multipliers. These multipliers were key for modelling how changes in occupational structures, especially shifts towards more innovative work, transform into sectoral demand for intangible capital GLOBALINTO dataset is the linked employee-employer data where occupational intangible capital can be calculated after knowing the intermediate input and tangible capital multipliers for one unit of intangible-labor work. The multipliers show how intangible labor costs need intermediate input and tangibles to become intangible investment. The evaluation of these uses industry-level input-output data over European intangible capital producing business services.

The data here originates from the GLOBALINTO survey, which focuses specifically on how firms invest in various categories of intangible capital and how these investments relate to digitalization in eight European countries. The total number of firm observations is around 1700 firms with higher weight on large countries like Germany, France, The UK than in the smaller countries like Finland, Denmark, Norway, Slovenia, and Greece.

5.2 Results and Analysis

This section presents the results from empirical analyses that covers all firms in the GLOBALINTO survey with approximately twice the amount of reporting firms from large countries. The analysis aims to explore the relationship between automation exposure, intangible capital investments, and productivity outcomes across different sectors. The industries covered in the survey are manufacturing and business services that can be considered as the most intangible intensive sectors at least in terms of R&D. Initially the results are descriptive, followed by regression analysis to quantify the relationships. The categorization to high-and low-productivity manufacturing, knowledge-intensive services, and other services follow OECD and Eurostat classification, see Appendix Table A. 3.

5.2.1 Descriptive statistics

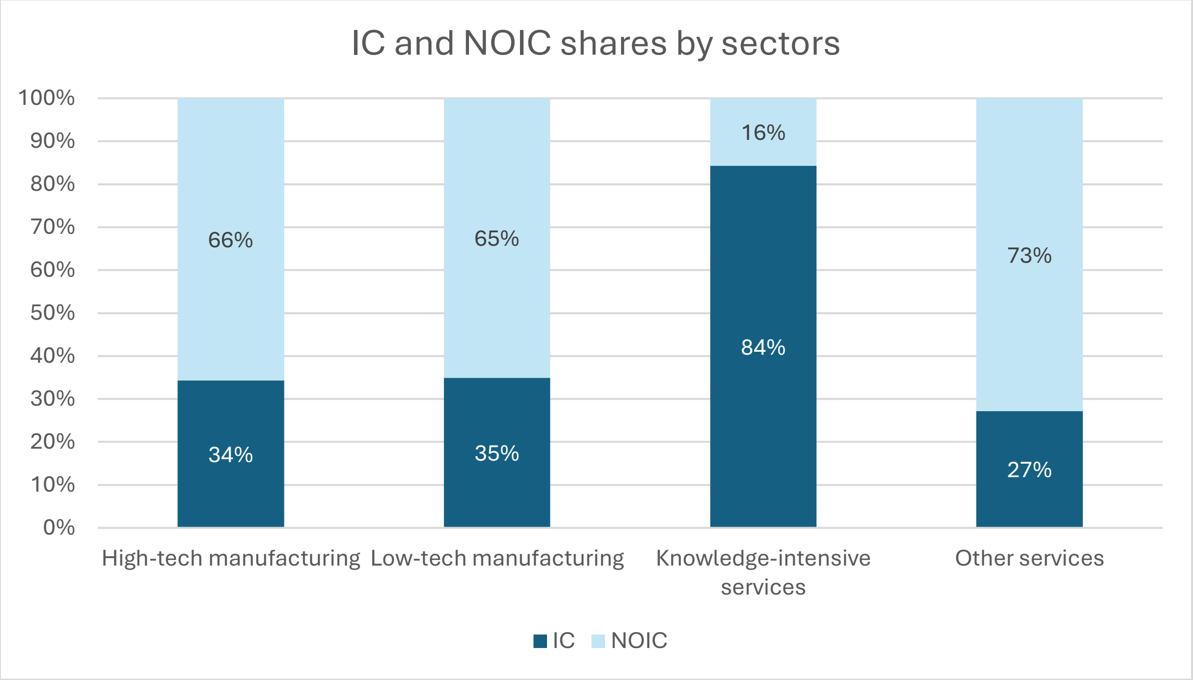

Figure 1. IC and NOIC shares by sectors

Figure 1 shows the baseline distribution of work between IC and NOIC work occupations across four sectors. These shares reflect the composition of labor in each sector before any AI-related adjustments to explain how exposed each sector is to AI-driven transformations based on occupational structure.

In knowledge-intensive services, IC roles dominate the workforce, accounting for 84% of all employment. This reflects the sector's heavy reliance on cognitive tasks, roles that are professionals, managers, and technicians. This high IC share suggests that automation is less likely to displace workers and more likely to augment existing capabilities according to Acemoglu & Restrepo (2018) and Bessen (2018). In contrast, high-tech and low-tech manufacturing have more balanced work structures. High-tech manufacturing shows 34% IC and 66% NOIC split, while low-tech manufacturing Shows 35% IC and 65% NOIC split. Although these sectors employ highly skilled engineers, a significant portion of work remains routine and operational (NOIC), including assembly, maintenance, and machine operation. These NOIC roles are more vulnerable to AI-driven automation. Other services show a relatively low IC share of 27% and NOIC share of 73%. This structure suggests high exposure to automation risk. Many of the tasks in this sector, like clerical work, are susceptible to AI-driven automation. This sector may experience both significant displacement of NOIC work and a need for retraining to support emerging IC tasks.

In summary, these IC and NOIC distributions provide foundation for interpreting the sector-specific impacts of AI-driven automation. As emphasized in prior theory, AI is expected to reallocate work toward more intangible-capital related functions rather than eliminate work altogether.

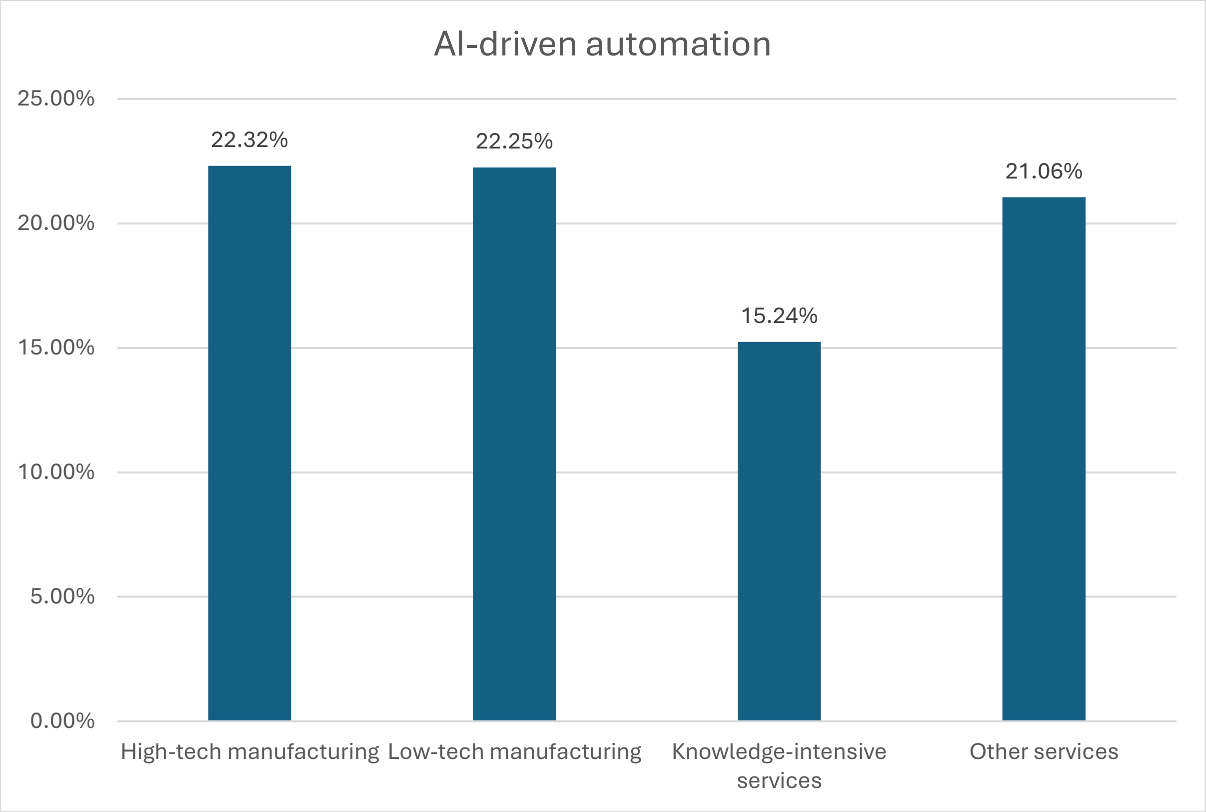

Figure 2. AI-driven automation exposure % by sectors

Figure 2 presents the average automation potential across four sector groups. According to the data, high-tech manufacturing and low-tech manufacturing sectors show highest automation exposure. This aligns with previous literature by Autor (2015) and Manyika et al., (2017), which highlight that sectors which rely heavily on routine, predictable tasks are more vulnerable to automation. Other services show moderately high exposure of 21.06%, reflecting the presence of routine service jobs, which involve repetitive manual or simple cognitive tasks. These are also increasingly targeted by AI-driven automation. In contrast, knowledge-intensive services display the lowest automation exposure at 15.24%. This sector includes professional, scientific and technical services that rely heavily on non-routine, cognitive and interpersonal tasks, like consulting, legal work, software development, and R&D. These tasks are less susceptible to current forms of AI-automation because they require problem-solving, abstract thinking, and complex human judgement. The differences highlight that automation exposure is not evenly distributed across sectors. Instead, it depends largely on the mix of occupations and the nature of tasks withing each sector.

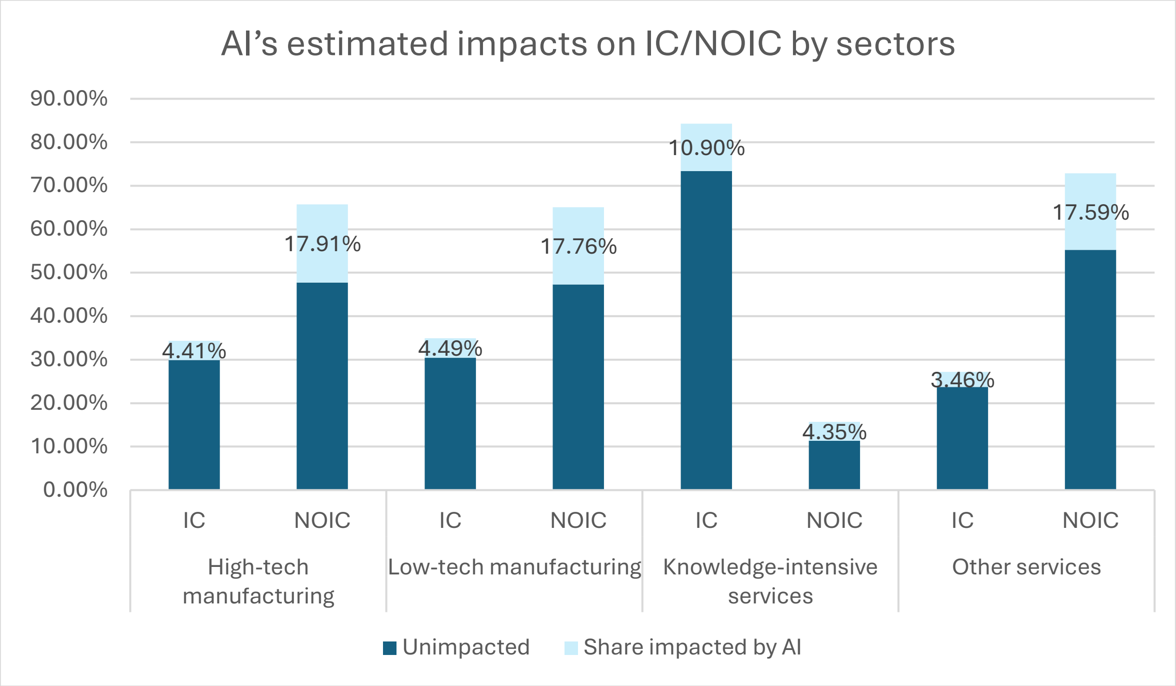

Figure 3. AI’s estimated impacts on IC/NOIC by sectors

Figure 3 shows how AI-driven automation is estimated to impact IC and NOIC share of work across different sectors. IC and NOIC work combined represent 100% of the work.

Unlike Figure 2, which focused on overall automation exposure, this figure highlights how shares of IC and NOIC work are differently affected by AI. The Figure 3 shows that AI has a relatively strong impact on NOIC shares in every sector except knowledge-intensive services, while only small portion of IC work is impacted. On the opposite, knowledge-intensive services show a strong augmentative effect of AI on IC occupation. The Figure 3 further shows how AI's influence is uneven not only across sectors but digs deeper how the differences emerge. These estimated shares of AI-impacted IC and NOIC work is used to calculate the intangible multipliers used in the productivity analysis.

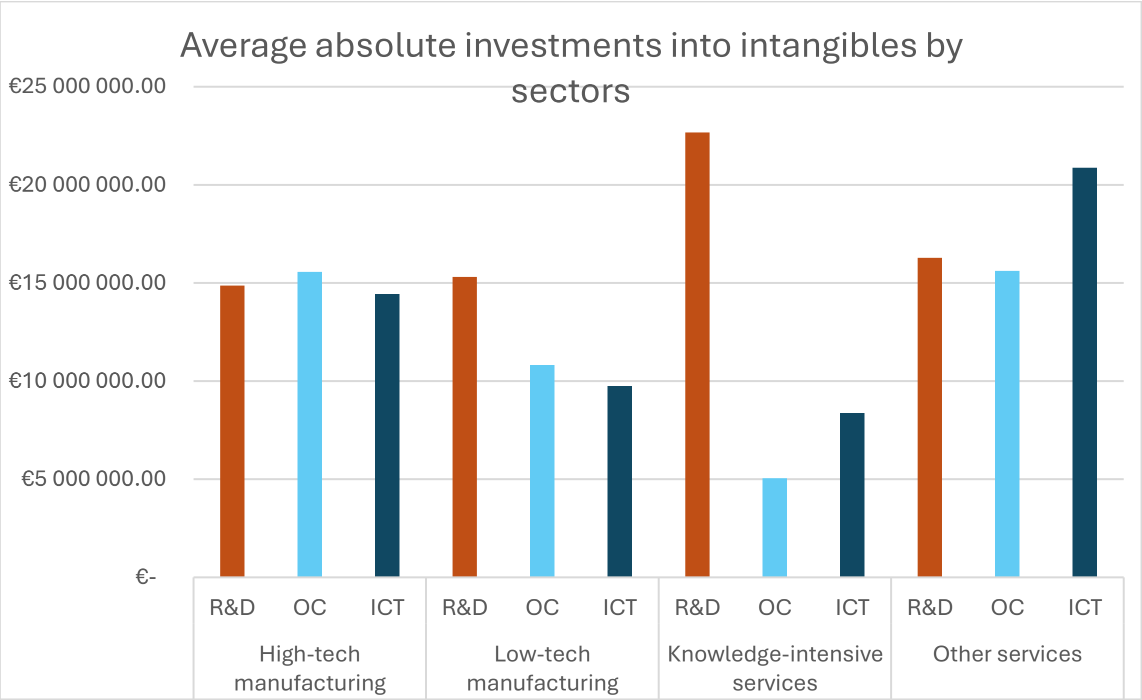

Figure 4. Absolute average intangible investments by sectors

Figure 4 shows the average absolute levels of investment across three main intangible capital categories, Research & development (R&D), organizational capital (OC), and information and communication technology (ICT) by sectors. This visual shows the distinct sectoral differences for intangible investments, which are connected to each sector's occupational structures and tasks withing occupations (Corrado et al., 2022).

Intangible investment multipliers are also based on the share of each intangible category out of all intangible investments by sectors.

Knowledge-intensive services show a strong focus on R&D with an average exceeding €22 million. The high R&D intensity in knowledge-intensive services emphasizes the role of intangible inputs in facilitating AI adoption. These firms are likely to invest in R&D not only to generate new products and services but also to complement AI capabilities through innovation complementarities (Bresnahan & Trajtenberg, 1995).

In contrast, organizational capital investments are highest in other services and high-tech manufacturing, with both sectors showing similarly high levels. This pattern indicates that firms in these sectors are allocating significant resources to internal structures, management practices, and coordination systems which are key components for adapting to AI-driven transformation. As discussed in theoretical framework, organizational capital enhances a firm’s absorptive capacity (Cohen & Levinthal, 1990), which is critical for integrating new technologies like AI into existing workflows. While knowledge-intensive services still invest in organizational capital, their level is significantly lower, which may reflect their already higher baseline of IC-intensive work and more stable organizational configurations. The substantial OC investments in other services, a sector with higher NOIC shares, likely reflect efforts to manage increasing complexity and digitalization through organizational reforms. This supports hypothesis H1, which proposes that AI-induced productivity gains depend not only on the presence of technology but also on complementary intangible assets like OC that enable firms to transform their internal operations effectively. ICT investments were the highest in other services, where digital infrastructure may be more scalable way to improve performance. The strong ICT investment in service-heavy and highly susceptible to AI-driven automation suggests that firms in these industries prioritize software and data systems as enablers for AI integration.

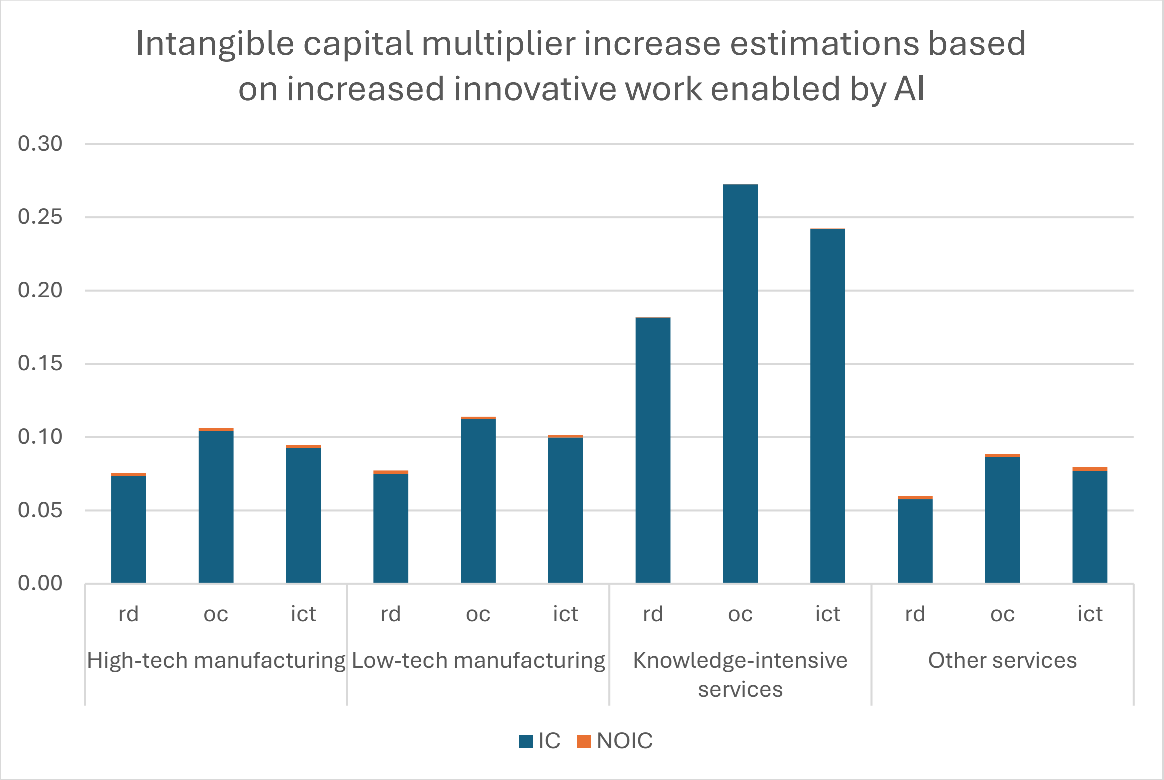

Figure 5. Intangible capital multiplier increase estimation based on increased innovative work enabled by AI

Figure 5 presents the estimated increase in intangible investment multipliers across sectors, based on projected shifts in work content due to AI. The estimation method is based on two main assumptions. The first assumption is that 80% of NOIC work does not contribute to intangible capital formation, and only 10% of displaced NOIC workers can realistically be reallocated to IC work. This constraint reflects educational, and skill mismatches as highlighted in previous literature (MGI, 2018).

The second assumption is that the investment multipliers are adjusted in two steps. Initially, the IC work in each sector is rescaled to reflect a hypothetical state where all IC work is fully innovative.

This is done by applying inverse labor share from Piekkola, H. (2024, Table 6.2). Then, AI's augmentative effect on IC work is added to reflect on IC work is added to reflect how AI enables higher productivity and innovative potential per worker. This is then distributed across three intangible categories weighted by investment intensities. All formulas are calculated separately for R&D, OC, and ICT, as the innovative shares and investment priorities vary across categories. For each sector the following calculations were made to create the intangible multipliers.

1) **Adjustment among IC workers:**

Normalized Innovative shares, for each R&D, OC and ICT from Piekkola, H. (2024, Table 6.2) to calculate the full innovative capacity.

$$NormalizedShare_i = \frac{1}{\alpha}\ , \ \ Where\ \alpha = (0.6, 0.4, 0{,}45) \tag{1}$$

Estimated AI impact on IC work by combining the total impact across all IC occupations, using Eurostat occupation shares by NACE-letter and Midpoint occupation-specific AI-driven automation estimates. Initially, AI exposure was calculated at the NACE-letter level. Then, average values across NACE-letters were aggregated to present sector-specific AI exposure.

$$\sum_{i=1}^{n}(OccupationShare_{IC}\ \times OccupationImpact_{AI}) = AI_{IC} \tag{2}$$

Calculating for growth in innovative work.

$$AI_{IC}\ \times NormalizedShare_i = InnovativeGrowth_i \tag{3}$$

Calculating new Innovative share for each intangible category.

$$\frac{1+InnovativeGrowth_i}{NormalizedShare_i} = NewInnovativeShare_i \tag{4}$$

Finally, the IC impact portion of the total multiplier

$$NewInnovativeShare_i\ \times NormalizedShare_i = ICMultiplier_i \tag{5}$$

2) A shift from Non-IC to IC work

Non-intangible NOIC workers that qualify for IC work, assuming 10% of NOIC workers qualifying for transition and 80% representing the non-innovative share of NOIC workers.

$$NOIC_{share} \times 0.10 \times 0.80 = Qualified_{NOIC} \tag{6}$$

Estimated AI impact on NOIC work. Average occupation shares of each sector calculated similarly to sector specific IC (2) impact.

$$\sum_{i=1}^{n}(OccupationShare_{NOIC} \times OccupationImpat_{AI}) = AI_{NOIC} \tag{7}$$

Intangible shares of all intangible investments considering the sectoral differences in intangible investments.

$$\frac{I_i}{I_{Total}} = IntangibleShare_i, Where\ i = R\&D, OC, and\ ICT\ investments \tag{8}$$

Calculating NOIC multiplier that will be combined with IC multiplier.

$$Qualified_{NOIC} \times AI_{NOIC} \times IntangibleShare_i = NOICMultiplier_i \tag{9}$$

3) Combined impact on Innovative growth in each intangible category

Total multipliers for each intangible category in each sector, accounting for sectoral AI-driven automation impacts, investment priorities and IC/NOIC occupation shares.

$$NOICMultiplier_i + ICMultiplier_i = \boldsymbol{TotalMultiplier_i} \tag{10}$$

In contrast to the AI exposure shown in Figure 2, the results in Figure 5 show the largest multiplier increase in knowledge-intensive services, especially in OC and ICT categories. This sector has the highest IC work share of 84%, meaning that a relatively small AI-induced shift further amplifies their intangible investment potential. This is in line with

Brynjolfsson et al., (2017) J-curve effect, where sectors that have already built intangible infrastructure like knowledge and knowhow in IC workers see faster returns from AI as completed to human capabilities.

In high-tech and low-tech manufacturing, the estimated increases are moderate but still significant. While these sectors experience relatively high automation exposure, their baseline IC share is lower, and the transition from displaced NOIC work into IC was constrained by the 10% reallocation assumption. Regardless, AI still enhances the innovative work being done by existing IC labor, especially in R&D and ICT, reflecting the growing role of production technologies, software and skilled workers in manufacturing.

Other services show the smallest multiplier growth. This outcome shows that a lower IC share and higher share of routine, low-skill jobs that are more susceptible to automation are less likely to translate into innovative roles. These results align with the literature on skill-biased technological change (Manyika et al., 2017) and the concern that sectors dominated by NOIC work face structural barriers to capturing full benefits of AI-driven innovation without extensive complementary investments in human capital and organizational capacity (Calvino & Fontanelli, 2023).

In summary, these results align with the hypothesis that AI’s impact on intangible capital is strongest in sectors that have already a significant share in IC labor and are equipped with complementary capabilities. The skilled workforce determines the firm’s ability to benefit from AI-driven benefits.

Table 2. Summary Statistics of Key Variables

Variable	Obs.	Mean	Std. Dev.	Min	Max
Sales/employees	290	269 579.7	686050.3	452.02	1.00E+07
Employees	290	406.555	1455.06	20	18396
Sales	290	7.18E+07	1.88E+08	13100	2.14E+09
Employees in R&D	290	23.517	58.389	1	700
Digit	290	6.117	2.246	3	15
OC investments	290	4.02E+07	1.86E+08	655	2.98E+09

Table 2 presents the summary statistics for the key variables used in the regression analysis with 290 observations. The average firm in the dataset has approximately 406 employees with a significant standard deviation of 1455, showing a wide range of firm size where smallest firm is 20 employees and largest firms with over 18 000 employees. The average labor productivity measured as sales per employee is approximately € 269 580 with high standard deviation with a minimum of approximately € 452 and maximum of 10 million. Similarly, total firm sales also vary significantly ranging from € 13 100 to over € 2.14 billion. Firms employ on average approximately 24 R&D employees, but the distribution ranges with some firms employing up to 700 in R&D. The digitalization variable (Digit) which is combination of three survey question on Likert scale on 1-5 where 5 represents investments "*to a great extent*" and 1 representing "*not at all*", into hardware, digital, and bioinformatics related technologies. The organizational capital (OC) investments have a mean of approximately € 40.2 million, with high standard deviation showing differences from firms investing less than € 1000 to those that invest nearly € 3 billion.

5.2.2 Regression results

Table 3. Regression analysis results: AI vs. no-AI OLS and probit-models

Variables	Sales/employees (AI)	Sales/employees	Innovator (probit-AI)	Innovator (probit)
Log of (R&D emp * Estimated AI Exposure)	-0.084^{*}		0.016	
	(0.046)		(0.082)	
Log of (Digit * Estimated AI Exposure)	-0.071		0.697^{***}	
	(0.128)		(0.233)	
Log of (OC * Estimated AI exposure)	0.302^{***}		0.010	
	(0.027)		(0.047)	
Firm size: 20-49 employees	0.302	0.303	-0.369	-0.373
	(0.189)	(0.189)	(0.329)	(0.328)
Firm size: 50-149 employees	0.053	0.053	-0.211	-0.213
	(0.171)	(0.171)	(0.295)	(0.295)
Firm size: 250-499 employees	-0.287	-0.286	-0.489	-0.487
	(0.182)	(0.182)	(0.313)	(0.313)
Firm size: 500+ employees	-0.863^{***}	-0.858^{***}	-0.060	-0.053
	(0.201)	(0.201)	(0.353)	(0.354)
High-tech manufacturing	0.281	0.283	-0.365	-0.348
	(0.202)	(0.201)	(0.345)	(0.344)
Low-tech manufacturing	0.173	0.177	-0.299	-0.287
	(0.199)	(0.199)	(0.342)	(0.341)
Knowledge-intensive services	-0.149	0.000	0.569	0.000
	(0.213)	(.)	(0.373)	(.)
Denmark	-0.215	-0.218	-0.251	-0.250
	(0.174)	(0.174)	(0.311)	(0.311)
Finland	-0.091	-0.089	-0.411	-0.408
	(0.167)	(0.167)	(0.298)	(0.298)
France	0.102	0.101	-0.519	-0.517
	(0.196)	(0.196)	(0.346)	(0.346)
Greece	-0.047	-0.051	0.124	0.125
	(0.163)	(0.163)	(0.294)	(0.294)
Slovenia	-0.230	-0.233	-0.171	-0.166
	(0.156)	(0.156)	(0.279)	(0.278)
UK	-0.098	-0.101	-0.367	-0.365
	(0.179)	(0.178)	(0.321)	(0.321)
IC multiplier dummy		-0.122		0.672^{*}
		(0.210)		(0.368)
Log of R&D emp		-0.097^{*}		0.011
		(0.052)		(0.093)
Log of Digit		-0.069		0.700^{***}
		(0.128)		(0.233)
Log of OC		0.302^{***}		0.010
		(0.027)		(0.047)
Cons	7.610^{***}	7.659^{***}	-0.705	-0.651
	(0.534)	(0.530)	(0.939)	(0.933)
R^2	0.436	0.436		
Adjusted R^2	0.403	0.403		
Pseudo R^2			0.128	0.128
Log likelihood			-169.435	-169.448
N	290	290	290	290

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3 presents the results from OLS and probit models analysing the relationship between intangibles and AI exposure with two outcome variables. The first two columns show the OLS regressions estimating productivity, with and without AI-weighted multipliers for each intangible category as presented in Figure 5. The third and fourth columns present probit model estimates for the probability of a firm being classified as an innovator with and without AI multipliers. The OLS models explain approximately 43.6% indicating a relatively strong model fir for cross-sectional data.

The variable log of (R&D emp) with and without AI multipliers show small difference at under 10% statistical significance where the coefficient for AI is although negative (-0.084) but slightly less negative compared to the results without AI multiplier (-0.097) indicating that AI increases productivity of R&D or at least reduces the negative association with labor productivity. While R&D is commonly viewed as a productivity-enhancer, the findings show that R&D employment is negatively associated with labor productivity. This can potentially be due to delayed effects or exceptional circumstance. The estimation period overlaps with COVID-19, during which revenues declined hence possibly impacting results negatively. This result is also in line with J-curve effect, regarding investment payoffs where the productivity impacts are delayed and thus not showing in cross-sectional analysis (Brynjolfsson et al., 2017). This result fails to confirm hypothesis H2 as the results are negative. It is noteworthy that even though the effects are negative, they are less negative compared to scenario without AI multipliers.

The log of (digit) when interacted with AI exposure, is not significantly linked with productivity, but it shows a strong and statistically significant positive effect on innovation probability. Similarly, the variable without AI multiplier the innovation is statistically significant in the probit mode. These results suggest that digital investments play an important role in innovative activities and supports hypothesis H3 when looking at literature by Bresnahan and Trajtenberg (1995). Although digital investments do not show a direct positive association with labor productivity in the OLS results, they are strongly associated with innovation outcomes in the probit model. This pattern is consistent with the framework of general-purpose technologies as described by Bresnahan and Trajtenberg (1995), who argue that the value of GPT's like AI, emerges through the ability to enable and complement innovation, rather than through immediate productivity gains. It supports hypothesis H3, although the impact is observed through innovation outcomes rather than productivity which convert into productivity in the long run.

The coefficients for organizational capital are nearly identical with and without AI-adjusted multipliers, and both are statistically significant. This indicates that it is a consistent and positive predictor of labor productivity. How ever the similarities in the results suggest that AI exposure does not amplify the productivity effect of OC. Therefore, while this result supports hypothesis H1, confirming that OC contributes to productivity, the results also show that this effect is stable and independent of sector-level AI exposure. This strong productivity impact from OC is also consistent with concept of absorptive capacity (Cohen & Levinthal, 1990), which emphasizes that firms with strong organizational structures are better prepared to implement and benefit from new technologies and as a result improve productivity.

The IC multiplier dummy represent firms that are highly exposed to AI in a way that transforms work structure towards IC-occupations. The probit results show that IC multiplier dummy is positively associated with innovator status at the 10% significance level, suggesting that high level of AI adoption is linked to greater likelihood of innovation. This supports the view that AI functions as a technological input and organizational transformation mechanism enabling more innovations. This further supports the GPT perspective (Bresnahan & Trajtenberg, 1995), which argues that technologies like AI enable innovation when integrating with firms' organizational processes. Corrado, Hulten, and Sichel (2005) also argue that organizational capital enables long term productivity especially when new technologies are introduced. This indirectly aligns with the IC multiplier dummy, which captures the structural shift towards IC type work due to AI and as a result creating stronger conditions for new innovative technology solutions like AI indirectly supporting H1. Finally improved or the same output elasticity shows that AI has important positive scaling. Firms have higher level intangibles at improved or no decrease in returns on intangibles.

It is also noteworthy that the coefficients for firms with more than 500 employees is significantly negative in both OLS models, and slightly more so in the AI-weighted regression with coefficient of -0.863 compared to -0.858. This suggests that larger firms are on average less productive per employee and further may benefit less from AI-driven productivity gains. This result can be explained by Hall & Khan (2003) who argue that larger firms are firms are generally better positioned to adopt new technologies due to better risk management and better access to complementary assets, but the authors also highlight that it is also dependant on skilled labor and capital equipment which could as a return impact larger firms ability to capitalize on benefits of AI. Additionally, Hall & Khan (2003) provide another explanation to the negative results in larger firms, as due to the decision to postpone the implementation of new technology like AI due to uncertainties like COVID-19 in this instance. As the implementation of new technologies is costly and irreversible (Hall & Khan, 2003).

In summary, the empirical results partially confirm all three hypotheses. Hypothesis H1 is supported by the consistently positive impact of OC productivity and by the shift towards IC intensive work as an enabler for AI. Hypothesis H2 receives support, since R&D is negatively associated with productivity, but the AI-adjusted version is slightly less negative, suggesting weak complementarity and the result is possibly impacted by exceptional circumstances. Hypothesis H3 is supported in terms of innovation, rather than immediate productivity, supporting the broader perspective where AI’s impact on firm outcomes is shaped by innovative capabilities that are enabled by strong ICT infrastructure.

5.3 Summary of results

This thesis investigated how AI-driven automation exposure interacts with intangible capital to influence productivity and innovation across sectors. The descriptive analysis first highlighted differences in occupational structures and automation exposure across sectors. Knowledge-intensive sectors consisted of 84% share of IC work, suggesting they are less exposed to routine replacing AI-driven automation and more likely to benefit from AI as a complement to skilled work. In contrast other remaining sectors, low- and high-tech manufacturing consisted roughly of 65% NOIC work which are more vulnerable to automation displacement. Other services had the highest AI-driven automation exposure while simultaneously occupations combined had the highest NOIC shares of all four sectors. These occupational distributions were used to construct AI-multipliers, estimating how AI exposure affects the need for intangible capital across sectors.

In the regression analysis organizational capital showed the strongest and most consistent positive effect on labor productivity in both regression models. However, the similarity in results with and without AI exposure suggests that AI scales the productivity, but it does not amplify the productivity of AI while also confirming the H1. R&D employment was negatively associated with productivity in both models, though the effect was slightly less negative in the AI-adjusted model. This supports the hypothesis H2, suggesting limited short-term complementarity between AI and R&D work. The result aligns with the J-curve effect (Brynjolfsson et al., 2017), where R&D investments and AI adoption generate long term, and not immediate returns. ICT investments did not significantly predict productivity but were strongly associated with innovation probability in the probit models. This confirms hypothesis H3 but from the perspective of innovation, indicating that ICT supports the firm’s ability to innovate under AI exposure. This result is consistent with GPT theory (Bresnahan & Trajtenberg, 1995) which views AI as technology that enables new innovations rather than immediate efficiency gains. The IC multiplier dummy reflecting the AI-induced shift towards IC-work was positively associated with innovator status at the 10% level and increase the level of intangibles thus provoking higher scaling. This implies that firms with stronger shifts towards IC work are more likely to engage in innovation, reinforcing the role of AI as transformative technology. This indirectly supports H1, through its link to innovative potential.

6 Conclusions

Artificial intelligence has emerged as a general-purpose technology capable of transforming production, labor markets, and organizational structures. Unlike earlier technologies that primarily automated tasks, AI's capabilities extend into cognitive and decision-making domains, changing the very nature of work across sectors. How ever GPT's like AI do not generate productivity gains on their own, and their impact is largely dependent on complementary assets. This study aimed to explore how sectoral differences in AI-driven automation potential interact with these intangible capitals to shape firm productivity and innovation outcomes.

While the empirical analysis examined OC, R&D and ICT separately, the findings show a broader conclusion, where the intangible capital types are interdependent, especially under AI-driven transformation. Organisational capital for example showed the most consistent positive association with productivity, which is crucial for supporting R&D work and ICT deployment. R&D, while negatively associated with short-run productivity, represents the firm's capacity for generating new knowledge, which must be structured, scaled, and applied. These tasks are heavily dependent on strong organisational capital. Similarly, the ICT investments are most impactful through enabling innovation processes, as shown in their strong effect on innovator status. The interdependence is also visible in IC multiplier dummy, which captures AI-driven shifts towards more IC-type work. These roles often require ICT infrastructure, and they benefit from innovative cultures that are guided by organizational capital. In this sense IC-work reflects the intersection of all three intangible domains as it is enabled by ICT, driven by R&D and coordinated through OC.

It becomes clear that these intangible types operate as a system rather than isolated assets. Intangible capital is synergistic in nature meaning that the value of one increase with the presence of others. In the context of AI, these complementarities are particularly important. As emphasized in GPT theory (Bresnahan & Trajtenberg, 1995), the productivity effects of GPT's like AI depend on the availability and alignment of complementary inputs. This thesis provided empirical support showing that productivity and innovation benefits are realized more clearly in firms and sectors where these intangible investments are already developed.

Several limitations should be acknowledged. First, the automation exposure estimates are derived from midpoint projections and are applied uniformly across firms in all sectors, ignoring sectoral differences in occupations. Second, the investment multipliers are based on assumption like 80% NOIC work is being non-intangible and only 10% of displaced NOIC labor shifting into IC tasks. These estimations simplify the real world and do not fully account for firm-specific adaptability. Third, the model uses cross-sectional data, which limits its adaptability to capture time-lagged effects. Intangible investment, especially R&D and OC, often yield benefits over time and hence time-series data would be better to capture these dynamics. Additionally, matching multiple datasets introduces potential inconsistencies in classification and timing possibly impacting the precision.

This thesis highlights several areas for future research. First, the analysis was conducted using cross-sectional data, which limits the ability to assess dynamic processes like restructuring, learning curves, and delayed returns from innovation. For example, the J-curve hypothesis (Brynjolfsson et al., 2017) suggests that the benefits from R&D and AI integration are not immediate but realize over time. To address this, future studies should utilize panel data to capture long-term impacts and to better understand the temporal dynamics of AI adoption and intangible investment impacts. Second, while this study used estimated AI automation exposure and occupational structure to derive sectoral intangible multipliers, future research could benefit from firm-level AI adoption data. This data would allow more detailed and accurate assessment of how individual firms implement AI and how this interacts with their intangible capital investments. Finally, as AI technologies evolve, distinguishing the different types of AI like generative AI vs. predictive analytics may become more important when assessing their interaction with intangibles. Different forms of AI may require different complementary investments and impact productivity differently. In conclusion, this thesis presents that the productivity benefits of AI depend not only on sectoral AI-exposure, but also on composition, coordination, and interaction of intangible capital assets.

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Appendix

Table A.1 Automation by professions, McKinsey Midpoint 2030 estimations.

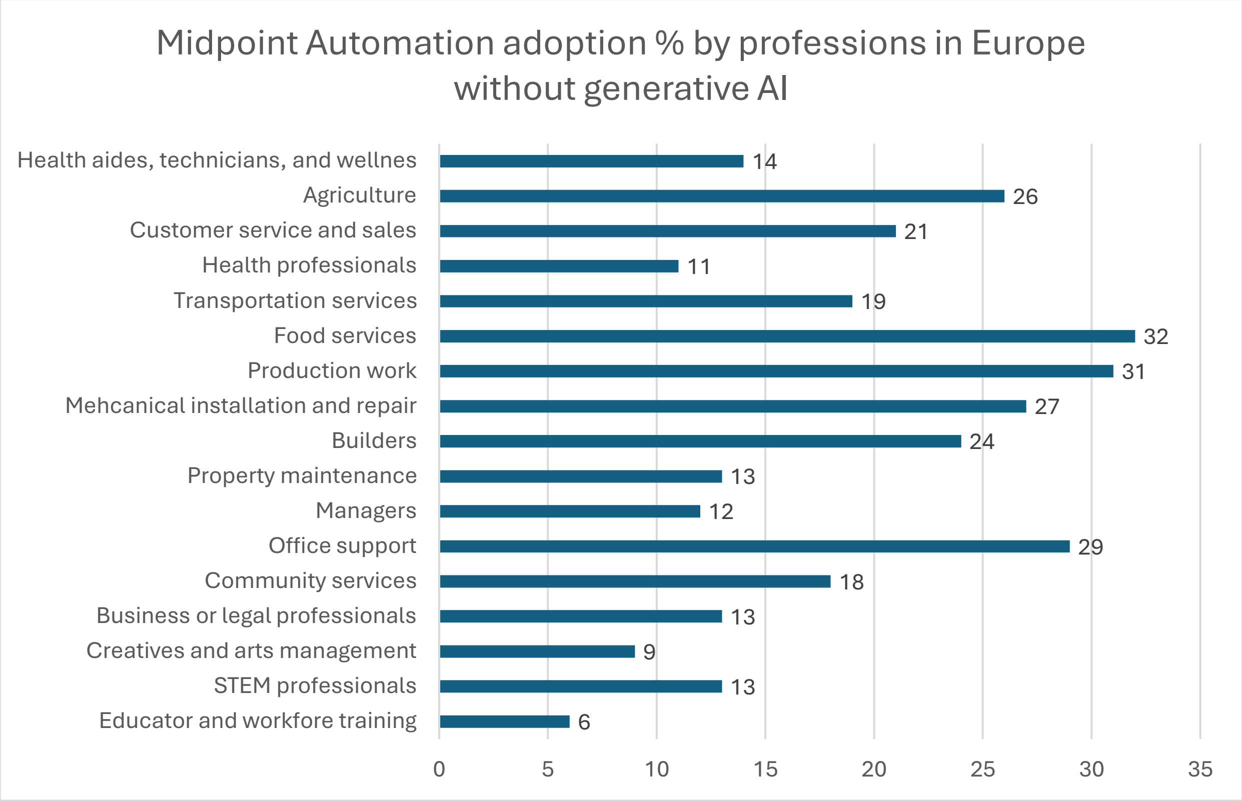

Table A.2 Innovative labor shares

OC	R&D	ICT
40 %	60 %	45 %

Adapted from Piekkola et al., in Bloch, C., Protogerou, A., & Vonortas, N.S. (Eds.). (2024). Intangible Assets, Productivity and Economic Growth: Micro, Meso and Macro Perspectives. Routledge.

Table A.3 Industries by technology type (firms with at least 5 employees on average in the selected industries)

Technology type	Main industries	Other	Value added shares in 2017, %			
			FIN	NOR	DEN	SLO
High-tech manufacturing	Electronics 21 and Pharmacy 26		4.5	1.05	12	6
Medium-high technology manufacturing	Chemical 20, electrical equipment 27, machinery and equipment 28	Motor vehicles 29, other transport 30	10.5	5	11	13.6
Medium-low technology manufacturing	Refined petroleum 19, rubber and plastic products 22, basic metals 24	Repair and installation of machinery and equipment 33–34, energy 35	14.9	19.7	9	25.1
Low technology manufacturing	Food 10, textile 13, paper 17	Beverages 11, tobacco 12, textiles 13, wearing apparel 14, leather 15, wood and wood product 16, printings 18, furniture 31, other 32	10.8	5.8	10	8.1
KIS market (knowledge-intensive market services, excl. finance, and high-tech services)	Transport 50–51 (not land), publishing 58, telecommunication 61, arts, entertainment, and recreation R	Motion picture 59 programming, broadcasting 60, other professional activities 74, 75, 78, 80	12.0	14.1	9	7.5
ICT services	Computer programming, consultancy 62, information service activities 63		7.3	4.7	4	2.5
R&D services	Architectural, engineering 71, R&D 72		3.8	4.5	8	2.2
OC services	Legal 69, head office 70, advertising, market research 73		3.1	3.7	4	1.8
Other private services	Wholesale trade 45–47, land transport 49, warehouse 52, accommodation, food and beverages 56, real estate 68	Rental and leasing 77, travel agency 79	33.1	44.1	33	33.4

Use of AI

Artificial intelligence tools, specifically OpenAI’s ChatGPT models 3.5 and 4.0, were used as research assistants during the thesis process. AI assistance was applied to supporting STATA code development, aiding in the search of relevant academic sources and theoretical frameworks. Assisting with idea development and clarification of complex concepts. Improving clarity and quality of written English text. Supporting translation between Finnish and English. All cited arguments presented in this thesis were verified from original sources. The AI tools were to support academic writing and research workflow.