FORSEE

Forging Successful AI Applications for European Economy and Society

D5.1 Report on Digital SMEs perspectives on economic viability

Project Information
Project Number: 101177579
Project Title: Forging Successful AI Applications for European Economy and Society - FORSEE
Funding Scheme: HORIZON-CL2-2024-TRANSFORMATIONS-01-06
Project Start Date: 1 February 2025

Deliverable Information	
Title	Report on Digital SMEs perspectives on economic viability
Work Package	WP 5. Researching AI impact on Economy and Society
Lead Beneficiary	DIGITAL SME Alliance
Due Date	30/09/2026
Revision Number:	V1.0
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Dissemination Level	PU - Public
Deliverable Type	Other

Revision History			
Version	Changes implemented by	Revision Date	Brief description of changes
V1.0	authors above	21-09-2026	typos

Approval Procedure			
Version	Deliverable Name	Approved by	Approval Date
v1.0	D5.1 Digital SMEs perspectives on economic viability	Coordinator PI	29-09-2026

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FORSEE: Forging Successful AI Applications for European Economy and Society

Researching AI impact on economy and society

The capabilities of artificial intelligence (AI) are advancing rapidly, yet understanding what constitutes successful AI for society and the conditions that enable its effective deployment remains limited. AI may bring economic growth, knowledge creation, and broader societal benefits, but realising this potential depends on developing and integrating applications that are not only technologically and economically successful but also socially and ethically. AI applications are embedded within complex social contexts, reflecting and shaping aspirations, biases, and inequalities; thus, understanding AI success requires attention to these broader dimensions.

The FORSEE project (*Forging Successful AI Applications for European Economy and Society*) adopts a sociological perspective to examine these dynamics, focusing on how different stakeholders define success and how controversies, and unequal distributions of risks and benefits are articulated and potentially resolved.

This cluster of research papers examines AI's impact on the economy and society, bringing together business and labour perspectives to explore how expectations of economic benefits relate to changes in working life. It comprises three interrelated reports. The first report **explores SMEs' perspectives on the economic viability of AI adoption**, focusing on productivity, profitability and competitiveness, alongside implementation costs, regulatory requirements and dependence on larger technology providers. The second **examines trade unions' perspectives on AI's implications for employment, working conditions and organisational restructuring**, identifying potential benefits, risks and competing expectations in the workplace. The third integrates these findings to **analyse transformations in labour processes**, including algorithmic management, and consider their implications for productivity, efficiency and the wider economy. Together, these reports connect firms' assessments of AI adoption with workers' concerns, offering a multidimensional understanding of how its benefits, costs and risks emerge and are distributed.

The present report focuses on how digital SMEs understand and assess AI's economic viability, providing insights into their experiences and the conditions under which anticipated gains translate into business value.

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Executive Summary

This report examines how European digital small and medium-sized enterprises (SMEs) understand and assess the economic viability of artificial intelligence (AI) adoption. It draws on accounts from 20 qualitative interviews with SME executives across 12 EU Member States, collected between April and July 2026. Thematic analysis, informed by the Social Construction of Technology and the Sociology of Expectations, explores how the anticipated benefits compare with implementation experiences. While these findings cannot be seen as representative of all European SMEs, they nevertheless offer important analytical insights into how some SMEs view AI systems and their adoption.

Productivity through the augmentation of human workers emerges as the main benefit associated with AI adoption. Participants describe existing teams undertaking more projects, performing a wider range of tasks and delivering improved outputs. Time savings allow effort to shift towards design, integration, review and client engagement. AI capability can also strengthen credibility and access to market share as SMEs signal their competitive advantage.

However, none of the participants establishes a clear link between AI adoption and increased profitability. Perceived productivity gains are often assessed through informal estimates, and their magnitude and relation to AI remain uncertain. Expanded capacity does not automatically reduce expenditure or generate additional revenue; GenAI adoption can increase costs and squeeze margins without corresponding revenue gains, echoing the GenAI divide between widespread adoption and limited economic returns.

Positive expectations and concern about falling behind nevertheless encourage continued investment, while practical experimentation leads firms to revise initial assumptions.

Changes regarding the workforce are similarly mixed: no participant reports AI-related job losses within their firm, yet several describe delayed or avoided recruitment. These findings suggest the operation of two related risks: the first is the risk of job stagnation and the second is that of workers' lack of acceptance of new technologies as they fear for their own job.

Making AI economically sustainable requires organisational investment beyond purchasing tools. Costs include testing, data preparation, integration, training, security, human oversight and maintenance. Staff must verify outputs and assume responsibility, potentially creating additional review work. Dependence on large technology providers compounds these challenges through uncertain prices and costly switching, alongside concerns about data protection and compliance with the EU regulatory framework. European hosting and open-source systems offer greater control but require resources and expertise. Public funding can support development, although access difficulties, and delays can constrain its contribution to commercial viability.

The report concludes that reported productivity benefits coexist with uncertain profitability and substantial dependencies. Longer-term economic viability depends on whether SMEs can convert expanded capabilities into sustained value while managing costs and organisational demands. Longitudinal research incorporating financial evidence and employees' perspectives is needed.

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Section 1: Introduction

Artificial intelligence features prominently in international debates about how technology can drive innovation and economic growth. Recent advances in generative AI, the rapid expansion of commercial applications and European policy efforts to strengthen digital competitiveness have brought AI from the margins of technological experimentation into the forefront of strategic consideration for firms across sectors in Europe. This development is particularly significant for small and medium-sized enterprises[1], especially as industry narratives promote AI as a means of extending the capabilities of small teams and saving time on tasks characterised as repetitive, and supporting new products and services. In parallel, these anticipated benefits coexist with resource constraints, implementation costs and uncertainty about the returns that AI adoption can generate. Understanding whether and under what conditions AI is economically viable for SMEs therefore requires examining how a multitude of interdependent factors, both internal and external to the organisation, interact to shape the firm's ability to convert technical improvements into sustained economic value.

Research in AI adoption identifies potential improvements in efficiency, quality and innovation, alongside barriers involving skills, data, funding and organisational capabilities (Schwaeke et al., 2024). Yet the relationship between adopting AI and improving a firm's economic position is not straightforward. Completing a task more quickly does not necessarily reduce expenditure or generate additional revenue. Saved time may be redirected towards other activities, absorbed by verification and coordination, or used to improve quality without changing what customers are willing to pay. Similarly, developing an AI-enabled product does not ensure sufficient demand to recover its development and operating costs. Task-level benefits must therefore be distinguished from firm-level financial returns.

This report examines the **economic viability of AI adoption for European digital SMEs**, understood as the capacity to generate realised or reasonably expected benefits that justify the costs and resources required to introduce, operate and maintain AI while sustaining economic value over time. This definition draws on Zamfir et al.'s (2016) discussion of returns relative to invested resources, alongside their recognition that return on investment (ROI) alone can overlook non-financial benefits and favour short-term performance over longer-term strategic objectives. Applied to AI adoption, this perspective encompasses profitability, avoided expenditure, expanded capabilities and access to business opportunities, while considering the timing and uncertainty of returns. The analysis does not assume that time saving, productivity and profitability are interchangeable. Instead, it examines how SMEs themselves distinguish and assess these outcomes, including where formal measurements are unavailable or benefits remain prospective.

[1] The European Commission defines SMEs as organisations with fewer than 250 employees and an annual turnover below EUR 50 million or a balance sheet total of up to €43 million (European Commission 2023; see also Schwaeke et al., 2024, p. 1300). The vast majority of European companies fall into this category, with some estimates suggesting that SMEs account for as much as 99% of all businesses across Europe (Watney and Auer, 2021).

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The report builds on earlier research undertaken within the FORSEE project. The report *Narrative framework on success among SME representatives*, examined how digital SMEs developing and deploying AI understood and anticipated success. It identified high and positive expectations concerning technological performance, efficiency and wider societal contributions, alongside constraints relating to funding, infrastructure, technological dependence and regulation (Minotakis et al., 2026). The present report expands this earlier FORSEE research by moving from narratives of anticipated success to the reported and perceived economic effects of AI adoption in practice. The central research question is:

> **How do European digital SMEs understand and assess the economic viability of AI adoption?**

The report examines how digital SMEs experience and assess changes in working time, productive capacity, operating costs, revenues, profitability, competitiveness and longer-term business viability. Particular attention is given to the relationship between expectation and outcome: how anticipated benefits motivate experimentation and investment; how implementation produces practical evidence of benefits, limitations and costs; and how these experiences subsequently reinforce, revise or challenge earlier expectations. The analysis therefore does not assume that greater task-level efficiency automatically results in improved profitability. Instead, it investigates the conditions under which time savings and expanded capabilities can be converted into economically valuable outcomes, as well as the organisational, market, infrastructural and regulatory factors that affect SMEs' ability to capture and sustain that value.

The study draws on accounts from 20 representatives of digital SMEs headquartered in 12 EU Member States, collected between late April and July 2026. It focuses on firms already engaged in AI adoption, including internal deployment and integration into products and services. The evidence concerns participants' reported experiences and interpretations rather than independently audited financial performance. The analysis is informed by the Social Construction of Technology and the Sociology of Expectations, which direct attention to differing criteria of success and the influence of anticipated futures on present business decisions.

The report is organised into seven sections. Following the introduction, **Section 2** presents the theoretical framework, drawing on the Social Construction of Technology and the Sociology of Expectations to explain how expectations shape AI adoption. **Section 3** reviews existing research on the anticipated benefits, barriers and current patterns of AI adoption among European SMEs, alongside the influence of the policy environment. **Section 4** outlines the research design, sampling, data collection and analysis, ethical considerations and limitations. **Section 5** presents the interview findings, moving from the complexity of adoption and the internal and external factors shaping implementation to how SMEs assess economic viability through productivity, expanded capabilities, time savings, improved quality and market signalling. It also examines the difficulties of converting these benefits into financial returns. **Section 6** discusses the broader implications of the findings, particularly the relationship between expectations and profitability, technological dependence and changes in work and employment. Finally,

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Section 7 draws together the main conclusions concerning the conditions and uncertainties shaping the longer-term economic viability of AI adoption.

Section 2: Theoretical framework

This section lays the theoretical foundations to examine how European digital SMEs experience the economic impacts of deploying artificial intelligence.

Contrary to canonical theoretical accounts of technological implementation and acceptance (Davis, 1989; Rogers, 1962/2003), the FORSEE research consortium claims technological adoption is not a normative, linear, purely technical or solely business decision. Rather, it is a dynamic process shaped by a variety of factors including market narratives, vendor offerings, competitor strategies, investor interests, workplace experimentation, customer demands, and policy agendas. SMEs experience and consider these factors into making decisions for their business models, allocation of resources, and framings of economic success.

Further research conducted within FORSEE Work Package 4 - looking into societal acceptance and criteria of success - supports this approach. Its analyses of social-media and news discourse demonstrated that AI success and failure are constructed around competing understandings of utility, economic performance, technological progress, employment and human agency (Papaevangelou et al., 2026a, 2026b). The analysis of the legal challenge landscape further showed that regulation, compliance obligations, accountability and legal uncertainty influence which AI applications are considered feasible and sustainable (Taylor et al., 2026).

In order to examine this multiplicity of social forces shaping AI adoption by SMEs, this report is theoretically informed by the paradigm of the Social Construction of Technology (SCOT), and specifically the Sociology of Expectations (SoE) to empirically examine unexplored aspects and effects of AI adoption, such as competitive signalling, productivity enhancement, organisational change, infrastructural dependence and regulation challenges (Minotakis et al., 2026).

2.1. Social Construction of Technology (SCOT) and the Sociology of Expectations (SOE)

The SCOT contests linear understandings of technological innovation positing that change occurs naturally and universally from the inherent superiority of a technological system or artefact. **SCOT demonstrates that technologies display *interpretive flexibility*: different social groups attribute different uses and meanings to the same artefacts, identify different opportunities and problems, thus applying different criteria of success** (Pinch and Bijker, 1984). As such, technological development and adoption is not predefined, but it is dynamically constructed by different social forces, each time pointing to different

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technological designs, uses, and benefits. This is of particular relevance to AI, a complex technology that is neither uniform nor stable, but consists of heterogeneous development approaches, different models and different manifold applications for users and businesses. Within the limits of its affordances and capabilities, the same AI system may be understood as an inexpensive personal assistant, a coding tool, a product component, an unreliable system requiring verification, a threat to data privacy, or an amusing novelty. Its significance depends on the use cases and on the actors evaluating it.

The Sociology of Expectations applies SCOT's constructive analytical lens to study the role of expectations in shaping technological and scientific innovation, aiming to interrogate and problematise pragmatist perspectives that *a priori* draw a clear boundary between expectations and outcomes of innovation (van Lente, 2012, p. 775). Expectations are defined as "real-time representations of future technological situations and capabilities", acting as "wishful enactments of a desired future" (Borup et al., 2006, p. 286). As a research field, **SoE explains how technologies and their utility and value are shaped by future-oriented, promissory narratives and claims rather than solely by existing capabilities or demonstrated performance** (Konrad et al., 2017).

Consequently, Borup et al. (2006, p. 289) describe expectations as constitutive and performative forces that legitimise new technologies, organise this promissory space by situating actors and defining roles, picture potential applications, and mobilise financial resources for market investment (Pollock and Williams, 2010). Therefore, expectations establish and broker networks of relationships between different actors ranging from scientists and engineers, policymakers, NGOs, to investors, potential users and businesses (Borup et al., 2006), that dynamically circulate, overlap and vary, gain and lose influence.

2.2. Dynamics in the shaping of expectations

According to Brown and Michael (2003), expectations are not uniform, stable or linear, but vary between actors and change over time (Brown and Michael, 2003; MacKenzie, 1998[2]). In this light, **expectations around emerging technologies tend to adopt a language of promise, and often of urgency and hype, portraying technologies overly optimistically as "groundbreaking" or "revolutionary"** not by accident, but as a necessary requirement **to attract attention and mobilise investment** (Geels and Smit, 2000, p. 882). Contrarily, expectations around more established technologies resort to the preservation of already existing networks of actors and activities (Brown and Michael, 2003, p. 16).

Beyond being temporally dynamic, expectations exhibit considerable diversity. Consequently, they may be classified into distinct levels based on whether they are narrowly or broadly held (van Lente, 1993). These can range from micro-level or firm- and research group-specific expectations, meso-level or technological field-wide expectations, up to macro-level or societal expectations (Ruef and Markard, 2010; van Lente et al., 2013). **The performative and constitutive forces of expectations can be summarised in three**

[2] Donald MacKenzie (1998) coined the term 'certainty trough' to refer to differing levels of expectations depending on the depth of knowledge on a certain area. Accordingly, experts in a given field tend to have less hyped/ exaggerated expectations compared to others possessing more basic/superficial understanding.

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crucial aspects: raising attention and legitimising investment; providing directions of research and development; and aligning different actors together in coordinated technical development (van Lente, 2012, p. 773).

This complex and dynamic interplay of multiple, competing and overlapping expectations of different social stakeholders enacts and shapes the future of technologies. Terms such as visions, promises, and imaginaries are frequently used interchangeably with expectations to describe the constitutive and competitive imaginings of technological futures (Bakker and Budde, 2012; Borup et al., 2006; Rohracher and Konrad, 2024).

2.3. Expectations and Hype-Disappointment cycles around AI

Another central concern in the SoE has been to understand the **trajectory and evolution of expectations over time** (Konrad et al., 2017). Examining these temporal patterns of expectations dynamics is known as hype-disappointment cycles (Borup et al., 2006, p. 291; van Lente et al., 2013). **'Hype cycle'** was initially introduced by the US consulting company Gartner to provide a 'folk theory' interpretative visualisation of the evolution of expectations around information and communication technologies (Rip, 2006, p. 352), that has often been criticised as over-simplistic and linear. On this basis, further research on hype cycles has attempted to identify varying patterns in the temporal evolution of expectations, tracing various trajectories of stimulated promises, excitement and disappointment in different technological and scientific cases of innovation (Dedehayir and Steinert, 2016; van Lente et al., 2013).

AI is being portrayed as a profound "promising technology" (van Lente, 1993), whose dynamics are "always driven by renewed and modified technological promises about its special powers and problem-solving capabilities" (Hirsch-Krinsen, 2023, p. 1642). Extending the theoretical lens of study of expectations around AI, scholars delve into critically examining expectations of AI, trying to trace the promises as well as the set of actors responsible for persuasively exaggerating and circulating them to favour their vested interests (Bareis, 2026; Galanos et al., 2026; Pollock and Williams, 2026). For example, Bareis (2026, p. 288) identifies 'hypers' as "rather problematic appropriators of futures": privileged social actors that exploit epistemic uncertainty to disseminate inflated expectations for opportunistic purposes, both positive (Chui and Yee, 2023) and negative (Centre for AI Safety, 2023).[3] Other scholars looking into expectations around AI (Bourne, 2024; Dodds et al., 2026) argue media outlets and promotional industries act as 'AI cheerleaders' elevating certain 'expert' voices and leading tech figures across digital media to mobilise audiences in adopting techno-elite's expectations, as in the recent case of US media amplifying hype around the metaverse (Jacobides et al., 2024; Maddocks et al., 2024). In this sense, **social stakeholders such as businesses and consumers are not passive spectators, but actively partake, assess, accept or negate a technology's capabilities**, often becoming active complicit collaborators in sharing and stabilising inflated expectations around emerging technologies (Galanos et al., 2026; Pollock and Williams, 2026).

[3] As Vinsel (2021) points out, critical research on hype can itself facilitate hype and researchers can themselves become inadvertent hypers.

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The FORSEE team adopts SoE's constructivist analytical lens and understands digital SMEs as active social stakeholders who navigate the different expectations and promises around generative AI's potential capabilities and benefits for their businesses. As active participants in these processes, digital SMEs evaluate these expectations around AI and assess to what extent they fulfill or diverge from the promises of its impacts. Drawing from previous FORSEE report findings (Minotakis et al., 2026), the present report aims to turn the spotlight from the analysis on the performativity of expectations informing AI adoption (Borup et al., 2006) to the materialisation of these visions and expectations in the form of economic benefits for European digital SMEs.

Section 3: AI adoption among European SMEs

SME adoption of AI is shaped by a combination of firm-level resources and capabilities, technological expectations, and the wider institutional and policy environment. An earlier FORSEE report identified four macro-level enablers and constraints for AI in European SMEs: the European funding landscape, the European regulatory framework, sustainability, and the pursuit of "digital sovereignty" (Minotakis et al., 2026). These conditions interact with the distinctive resource constraints of SMEs, which generally operate with less financial capital, smaller workforces and more restricted access to specialist expertise (Nooteboom, 1994; Penrose, 1959).

The growth of the European SME landscape is limited by a relatively small and conservative European funding landscape (Minotakis et. al., 2026). **Managers must balance operational efficiency, innovation and market expansion when allocating financial, human and technological resources.** Investment in AI may require redirecting resources from other projects, creating a trade-off between short-term stability and long-term learning. Decision-making is also frequently centralised: founders and senior managers can play a decisive role in adoption on the basis of their expectations about technological change, customers and competitors (Laforet, 2013). This can accelerate experimentation but can also expose the firm to speculative or premature commitments.

These decisions are also shaped by expectations about what AI may enable, as well as the risks it may pose. Promises of future demand and competitive necessity can legitimise investment, while concerns about data leakage, regulatory liability, rising usage charges, or provider dependence can delay adoption or encourage firms to pursue alternative approaches. Expectations are not fixed, however: firms can encounter AI through processes of experimentation and implementation, generating practical experiences that may reinforce, quality, or challenge initial assumptions. Hype is therefore treated as a particular form of inflated expectation, not as a synonym for every uncertain future claim (Konrad et al., 2017). **This creates a dual analytical task: examining how expectations about AI shape SMEs' adoption decisions, while also examining how SMEs themselves actively work on and communicate expectations to mobilise interest in their products.** Expectations are

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therefore not just something to which firms must respond; they can also become a strategic resource through which SMEs signal innovation, credibility, and future market potential.

This is particularly important because research on AI has historically centred on large corporations: firms with extensive resources, in-house data science teams, and the scale necessary to deploy advanced AI systems. In recent years, a growing body of work examining AI adoption by SMEs has arisen, recognising their distinct constraints and potential to benefit from AI-driven innovation (Agbaakin, 2025; Mohib et al., 2025; Wlock and Ślosarski, 2026). However, recent evidence suggests that SME adoption should not be understood simply as whether a firm has adopted AI. Adoption varies substantially in scale, application, organisational integration, and technological complexity, with SMEs often entering through relatively accessible, off-the-shelf tools before deciding whether to embed AI more deeply (OECD, 2025). **AI adoption is therefore better understood as an incremental, contingent and potentially non-linear process, in which experimentation, organisational capacity, expectations, and experience shape whether limited use develops into deeper integration.**

3.1 Expected benefits of AI adoption

Policymakers, businesses, and developers all tout AI's 'promise' to stimulate productivity and economic growth (Brynjolfsson et al., 2025; Chui and Yee, 2023). The rapid emergence of Generative AI (GenAI) in 2023 intensified these expectations, with research highlighting its potential to generate productivity gains and address complex challenges such as energy efficiency and climate change (Calvino et al., 2025; Mohammadi Lanbaran et al., 2024). From a SoE perspective, this period represents a critical juncture in which hype helps to mobilise investment and research around emerging technologies (van Lente et al., 2013). Since 2023, SMEs across diverse sectors have demonstrated growing interest in AI, with particularly strong attention directed towards Machine Learning and Natural Language Processing systems (Dinh et al., 2025; Khan et al., 2025; Segarra-Blasco et al., 2025).

The literature primarily **frames AI adoption by SMEs around productivity, efficiency, innovation, and access to new markets** (Schwaeke et al., 2024, p. 1298; Wilczynska et al., 2024, p. 12). Proponents of AI claim that its potential as a **general-purpose technology can enhance productivity or increase output quality, particularly within advanced economies** (Baily et al., 2023; Brynjolfsson et al., 2025; Noy and Zhang, 2023; OECD, 2025) - a narrative that is reinforced by AI developers themselves (Minotakis et al., 2026). This aligns with larger EU discourse that is encouraging expanded AI adoption (OECD, 2026; Schwaeke et al., 2024).

For example, AI could improve customer experience through data analytics, predictive insights, virtual assistants, and recommendation systems (Schönberger, 2023, p. 89). More broadly, anticipated benefits include increased productivity and profitability, cost and time savings, enhanced safety, and more sustainable resource use. These gains are expected to arise primarily through automation, personalised customer service, data-driven decision-making and predictive analytics, and accelerated innovation. While these benefits

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apply across firm sizes, SMEs' distinct resource constraints shape their capacity to realise them (Sánchez et al., 2025).

3.1.1 AI and productivity

In theory, AI has the potential to drive firms' productivity by automating tasks (e.g. writing, summarising, coding, editing, or translation), facilitating skill development, and "transforming" business operations (Calvino et al., 2025). However, evidence that AI has translated these expectations into actual gains is far from conclusive.

Studies have identified productivity gains in particular tasks and occupations. For example, access to a generative AI-based conversational assistant increased productivity among customer-support workers, with the largest gains among novice and lower-skilled workers (Brynjolfsson et al., 2023). AI has also been found to increase the productivity of accountants (Choi and Xie, 2025). Research by the European Central Bank found that the use of AI to generate or debug code could save workers nearly eight hours per week (Dias Da Silva et al., 2026). Baslandze et al., (2026) found that firms were experiencing productivity gains - especially those in the financial sector - but real gains were not as significant as company leadership perceived them to be. As such, productivity gains that are measured using workers' and executives' reported productivity gains merit an additional level of scrutiny (Ranganathan and Ye, 2026).

The extent of AI-related benefits vary considerably by worker experience and context (Doorley et al., 2026). Experienced open-source developers, for example, were 19% slower when using AI tools (Becker et al., 2026), while other research finds that more experienced workers may see smaller gains or declines in output quality (Brynjolfsson et al., 2025). Moreover, evidence of productivity gains at the task level has not yet translated into clear AI-driven growth at the macroeconomic level (Baslandze et al., 2026).

Historical experience with electrification and information and communication technologies (ICT) shows that "technological revolutions only raised aggregate productivity after substantial organisational change and institutional adaptation" (ILO, 2026, p. 1). This echoes the "Solow Paradox", in which the contribution of computers was initially difficult to detect in aggregate productivity statistics. Brynjolfsson et al. (2017) described AI as a "redux of the Solow Paradox", arguing that its most significant benefits may only emerge once firms have learned how to integrate the technology effectively. Recent evidence from US manufacturing supports this possibility: McElheran et al., (2025) find that industrial AI adoption initially reduced productivity before generating longer-term recovery and growth, consistent with a productivity "J-curve". At sectoral and macroeconomic levels, clear AI-driven productivity growth has likewise yet to appear in official statistics (ILO, 2026). Yotzov et al. (2026) echo this reality as their research found very limited productivity gains associated with AI across four major economies in the US, UK, Germany, and Australia. Researchers from MIT examining AI implementation in US businesses (Challapally et al., 2025), term this disparity as the "GenAI divide": despite the widespread AI adoption, only 5% of companies have reported increased profits. Even private sector research supports the claim that AI has not yet created sustainable value for firms: a 2025 survey by McKinsey

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found that 94% of firms reported not seeing 'significant' value from investments in AI (Montard et al., 2026).

When productivity is enhanced, time saved does not necessarily translate into greater profitability. AI introduces costs associated with subscriptions, compute, integration, verification, training, security, coordination, compliance, failed pilots, or the time associated with managing AI. Workers may also spend significant time "botsitting" - providing the work required to make AI usable, including feeding it missing context, checking its outputs, debugging its mistakes, rerunning prompts, and cleaning up the confident-but-wrong answers AI leaves behind (Glean, 2026; Hinds and Leonardi, 2026). AI can also exacerbate coordination neglect - the tendency to underestimate the time and effort required to coordinate work - by producing outputs that appear complete before the work of review and approval is finished (Glean, 2026; Heath and Staudenmayer, 2000; Hinds, 2026). These activities can offset other efficiency gains. As the productivity paradox literature suggests, returns from new technologies depend on complementary investments in skills, processes, and organisational change (Brynjolfsson et al., 2017). This research complicates the notion of "time saved" as an indicator of AI success.

Why, then, are firms continuing to adopt AI if these economic returns are uncertain? One possibility is that firms expect AI to contribute to longer-term economic goals - a narrative that is widely promoted by European policy and business leaders. Another possibility is competitive signalling. As AI becomes associated with technological sophistication and strategic foresight, adopting it can signal credibility to investors, customers, and business partners. Institutional theory suggests that organisations align with dominant technological norms partly to maintain legitimacy (DiMaggio and Powell, 1983), while corporate reputation affects stakeholder assessments and access to resources (Fombrun and Shanley, 1990). When AI is widely framed as transformative and strategically necessary, an SME may feel pressure to display engagement even when operational returns remain uncertain.

3.2 Barriers to adoption

Research has also identified more specific barriers to SMEs' AI adoption. According to the 2026 D4SME survey of 2,000 SMEs from 12 OECD countries, time constraints, maintenance costs, skills gaps, and cybersecurity concerns present limitations (OECD, 2026a). Funding is also a concern for SMEs who may lack the resources to invest in compatible infrastructure, update incumbent systems, and attract skilled talent (Schwaeke et al., 2024; Schönberger, 2023; Ulrich and Frank, 2021). Limitations in data quality and availability present an additional challenge for SMEs at all levels of digital maturity (Dinh et al., 2025; Szedlak et al., 2020; Ulrich and Frank, 2021). Smaller firms are also less likely to have the resources to implement processes designed to ensure ethical AI use (IEEE SA, 2026).

Regulation constitutes a distinct challenge, shaping expectations in its own right. While large technology firms often operate within relatively light regulatory environments and possess the influence to shape or circumvent rules to their advantage (Couldry and Mejias, 2019), SMEs frequently express concerns about the high compliance costs and confusion

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arising from overlapping or contradictory regulatory frameworks (Watney and Auer, 2021). In addressing these issues, scholars emphasise the importance of initiatives supporting SMEs' access to infrastructure, data, and funding for digitalisation efforts (Watney and Auer, 2021; Zimmermann, 2021). Critically, however, there is a pervasive information gap preventing SMEs from accessing critical funds for AI development and adoption (OECD, 2026a).

3.3 State of play of SME AI adoption

AI adoption is expanding across European businesses, although diffusion remains uneven across firms and sectors. Falling computing and infrastructure costs, alongside the availability of cloud services and platform-based tools, have lowered barriers to entry, with AI use particularly prevalent in information and communication activities (62.52%) but increasingly extending across other sectors (Eurostat, 2026; OECD, 2025).

This expansion has been accompanied by the rapid commercialisation of generative AI. The emergence of widely accessible models from US and Chinese technology companies has generated substantial media attention, public commentary, investment, and experimentation, while the availability of subscription-based tools for coding, administrative work, creative production, and analytical tasks has reinforced generative AI's potential as a general-purpose technology. As van Lente et al. (2013, p. 1617) note, emerging technologies with general-purpose applications generate diverse expectations and can significantly reshape perceptions of technological possibilities. At the same time, evidence on the economic returns to AI remains mixed: reports document productivity and revenue gains in some contexts (IBM, 2024; Sajadieh et al., 2026), while others find that increases in individual productivity have not yet translated into measurable improvements in profitability (Challapally et al., 2025). Nevertheless, annual assessments indicate continued acceleration in business investment and experimentation with AI (Maslej et al., 2025).

Within this broader diffusion, SMEs continue to lag behind larger firms. In 2025, 19.95% of EU enterprises with at least ten workers reported using AI, compared with 17% of small enterprises, 30.36% of medium-sized enterprises, and 55.03% of large enterprises (Eurostat, 2026). The disparity is particularly pronounced for more complex applications: autonomous robots, vehicles, and drones were used by 7.2% of large firms compared with just 0.7% of small firms. By contrast, the gap for natural language generation was narrower, at 16.7% among large firms and 4.6% among small firms, reflecting the relative accessibility of GenAI tools (OECD, 2025). GenAI has consequently become an important entry point for smaller firms, as off-the-shelf applications can be adopted with relatively limited technical infrastructure or investment. However, access does not necessarily translate into organisational transformation: only 29% of SMEs report applying GenAI to their core activities (OECD, 2025). Moreover, the SME–large-firm gap is widening in AI adoption, in contrast to gaps in more established forms of digitalisation, such as having a website or accepting online orders (OECD, 2026a).

This uneven adoption is closely linked to differences in digital maturity and organisational capacity. The OECD defines digital maturity as the extent to which "an organisation has

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integrated digital technologies into its operations, strategy, and culture, including both the technical adoption of tools and the human and organisational capabilities needed to use them effectively, such as workforce skills, leadership, and openness to innovation" (OECD, 2026a, p. 17). AI adoption therefore depends not simply on access to AI technologies, but on the complementary organisational capacities required to deploy and integrate them effectively, including digital infrastructure, data practices, ICT skills, leadership, and openness to innovation. More digitally mature firms are consequently better positioned to adopt AI, while adoption can itself contribute to digital maturity by strengthening data practices and organisational capacity (OECD, 2025; McElheran et al., 2024). This creates the potential for cumulative differences in adoption, whereby firms that already possess stronger digital capabilities are better placed to experiment with and integrate increasingly sophisticated AI technologies. Evidence from Ireland illustrates this uneven starting point: AI adoption among Irish SMEs ranges from 3.5% among digitally intensive firms to 0.9% among low-intensity firms, suggesting the potential emergence of a two-tier digital economy in which already advanced firms are better positioned to capture AI-related productivity gains (Doorley et al., 2026). Across OECD countries, roughly half of SMEs have only basic or developing digital maturity, while just 20% are classified as advanced or transformative (OECD, 2025).

These differences also mean that SME adoption should not be understood as a simple distinction between 'adopters' and 'non-adopters'. Firms that do not use AI may differ in their awareness of available technologies, resources, experimentation, perceived risks, organisational capacity, and assessment of whether AI offers a viable business case. Non-adoption may therefore reflect not only limited capabilities or resources, but also a deliberate and potentially rational decision based on a firm's activities, priorities, values, or perceived risks. This is important given the tendency within some management research to treat digital transformation as inevitable and innovation as inherently desirable. As noted in a previous FORSEE report, such techno-optimist framings can position barriers primarily as technical problems to be overcome through further innovation, while overlooking SMEs for which AI has limited practical relevance or whose incentives to adopt are weak (Minotakis et al., 2026).

For SMEs that do engage with AI, adoption is better understood as an incremental and non-linear process shaped by the interaction between the technologies firms can access, how they use them, and their organisational capacity to integrate them (OECD, 2025). Rather than moving directly from non-use to full organisational transformation, firms may begin by experimenting with AI in discrete tasks and gradually assess its usefulness before deciding whether, and how far, to embed it within their operations. Adoption can therefore develop incrementally and with a certain degree of caution, from limited experimentation and task-level use through to broader operational integration and, in a smaller number of cases, AI becoming central to the firm's business model (Mikalef and Gupta, 2021; Rogers, 2003; Tornatzky and Fleischer, 1990). This process is shaped by the resources and capabilities available to the firm at each stage, meaning that organisational capacity influences not only whether an SME adopts AI, but also how deeply it can integrate it.

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At the lower end of this spectrum are AI functionalities embedded within existing digital tools, such as spam filters and grammar checkers, alongside off-the-shelf applications used for specific creative or analytical tasks, such as using ChatGPT to produce social media content (OECD, 2025). These accessible tools provide a relatively low-cost route into AI for resource-constrained SMEs, and the D4SME survey finds that most OECD SMEs engage with AI in these more limited ways, characterised by the OECD as AI Novices and AI Optimisers (OECD, 2026a). Further along the spectrum, fewer SMEs experiment with more resource-intensive foundation, multimodal, or agentic systems, which require greater levels of data, skills, investment, and governance capacity (OECD, 2026a). There is some evidence that greater involvement in AI development can generate higher returns: French firms developing AI internally have been found to achieve greater returns than those sourcing AI externally, though achieving these long-term gains through internal development is also considerably more demanding in terms of capabilities and resources (Calvino and Fontanelli, 2024).

The nature and depth of adoption also position SMEs differently within the wider AI value chain. A firm developing or substantially modifying an AI model assumes different costs, capabilities, and responsibilities from one deploying an externally developed application programming interface, while a consultancy may use AI internally while simultaneously integrating AI capabilities into solutions for clients. SME AI adoption should therefore be understood in terms of how firms incrementally engage with AI, the organisational capacities underpinning that engagement, and the depth and purpose of integration, rather than captured through a single adopter/non-adopter measure. This perspective recognises both the uneven conditions under which SMEs encounter AI and the varied pathways through which experimentation may, or may not, develop into deeper organisational adoption.

3.4 How the policy ecosystem shapes SME AI adoption

European policy advances a pro-AI adoption agenda while also shaping the conditions under which adoption occurs. AI is increasingly framed as a driver of economic growth and European competitiveness, with governments across the EU and G7 promoting AI adoption through national strategies, research initiatives, and targeted support for SMEs (OECD, 2026a; Schwaeke et al., 2024). Analysis of AI policies, guidelines, and regulations issued by supranational bodies between 2018 and 2025 revealed a shift in governance discussions away from AI ethics principles towards compliance (Golpayegani et al., 2026). While these frameworks frequently acknowledge social and ethical risks, they increasingly position AI as a strategic driver of economic growth and global competitiveness.

European policy discourse is itself part of the expectation environment. The Draghi report presents digitalisation and AI investment as central to closing Europe's productivity and innovation gaps (Draghi, 2024). The AI Continent Action Plan and InvestAI initiative aim to mobilise €200 billion and expand computing infrastructure, data access, skills and adoption, particularly among SMEs (European Commission, 2025). These initiatives align with EU 'Path to the Digital Decade' goals, which by 2030 aim to reach 90% of SMEs with at least a

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basic level of digital intensity (71.4% as of 2025) and 75% EU enterprises using AI (20% as of 2025) (European Council, 2026).

This policy push is closely tied to the larger goal of strengthening European "digital sovereignty," positioning AI as both a driver of industrial transformation and a strategic area for European competitiveness and independence. However, digital sovereignty is contested: institutional actors tend to emphasise European investment and infrastructure, while SMEs and civil society place greater emphasis on regulatory capacity and accountability for large technology companies (Farries et al., 2026). This distinction is important because SMEs are both beneficiaries of the emerging AI ecosystem and dependent upon it (Minotakis et al., 2026). SMEs are more likely to adopt embedded or off-the-shelf AI tools than develop systems in-house (OECD, 2026b). While external models, cloud services, and APIs allow firms to access AI capacity at a relatively low cost, this leaves them dependent on providers' pricing, data policies, model availability, and technical standards, while creating switching costs and limiting bargaining power (Cutolo and Kenney, 2021; Jacobides et al., 2018). As previous FORSEE research finds, limited access to infrastructure can reinforce regulatory and data risks, constrain funding opportunities, and deepen dependence on larger, non-European providers (Minotakis et al., 2026). SME AI adoption therefore needs to be understood not simply as a firm-level decision, but as one shaped by wider technological, policy, and infrastructural dependencies.

Within this broader policy ecosystem, regulation is particularly important because it can simultaneously enable and constrain adoption. The EU's regulatory framework - anchored in the EU AI Act and GDPR - aims to provide this clarity by enhancing trust and harmonisation across the single market (Eberhardsteiner, 2025). The AI Act adopts a risk-based approach, imposing increasingly stringent obligations according to the risk level posed by an AI system - meaning that internal use of a general-purpose assistant and the use of an AI system for recruitment carry different requirements (EU Artificial Intelligence Act, 2024). The AI Act also marks a broader shift in EU AI governance from ethics-based principles towards risk management and regulatory compliance embedded in hard law (Golpayegani et. al., 2026). While this provides a common framework for identifying and mitigating AI-related risks, it may also prioritise legal conformity over wider ethical and societal considerations, encouraging a 'tick-box' approach to compliance (Farries et al., 2026).

FORSEE findings indicate overall stakeholder support for EU regulation, but with important qualifications. SMEs broadly support regulation as a means of countering Big Tech dominance and strengthening the European AI sector, but call for proportionate, sector-specific rules, clearer implementation guidance, and enabling measures such as funding and shared infrastructure, given concerns about compliance costs, regulatory complexity, and overclassification of AI as high-risk (Farries et al., 2026; Minotakis et al., 2026).

Despite these potential benefits, regulation does present practical challenges for SMEs. Compliance can generate significant internal, external, and opportunity costs through the managerial and technical time, documentation, risk assessment, employee training, legal

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advice, auditing and testing. Because some of these costs are relatively fixed regardless of firm size, they can absorb a greater share of SMEs' resources, thereby weakening intention to invest in or experiment with AI technologies (European Commission, 2021; Renda et al., 2021; Veale and Zuiderveen Borgesius, 2021). Regulation - however - should not be understood simply as overhead. Regulatory clarity can support SMEs' adoption intentions by lowering legal and reputational risks while facilitating market entry and acceptance of AI tools (Blind, 2012; Minotakis et al., 2026).

Section 4: Methodology

4.1 Research design

This study uses a qualitative design to examine how European digital small and medium-sized enterprises understand and assess the economic viability of adopting and deploying artificial intelligence. In-depth semi-structured interviews were selected because they allow participants to describe firm-specific experiences while also articulating expectations, uncertainties and interpretations of the wider AI economy.

The study applies thematic analysis with attention to how respondents constructed and justified economic viability. The coding framework was developed iteratively: some initial codes were derived from the literature and the study's conceptual framework, while others emerged inductively from the interview data. Interpretation is informed by the Social Construction of Technology and the Sociology of Expectations, examining differing understandings of success and how anticipated benefits influence investment and organisational decisions.

4.2 Sampling and participants

Participants were recruited by the European DIGITAL SME Alliance through its European SME network. Eligible firms had to meet SME criteria, be headquartered in an EU Member State and actively use AI. This approach provided access to firms with practical experience of implementation, enabling examination of benefits, costs and commercial uncertainties beyond initial intentions to adopt. The sample comprises 20 representatives of digital SMEs headquartered in 12 EU Member States[4].

The table below gives an overview of the participants characteristics and AI-adoption profile, including participants' roles, company characteristics, business models and sectors, as well as the geographical distribution of the firms. It also presents transcript-based analytical classifications of each company's relationship with AI: whether it primarily develops AI capabilities, deploys third-party technologies or combines both approaches; its stage of AI adoption; the architecture on which its AI use relies; and the principal role of AI within its activities. Company-size categories follow the EU definitions of micro, small and medium-sized enterprises. Where an exact headcount or other relevant information was not explicitly provided, the classification was inferred cautiously from the interview context.

[4] This is a separate empirical sample from the interviews used in FORSEE Deliverable D3.1.

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Table 1. Interview sample and AI-adoption characteristics

ID	Job title	Business model	Size	Sector	Company headquarters	AI role	Architecture	Primary AI use
1	CEO	B2B software	Small	Privacy / private 5G software	Finland	Hybrid	Mixed	Mixture
2	Founder; CEO	B2B digital consulting and sales brokerage	Micro	Digitalisation	Romania	Deployer	Third-party	Mixture
3	Founder; CEO	B2B consulting plus subscription platform	Micro	Standardisation / strategic intelligence	France	Hybrid	Mixed	Mixture
4	Founder; CEO	Freemium SaaS plus enterprise API	Small	Video conferencing	Spain	Deployer	Third-party	Mixture
5	Founder; CEO	B2B services and R&D partnerships	Medium	Digital communication and software	Italy	Deployer	Third-party	Internal operations
6	Founder; CEO	Platform/SaaS; B2C–B2B data marketplace	Medium	Privacy and data economy	Ireland	Hybrid	Mixed	Product/service integration
7	Managing Director	B2B design, digital services and training	Small	Advertising; UI/UX; vocational training	Bulgaria	Deployer	Third-party	Mixture
8	Co-Founder; Director; CTO	B2B SaaS cloud platform	Small	Cloud services	Belgium	Developer	In-house	Mixture
9	Co-Founder; CEO	B2B R&D/consulting plus product development	Micro	Technology; audio/data workflows	Spain	Hybrid	Mixed	Mixture
10	Co-Founder; CEO	B2B consulting and software projects	Micro	Technology; blockchain; cybersecurity	Netherlands	Deployer	Third-party	Mixture

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11	Co-Founder	B2B custom AI software plus product suite	Small	Software development and AI services	Greece	Hybrid	Third-party	Mixture
12	Founder; CEO	B2B boutique agency/consulting plus SaaS products	Micro	Digitalisation and business automation	Romania	Hybrid	Mixed	Mixture
13	Co-Founder; Co-CEO	B2B custom network and software solutions	Small	Network management / telecom software	Germany	Deployer	Third-party	Mixture
14	Co-Founder; CEO	B2B SaaS/content-tech plus R&D partnerships	Micro	Culture and education technology	Italy	Hybrid	In-house / self-hosted	Product/service integration
15	Founder; Company Vice-President	B2B ICT consulting and software services	Medium	Technology / ICT services	Spain	Deployer	Third-party	Mixture
16	Co-Founder; CTO	B2B professional services	Small	Accounting and IT	Greece	Deployer	Third-party	Mixture
17	AI & SaaS Strategy Consultant	B2B consulting plus SaaS/MVP	Micro	Digitalisation; legal and regulatory consulting	Slovakia	Deployer	Third-party	Mixture
18	Co-Founder; CEO	B2G/B2B platform plus R&D partnerships	Small	IoT; smart cities; urban data analytics	Italy	Hybrid	Mixed	Mixture
19	Founder; CEO	B2B consulting transitioning to product	Micro	Software development and IT	Germany	Deployer	Third-party	Internal operations
20	Co-Founder	B2B SaaS	Micro	IT and cybersecurity	Germany	Deployer	Third-party	Internal operations

4.3 Data collection

Data was collected between late April and July 2026 using a common semi-structured interview guide, applied flexibly to each firm's circumstances. Topics covered AI use and motivations; anticipated and reported benefits; implementation, operating and compliance costs; revenue and margins; funding; customer responses; technological dependence; and

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organisational and workforce implications (see Appendix 1). Participants were asked to reflect on initial expectations, subsequent experiences and future prospects.

Most interviews were conducted in English, recorded and transcribed. Interview 2 was translated into English by one of the co-authors. Interview 18 consisted of written questionnaire responses, while Interview 20 was documented through interviewer notes because the participant declined recording.

4.4 Data analysis

The transcripts were coded in NVivo using a framework covering motivations, use cases, benefits, costs, market responses, funding, regulation and workforce implications. The framework combined categories informed by the research question and literature with distinctions developed during pilot coding. Passages could receive multiple codes where themes overlapped.

Coded extracts were compared across interviews and read within their full context. Reported outcomes were distinguished from anticipated benefits, while economic claims were assessed according to whether participants presented them as formally measured, informally calculated, estimated, anecdotally observed or not yet realised. These distinctions concern the basis of participants' claims, rather than independent verification.

The analysis kept time saving, expanded capacity, productivity and profitability analytically distinct. It examined how respondents connected operational improvements to avoided expenditure, revenue or market access, and how costs and dependencies qualified these connections. Contradictory accounts were retained, including cases where participants valued saved time while reporting no tangible financial return. SCOT and SoE informed interpretation of these patterns, particularly changing expectations and differing criteria for judging acceptable and economically worthwhile uses.

4.5 Ethics

All participants received information about the FORSEE project, the interview and the intended use of the material, and all provided informed consent. Recordings were transcribed and transcripts anonymised. Names, company names and other direct identifiers were removed or replaced, and the report uses interview numbers and broad descriptors. Quotation selection avoids unnecessary combinations of details that could identify specialised firms or senior respondents. In accordance with the information provided to participants, retained research data will be permanently destroyed by February 2028.

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Section 5: Interviews analysis and findings

This section analyses how the 20 participating digital SMEs understood the profitability and longer-term economic viability of adopting AI. The analysis follows the coding framework, particularly its categories concerning company use, motivations and expectations, benefits, economic outcomes, costs, concerns, regulation and workplace attitudes, while drawing analytical distinctions between realised and anticipated benefits.

It examines AI adoption as a process through which SMEs encounter opportunities, costs and constraints and assess whether continued investment is worthwhile. Section 5.1 introduces the motivations and practical complexity of adoption. Section 5.2 explores the internal requirements for making AI work, including implementation costs, human oversight and training, while Section 5.3 considers external conditions such as provider dependence, public funding and regulation. Building on these conditions, Section 5.4 examines how SMEs assess economic viability through expanded capacity, time savings, improved quality and market signalling, before addressing the limits to converting these benefits into financial returns.

Economic viability emerged not as a fixed property of an AI tool, but as a contingent sociotechnical achievement: value depended on the use case, the firm's existing expertise, the organisation of work, the ability to reach customers, the reliability and price of external infrastructure, and the regulatory conditions under which the technology could be used.

5.1 The complexity of adoption

Two factors seem to be the driving force behind SMEs adopting AI systems. First of all, **the positive expectations on productivity and increase in market share** played a crucial role in facilitating SMEs' engagement with AI. The anticipation relates both to the company's public image and its capability to deliver products. As interviewee 4 notes:

> AI is allowing us to appear and be more professional, customer-facing, not just in our communication, but also in the rate at which we're able to go to market and develop our products.

For interviewee 3, representing a micro firm that cannot yet afford to hire personnel, AI was crucial for **augmenting their personal capabilities**. As they describe it, they mapped their own recurring tasks with the following objective:

> I automated the work I'm doing in order to duplicate myself and basically use AI in order to develop capacity. It's more a question of capacity building.

Secondly, adoption was driven by the **fear of being left behind** by competitors that readily and effectively engaged with AI. In that sense, SMEs in our sample invested because they expected AI to become integral, for example, to digital work and considered delayed

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learning potentially costly. For interviewee 11, representing an SME in the IT sector, this is expressed in the following manner:

> If you resist, everybody knows that if you don't adapt and adopt new technologies at the same time as competitors, you cannot survive in the IT world, you're left behind.

Interviewee 15 considered that it would be harmful for their company to be seen as defensive or reactive to AI:

> We have to test, to try and see. I suppose we did not want to just stand by, we didn't want to assume this position.

Therefore, the decision to adopt AI was not evaluated only against current revenue; it was compared with the expected financial but also reputational costs of lacking expertise when competitors and customers have already begun to implement AI in their work. **The anticipated future was performative: it justified current expenditure, directed attention, anticipated customer engagement, and coordinated experimentation even where profitability evidence remained unavailable.** These expectations encouraged firms to experiment before robust evidence of profitability was available.

SMEs holding such positive expectations, however, **should not be assumed to uncritically accept all claims and promises associated with AI**. Interviewee 9 explicitly resisted treating AI as a silver bullet or making it the firm's identity.

> "[Implementing AI in the company's workflows] was an initiative from the beginning. We are not, so to speak, an AI-first company, but of course we want to keep an eye on what are the trends, what is useful for our products, for society overall, and how we can contribute to that from, in our case, a more ethical and sustainable way of doing it."

Interviewee 12 argued that customers should be sold measurable outcomes rather than the technology itself. Practical experience further disciplined expectations. Interview 11 recalled that early generative-AI tools initially felt "more like a pain rather than an advantage" because of hallucinations and the effort required to make them useful. These statements indicate how **SMEs moderate their expectations through experimentation** and attempt to construct credible estimates.

5.1.1 Adoption as a layered, non-linear sociotechnical configuration

In any case, it should not be assumed that adoption of AI is a relatively straightforward process. Interviewees stressed that the everyday **reality of adoption was more complex** than purchasing licenses for a single AI tool. Firms use different commercial GenAI chatbots and coding assistants through different enterprise subscriptions and APIs, experiment with open-source models, whereas some digital SMEs also develop models internally using local hardware. These different approaches to adopting AI are made according to AI licensing costs, type of tasks, desired performance/output and customer commitments.

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These different configurations highlight the varying economic impacts AI adoption can have. A fixed-price subscription used by an employee has a different cost from an API embedded in a product, where expenditure rises with customer use. Self-hosting can reduce exposure to data transfer but creates costs for hardware, electricity, maintenance and specialist staff. Access to open-source models reduces licence dependence but does not remove the need to operate and update the system. **The relevant unit of analysis is therefore not the model alone but the configuration of technology, data, infrastructure, routines and professional expertise around it.**

Interview 4 illustrates this practical combination:

> It would have been easy to just plug and send all of the audio conversation over to some US provider, but that didn't fit the promise that we make to our customers. We needed to make sure that the technological infrastructure and sub-processor or provider landscape caught up with our needs. So what we use are open-source models, which are hosted by some European hosting partners for us. Because when it comes to hosting AI and generative models, they're quite GPU-intensive, and hosting these models best works at a certain scale. For us it makes more sense for a hosting provider to capture many customers and then be able to provide those models to them at a certain scale, than for us to have to set up servers and have running costs, fixed costs, where we don't essentially use all the capacity all the time.

The firm used commercial tools internally but relied on open-source models hosted by European partners for customer-facing transcription, because operating permanently loaded language containers on its own GPU infrastructure was uneconomical. The participant described the decision as a scale problem: a hosting provider could share expensive capacity across customers, whereas the SME would carry fixed costs even when specialised language models were idle.

Interview 8 made the opposite choice for internal coding assistance, renting a powerful GPU server and running open-source models on machines the company controlled. Data sovereignty and confidentiality were central, but the company was still in an incubator phase. Interview 14 combined internally developed software, on-premise open-source models and temporary access to high-performance computing. Interview 18 used edge processing for computer vision and environmental analytics while adding LLMs for internal productivity and natural-language access. **These are not stages on a single ladder from simple to advanced adoption; they are different settlements between cost, control and capability.**

In that sense, experimentation is a crucial part of the process as adoption did not proceed linearly. Firms tested tools, abandoned use cases, switched providers and reopened earlier decisions when model capabilities changed. Interviewee 1 had allocated an engineer to AI-supported deployment and troubleshooting but stopped after several months because the results did not justify continued investment:

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> After several months we didn't see any major improvement, [so] we just abandoned the activity - until recently, when we are looking into that again to see if things have been evolving.

While the initial experimentation did not yield results, the underlying business need remained, and improvements in external models could make a previously unviable configuration worth testing again.

Beyond an initial organisational decision to engage with AI, multiple decisions can affect the path of AI adoption.

Interview 8 reported uneven adoption after moving from a single-engineer incubator phase to a larger GPU investment. Some engineers used the system intensively, while others barely used it and needed coaching. Interview 19 rapidly switched between models and rejected a tool that cost 600 EUR per week because the additional speed did not justify the price. Interview 16 reported both successful automation of some tasks and a failed attempt to extract data reliably from heterogeneous invoices.

The strongest results appeared in bounded and verifiable tasks: drafting and reformatting documents, code documentation, interface prototyping, test generation, summarisation, research support and repetitive administrative workflows. Outputs could be reviewed quickly by an experienced person, allowing errors to be absorbed into an iterative process.

> I've been using it selectively, and my team was using it selectively, for structuring big data bases for research and the synthesis of this research. Making repetitive tasks automated. (Interview 17)

By contrast, adoption became more costly where data were heterogeneous, outputs were difficult to verify, mistakes carried legal consequences or systems had to operate unattended in production. Interview 3 explained:

> The costs that I was not prepared to consider were mostly related to testing, integrating, and ensuring that the product really delivered the promise I'm making. And limiting non-compliance risks in anticipation of the AI Act.

Interview 18 captured the gap between demonstration and operational reliability. The participant reported that outdoor computer vision was affected by light, weather and occlusion, while failures in physical sensors could undermine any model:

> The gap between a convincing demo and a system that runs reliably in production, unattended, for months, was consistently underestimated.

This finding qualifies capability-centred narratives. A technically impressive model does not produce value until it is integrated with dependable data, hardware, monitoring, maintenance and customer support.

In the next section, we examine internal factors shaping AI adoption, encompassing challenges arising from SMEs' own limitations and those related to the characteristics of specific technologies.

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5.2 Internal factors shaping adoption

5.2.1 Costs extend far beyond subscription prices

Direct licence costs for major AI models were often low enough to permit experimentation. Participants mentioned individual or team subscriptions ranging from low monthly fees to approximately €100–€200 per user, while some firms relied partly on free tiers. For several deployers, these costs were negligible when compared to the costs of contracting or new hires (further discussed in 5.4.1.). Yet the interviews showed that licence price alone is a poor measure of the cost of adoption.

A fuller cost model emerging from the interviews includes at least four stages: **exploration, integration, operation and exit.** Exploration covers management attention, trials and staff learning; integration includes data preparation, process redesign, security and connection with existing systems; operation includes inference, monitoring, review, maintenance and customer support; and exit relates the possible costs of switching providers, rebuilding integrations or bringing a function in-house. Most firms could estimate the first invoice more readily than these lifecycle costs. **This produced a risk of economically evaluating adoption at the cheap experimental stage while underestimating the costs of dependable production.**

The economic risk is greatest when AI becomes embedded in a customer product. A change in token price, rate limit or model availability can affect the marginal cost and reliability of each customer interaction. Firms may be unable to pass the increase to clients immediately, particularly under fixed-price contracts. **The low fixed cost of experimentation can therefore develop into a less predictable variable cost at scale.**

First, firms incurred substantial learning, testing and integration costs. Interview 17 described the learning curve, compliance, governance and verification as "substantial" initial investments. Interview 3 emphasised the work required to test integrations and prevent regressions before a prototype could be shipped:

> And that's actually the reason why, today, the platform I developed is still in prototype status. I'm not going to ship that anytime soon, because I can't ensure that it has been tested in enough detail. […] The other cost, or the other hidden cost, is not just about the expertise, it's about ensuring that you can periodically test the system. Basically, there's this question of test automation because LLMs actually evolve. You can have different versions of a single LLM engine in just a few days. So, how do you ensure that there's no regression? That's this question of test and integration.

Interview 18 identified data quality, system integration and the gap between a convincing demonstration and unattended production as larger cost drivers than modelling itself.

Second, reliable product deployment could require investments in hardware and specialist labour. Interviewee 8 rented a dedicated GPU server for approximately €2,000

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per month to keep models and source code under company control. Interviewee 14 reported around €120,000 in expenditure, in addition to internal staff time, for an application involving five or six people part-time. Interviewee 12 argued that self-hosting and fine-tuning also proved costly as it required prohibitively expensive hardware and skills. The build-versus-buy decision was therefore a trade-off between visible infrastructure costs and less controllable provider dependence:

> We have a technical positioning where a lot of the team is more experienced on things like systems architecture, programming, front-end and back-end development, software testing. That's the main "point of genius". That's also a very good position to adopt AI from, because rather than our use of AI being restricted to using chatbots like ChatGPT and copying and pasting information from here to there, we jumped straight into designing architectures to automate our own operational pipelines, testing the existing solutions, and fitting the right mix of solutions for small business to integrate human staff members with AI agent staff members into unified operational pipelines, and really gaining a direct experience on both utilizing the massive frontier kind of development paradigms through providers like OpenAI, Anthropic, Microsoft's Azure, Google's own cloud, and so on. But also [do] a lot of on-premise deployments, self-hosted architectures, and SME-focused deployments, because we cannot afford to sell to our clients solutions that rely on enterprise APIs that might run them thousands, or tens of thousands, or hundreds of thousands of euros in inference costs. Instead, we have to design and deploy pragmatic solutions that augment their own value propositions and selling propositions while maintaining strict guardrails against ballooning costs, either on training or on inference.

Third, oversight and quality assurance were not optional add-ons. Interview 13 observed that rapid code generation also produced technical debt:

> There's a lot of code being produced very quickly, but you need to understand it. You need to somehow follow the process. So, it doesn't make it less work. It actually makes it a lot more work.

The work changed from producing every line directly to reviewing, testing, understanding and maintaining a larger volume of output. Interview 8 similarly described the emerging human role as managing an additional team: "you really start just being the manager, review the work, and give it instructions." Faster generation could therefore shift costs downstream into testing, documentation, security and maintenance.

Fourth, data protection and confidentiality shaped technology choices. Firms dealing with personal, medical, financial, proprietary or customer data frequently restricted public tools, anonymised inputs, used enterprise arrangements, or considered self-hosting. Interviewee 16 described a script that removed names and other identifiers before material was submitted to an external model. Interviewee 4 highlighted a customer preference for AI being off by default and for European legal jurisdiction:

> "[...] interestingly, also, we hide those AI features behind a checkbox most of the time. They're off by default, and that's also something that customers appreciate, the lack of AI. [...] So while some value it, many actually appreciate the fact it's not there.

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These practices required engineering and organisational effort but were also necessary to maintain customer trust.

Finally, provider dependence introduced uncertain future costs. Interviewee 11 described vendor lock-in as a combination of accumulated code, knowledge and working practices: once a project was built around a tool, switching became difficult, while providers could deprecate models or introduce more expensive replacements:

> The second thing is that those tools are somehow generating situations where you have a vendor looking at when you're using tool A for a specific purpose. It's really difficult within a project to hop to another tool, because all your knowledge, the codebase, all the skills that you have built will be there. So, that's another challenge, and sometimes this tool might have a new model, depreciate the previous one, and the new model is much costlier. So, you don't have visibility on how costs will be in the short-term horizon. So this is a problem. And when combined with the vendor lock in, it becomes quite big.

Interviewee 13 suspected that current prices did not reflect energy and infrastructure costs, leading them to expect a steady increase in token spending:

> For me, it looks underpriced, and I'm expecting, actually, at any moment, that they will pull up the prices to what it really costs. I mean, there's a thing called Claude Dash, where you can actually see how many tokens you have used, and one of my colleagues told me that he has used the equivalent of $2,400 in tokens on his 200 euro budget, plus he has actually used 24 kilowatt hours of power per day. And that means that even the cost of electricity is not reflected, even if you just pay for the electricity. It's more than what we pay at the moment for the tokens, so there's somebody who must be losing money at the moment.

Interviewee 19, by contrast, expected model quality to rise and token prices to fall, while acknowledging that the best models might become geographically restricted. **This discrepancy is of importance because it shows that SMEs are investing in AI under uncertain and heterogeneous assumptions about future prices and capabilities.**

5.2.2 Human oversight as part of the cost structure

Human oversight appeared throughout the interviews as both a normative commitment and an economic requirement. Participants consistently relied on domain expertise to specify tasks, detect errors, protect customer relationships and assume responsibility. Interviewee 4 summarised their perspective of accountability:

> It's always the person who hands in the work who is responsible. It's not Claude who did the work; you did the work.

Similarly, interviewee 1 stresses the importance of supervision for AI:

> The AI that is behaving or working in this kind of environment needs to be controlled. It needs to be supervised. [...] It would require a bit of effort to have some people that really know how the system is deployed, how it behaves, how it's accessing the data, how it's treating the data, and so on."

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This limitation was a common understanding among our interviewees. Interview 19 used AI to prepare legal and administrative options but felt obligated to check them with tax or legal professionals. Interview 17 repeatedly emphasised that responsibility remained with humans. Interviewee 7 noted that a part of their personnel is tasked with overseeing AI adoption and outputs:

> And they [staff members] are driving AI in this perspective to support us with very challenging ideas, suggestions, how to validate, how to make sure that it's not simply hallucinating, and how to adopt appropriately.

For interviewee 10, keeping a human in the loop was considered essential:

> We also always do this 'human in the loop' process, where we validate and verify the output generated by AI, because we always want to make sure that there are no risks or hallucinations or anything that could affect the overall quality of the projects.

Verification costs are often overlooked, yet they can potentially alter the cost–benefit balance**.** If an expert must reconstruct an entire output to establish whether it is correct, AI adoption may generate little or no net savings. Therefore, **economically viable adoption depends, among others, on whether the organisation has an affordable process in place for evaluating AI-generated outputs.**

From a SCOT perspective, this is a form of local closure. Firms accepted a system for one workflow while excluding it from another; permitted a tool with non-sensitive information while prohibiting customer data; or used AI internally for prototyping but not for contractual delivery. **These closures remained partial and reversible, reflecting continuous negotiation over what tasks is AI capable of undertaking**.

5.2.3 AI readiness and resistance

Although adoption was usually initiated by founders and senior managers, its **organisational success depended on employee participation**. Leaders could purchase licences or define strategic priorities, but staff had to decide whether AI is useful in their actual work and integrate it into routines. Interview 18 stated this directly:

> In a firm our size you cannot impose AI top down; it only works if the people building it believe in the approach.

Attitudes varied by professional identity, experience and prior exposure. Some technically confident employees were immediately curious; others saw unreliable output, threats to professional standards or possible job loss. Interviewee 4 described senior developers who required reassurance that AI was intended to enhance rather than replace their work. The company created a bi-weekly discussion in which staff compared what worked and what did not, allowing scepticism to influence tool selection.

Interviewee 12 described an initial transition from fear to experimentation:

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> First, they were scared. They thought, 'Look at how good this model is; it's gonna replace me.' Then they realised, 'I can do that tedious thing … faster, better and more reliably.' Then they were excited.

Interviewee 13 discovered that all developers had already experimented privately with AI, although some remained ideologically opposed to regular use. Interview 8 observed strongly uneven use after introducing self-hosted coding support. Interview 16's account of converging enthusiasm and caution shows that attitudes were dynamic rather than fixed categories:

> "We were divided into two tiers: people that really couldn't wait to see what they can do, and people who were very, very reluctant. […] What's interesting is that the enthusiasts kept using it. They were happy, but if they started with a level of *want to use* 9 out of 10, right now they're around 6. And the people that fought against it started with 2 *want to use*, now they're around 7 or 8, because they were more careful, so they tiptoed while using it and gained useful experience from it."

Practical experience made some promises less credible while making bounded uses more acceptable. Most firms relied on learning-by-doing, peer demonstrations and internal discussion rather than a settled professional curriculum. Interview 11 organised seminars, senior-led training and monthly internal meetups. Interview 16 held quarterly team training and encouraged employees to present successful uses. Interview 17 adopted a micro-learning philosophy that combined prompting with ethics, privacy, governance and validation skills. Interview 5 commissioned external training after an organisation-wide brainstorming process.

Nonetheless, practices remained varied. Some companies had internal rules prohibiting sensitive data or limiting particular models; others relied on informal professional judgment. **Decentralised experimentation created learning but also the possibility of shadow AI (use of unapproved AI tools without company knowledge or oversight from IT teams), inconsistent costs and confidential information entering external services.**

The next section will engage with **external factors** shaping AI adoption, encompassing concerns about SMEs relationship with Big Tech companies, public funding (or lack thereof), and costs of regulatory compliance.

5.3 External factors shaping adoption

5.3.1 Dependence on Big Tech and vendor lock-in

Accessible third-party models lowered the initial barrier to experimentation, but they also created strategic dependence. Providers determined model availability, usage limits, contractual permissions and price. Once a project accumulated code, prompts, integrations and staff habits around one provider, switching could become costly even when alternatives technically existed. **The resulting dependency was an unequal allocation of**

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commercial risk. SMEs purchased an input whose future properties they could not control and sold an output whose reliability they were expected to guarantee.

As already mentioned, this dependence directly correlates with SMEs' limited resources and concerns about cost fluctuation. A vendor could deprecate a model and introduce a more expensive replacement after the firm had built workflows around it. Interviewee 4 was already concerned about the dependency created by widespread internal use, particularly because the company was bootstrapped and needed to sustain expenditure from revenue:

> We're starting to hear that prices are about to go up, and that could eventually become a problem if the prices go up too much. [...] We have to make sure that we are profitable or able to sustain ourselves from our revenues.

Dependence also had a geopolitical dimension. Participants questioned whether European firms would retain affordable access to the best US or Chinese models and whether customer data could remain under European legal jurisdiction. Interviewee 6 described third-party AI use as a possible "cannibalization of European intellectual property" because prompts, code and know-how could be transferred into systems controlled elsewhere. Interviewee 8 refused public US coding services and instead ran open-source models internally. Interviewee 12 argued that, without Chinese alternatives, European firms would be "fully at the mercy" of private US companies. Interviewee 19, while more optimistic about the future decrease of token prices, still expected that access to the most capable models could be restricted geographically.

These different expectations generated different strategies. Interviewee 4's European video-conferencing business illustrates this relationship. The firm could have used a US provider for transcription, but this would have contradicted its commitment to European servers and sub-processors. It instead used open-source models hosted by European partners. The arrangement protected the firm's value proposition but restricted the provider landscape and could increase per-minute cost:

> "It would have been easy to just plug and send all of the audio conversation over to some US provider, but that didn't fit the promise that we make to our customers. We needed to make sure that the technological infrastructure and sub-processor or provider landscape caught up with our needs. And the same thing goes for an extension of this transcription, which is the ability to create summarizations and actionables and all the kind of stuff that people expect from meeting solutions these days. So here too what we use are open source models, which are hosted by some European hosting partners for us. Because we ourselves, when it comes to hosting AI and generative models, they're quite GPU-intensive, and hosting these type of models best works at a certain scale. For us, it makes more sense for a hosting provider to capture many customers and then be able to provide those models to them at a certain scale, than for us to try to have to set up servers and have running costs, fixed costs, where we don't essentially use all the capacity all the time."

Interviewee 15 prohibited the integration of external models into customer products unless the customer explicitly accepted the data-transfer implications. Overall, interviewees reported limiting some uses, creating data-handling rules, or moving towards local and European infrastructure but for the large majority in our sample, the objective was not

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complete independence, which respondents often regarded as unaffordable, but sufficient substitutability to avoid an irreversible commitment.

Furthermore, the relationship between SMEs and larger companies entails an asymmetrical competitive aspect. Interviewee 6 argued that small European AI firms lacked a marketplace and could struggle to qualify for procurement even when they possessed a strong product. Large providers controlled compute, models and distribution channels, while small firms competed intensely in crowded application markets; the competition to appropriate value remains uneven.

5.3.2 Public funding

Public funding occupies a prominent role in interviewees' perspectives. For Interviews 9, 14 and 18, national, regional and EU programmes supplied resources that small firms could not readily mobilise:

> "We see that as something important for trying to push forward some of the projects that we have internally, because we are bootstrapping at the moment, so we are more in need of that in order to scale a bit." (Interview 9)

For interviewee 14's co-funded R&D reduced the firm's exposure but covered only part of the visible expenditure:

> "In that case, part of the research and development has been co-funded by these programs. Together with that, we have participated in an Italian acceleration program of the city of Bologna. Also, in that case, we have been co-funded, so we have spent around 120,000 euro, and we have received a co-funding of 30,000 euro. Something like that. This is what is visible. The things that are not visible is the internal manpower—the additional manpower from myself or from colleagues of mine."

Interviewee 12 expressed frustration for a high-scoring but unsuccessful funding application:

> "We are an entirely bootstrap company. All of the revenues that we ever had are revenues that we generated ourselves through our work. We have wanted to and tried to apply last year for SME investments for digitalization, which was intended to help us buy some servers to help us in our AI adoption and growth, and be able to more cheaply access larger models that we could then do more work with that would then help us grow. [...] For a project, we scored a 93.5 percentile out of the top 100. Projects that scored 70 and some even under 70 were funded, but we were rejected. AI didn't help us one bit, one way or the other. It seems like what would help us would be a better comprehension of politics. Why did we get rejected with 93.5%?"

Public support potentially enables experimentation with AI, but intense competition, application delays and a mismatch between programme timelines and rapid technical change limited its capacity to secure commercial viability.

In any case, public funding still plays a role actively shaping AI adoption. For university spin-offs and R&D-oriented firms, participation in funded projects could generate knowledge, reference cases and consortium access that later supported commercial

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activity. At the same time, a roadmap organised around calls risked producing technically successful pilots without repeatable customer demand. Interviewee 18 went as far as to state that:

> Yes, funding availability clearly shapes which AI directions we pursue and when. I would be candid in the interview that for an SME of our size the funding landscape is not just support, it actively steers the roadmap, which has both good and distorting effects.

5.3.3 Regulation and compliance costs

Participants did not express a uniform pro- or anti-regulation position. Most supported the underlying objectives of European regulation of data protection, for example, interviewee 12 called European privacy and copyright protections basic human rights and described themselves as a strong supporter. However, our sample diverged on the impact of compliance requirements as, unsurprisingly, regulation was conceptualised in economic terms. Interviewees were more positive when customers recognised compliant design as evidence of quality and more negative when they carried the cost without gaining market access.

In that sense, interviewee 18 treated privacy-preserving design as part of the product architecture and a competitive requirement for public-sector customers. Interviewee 3 described AI Act compliance as "not a nice-to-have" but a condition of sustainable business. Responsible use of AI was considered as a factor potentially distinguishing SMEs from larger international providers, while compliance could also increase customer trust. In certain cases, regulation itself was considered as an opportunity for new products. Interview 17's regulatory-intelligence platform is a direct example: regulatory complexity generated a market need for tools that help smaller organisations interpret and document compliance.

Nonetheless, **support for regulation coexisted with concern about implementation.** Participants identified costs in legal interpretation, technical redesign, documentation, employee training, governance, monitoring and certification. Many of these costs were fixed, making them proportionally heavier for micro and small firms.

Interview 11 identified three continuing cost centres: specialist legal advice capable of understanding technical systems; translating requirements into development practice and retraining developers; and monitoring changing rules. In a similar manner, interviewee 14 reported allocating approximately 5-6% of a grant request to remaining updated on regulatory developments. Interview 3, despite working professionally with standards, reported that understanding relevant specifications required significant effort and that the implementation corpus was still difficult for SMEs to navigate.

In addressing compliance costs, interviewees often reported the lack of European infrastructure assisting SMEs on this subject. Interviewee 12 strongly supported European privacy and copyright rules but argued that SMEs lacked affordable European servers and models with which to implement compliant systems. The participant summarised the problem:

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> I am for the procedure of compliance, but in order to be compliant right now, there are not the support mechanisms or levers required to efficiently deploy compliant setups. Not for SMEs.

Finally, **regulation's impact extends beyond compliance costs into shaping particular uses of AI.** Interviewee 18 reported that the firm anonymised and aggregated data at the edge and avoided using biometric identification. The participant described this as a constraint that could rule out some use cases, but also as a competitive requirement for public-sector customers. Interview 13 used AI-generated code in the firm's own products but avoided handing such code to contract-development customers because of unresolved copyright and open-source licensing concerns. Interview 15 prohibited the incorporation of external models into customer products unless the customer accepted the implications for data transfer.

From a SCOT perspective, regulation participated in technological closure. It helped define which interpretations of a system were acceptable. This closure was not purely restrictive. By narrowing the space of legitimate designs, regulation could make expectations more credible to customers and funders.

5.4 Defining economic viability

The interviewees' explanations for pursuing AI adoption remained **mostly speculative** in the sense that a **well-defined route from adoption to profit was not articulated**. No interviewees report direct increases in profitability linked to AI whether actual or expected. Instead, they **attributed a variety of other indirect economic benefits, while simultaneously recognizing AI as itself a cost**. The interviews therefore reveal uncertainty about how SMEs are trying to understand the economic value of AI.

Interview 13 reported dramatic development acceleration but, when asked whether this had already generated revenue, replied: "I wish I could say yes. Nope." Contracts were in the pipeline, but the value had not yet been captured. Interview 14 had invested approximately EUR 120,000, supported by EUR 30,000 in co-funding, and had begun testing the market for an AI-enabled cultural product. Early sales demonstrated interest, not recovery of the full development cost. Interview 19's two-person firm considered AI indispensable to its current development pace but constantly compared subscription expenditure with the speed gained.

Interview 5 regarded adoption as strategically necessary but too recent to evaluate economically. Interview 13 described prospective contracts that would have been impossible to offer without AI, but acknowledged that the expected revenue had not yet materialised.

Some even recognised AI as a cost. Interview 5 expressed the productivity-profitability gap directly: "I can't see an economic benefit; it's a cost". The company had introduced a coordinated process across 58 employees and faced immediate licence and governance expenditure, while financial returns remained prospective. Interview 4 similarly reported that AI had probably reduced current margins because the company was paying several

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thousand euros per month in new licences, although the participant expected greater competitiveness and revenue later.

The economic appeal or viability of AI was articulated in four categories:

a) **Labour and capacities**
b) **Time**
c) **Market position and signalling**
d) **Improved quality of output**

5.4.1 Labour and capacities

Augmentation: AI as a tool assisting workers

Participants predominantly described the economic appeal of AI in terms of its potential to augment, rather than automate or replace, the capacities of existing workers. Interviewee 9 held that "For us, it's more like seeing AI as a tool that can work alongside humans and not replace them". Interviewee 11 demonstrated a clear skepticism of total automation:

> Of course, we need the people, and the same people that will help us to operate the AI, to monitor it, to validate it, and move on.

This view of AI as a tool came with a view of AI as something used by workers rather than something competing with them. Interviewee 4 explained how they wished their workers "to understand that these technologies are not out there necessarily to take their jobs, but to enhance their jobs". This kind of view entails workers learning, rather than being replaced:

> You just have a tool, but without know-how to implement it [...]. We have a Ferrari, but we don't know how to drive it. (Interview 2)

The adoption of AI was thus not expected to replace existing labour processes with fully automated ones, but to change them in terms of their content, enabling a reduction in time spent on routine tasks and greater time available to higher value tasks including specification, design, integration, review and client communication. Interview 10 described developers increasingly supervising tools and agents. Interview 18 reported that Generative AI shifted effort "toward higher-level design, integration and review and away from routine implementation." Interviewee 16 elaborated that:

> I don't want to replace humans with AI work, but I want to let humans use their brain for stuff that's more difficult, more high level, more complicated, and needs more critical thinking, and let AI take care of all the very, very important but repetitive and detail-oriented stuff.

Increased Productivity

The interviewees thus **expressed a clear vision of a division of labour between workers and machines**. By focusing on the elimination of mundane or repetitive tasks, the interviewees indicated the appeal of making workers more productive. Interviewee 5 explained how by:

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> Reducing time to deliver the more mundane activities, I'm freeing up resources in redundant-type activities. Those resources can then use their time in a much more strategic way, for business acquisition, or moving forward deadlines and deliveries of certain reports, or other work that they have to do.

Interviewee 11 made a similar point, holding that increased productivity "cannot happen if you don't have human operators in the pipeline." **Overall, this is one of the main economic benefits associated with AI across our sample: increased productivity through augmentation of human workers**. For interviewee 16, this was manifested in the marketing department:

> We have an internal marketeer that used to be able to support two or three clients as a premium service, and now she can support, I think, double that amount [...] more or less with the same resources.

For interviewee 10 this translated into an opportunity for their small business to undertake more projects:

> We are now able to work maybe simultaneously on two or three projects because we are a small team.

This may not entail only a quantitative increase, but also a **qualitative increase of different kinds of tasks**. Interview 17 estimated that work which might previously have required a multidisciplinary team could be performed by one or two people with AI-assisted tools. Interview 19 described access to design, legal and technical capabilities that the two-person company could not otherwise afford.

Interview 4 described the resulting expansion of individual capability:

> I now have the ability to do the work of a designer, a front-end developer, a back-end developer, a sysops person. I can basically roll 4, 5, 6 roles all into one, together with Claude, and I think that we are all going to start to be able to think a little bit more. We're much more empowered than we were previously.

This increased productivity does not necessarily reduce workload. Interviewee 18 reports that "Workload has not fallen, it has been redirected toward more ambitious work" while Interviewee 13 described staff "running like crazy". Whether or not the work was more intense than before varied. In all cases, work was said to be more productive. Interviewee 19 stated:

> I don't think the workload changed. We always worked a lot, ten-plus hours every day. What AI changed is the outcome. It pretty much multiplied the outcome by 100

Workers' acceptance as a precondition for successful AI adoption

This idea of AI as augmentation also had organisational or management functions. The above quotes indicate how shaping expectations is a continuous process; interviewees seek to present themselves as responsible adopters of AI and to foster workers' acceptance of this new technology. **Therefore, they move to challenge one of the main negative expectations associated with AI: technological unemployment and devaluation of the**

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remaining workforce. Refuting the possibility, paves the way for successful AI adoption. Several interviewees explained that the augmentation narrative reassured staff, preserved the value of professional expertise and ensured that accountability was still attributed to humans. Interviewee 12 explicitly connected perceived job security with willingness to adopt, contrasting its approach with firms that treat employees as disposable. Interviewee 18 acknowledges the pressure already placed on their workforce and thus justifies AI adoption.

> I see productivity gains as letting us take on more projects and do more with the same small team, rather than as a reason to cut people. AI augments a team that is already stretched.

Reducing hiring

Nevertheless, while full automation was not regarded as desirable, AI-driven augmentation of existing workers was reported to have an **indirect impact on employment**. Interviewees noted that AI influences their future hiring plans and considered avoiding or delaying hiring as an aspect of AI benefits. Interviewee 11 mentioned that AI had slowed the need to recruit additional staff:

> Instead of hiring 5 more people, we have been using more AI, which is a fraction of what 5 people would cost, in order to deliver the same thing.

Similarly, interviewee 8 noted that they were using AI "to augment the development process of our software" and that this enabled them "to make our development teams stronger without adding to the headcount", using the extra capacity to improve testing and documentation. Interview 19 stated explicitly that their two-person company no longer needed to hire for certain design, legal or development tasks which could be delegated to Generative AI:

> We gain capabilities that we wouldn't have otherwise without extra hiring.

For interviewee 19 there was a wider reduction of operational costs:

> [AI] reduces the cost of operating the company. [...] We don't need to spend that much on lawyers, advisors, etc. to simply operate the company.

These findings remain ambivalent, and further research is needed to clarify their broader significance and future development. It is possible that the identified tendency to reduce or pause hiring is more prevalent in the broader ICT sector, where the firms represented by interviewees 8, 11 and 19 operate; however, our data do not allow us to make such claims with certainty. Nevertheless, certain concerns can be raised in this regard. First, stagnation in hiring may result in a long-term loss of expertise for SMEs and contribute to an overall decline in job creation, given the key role of SMEs as employers within the EU. Furthermore, what interviewees reported may also represent a less explicit form of work intensification, as a stable number of workers are expected to undertake substantially more tasks post-AI introduction.

It should be noted that a small section of our interviewees expected growth in personnel due to the adoption of AI. Interviewee 3 hoped that AI-enabled capacity would increase

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revenue and make future hiring possible. Interview 16 expected the same workforce to serve more clients, improve margins and eventually attract more talent:

> I think what AI will allow us is the same people to serve more clients, but in a more documented and detailed way. This comes back to the first factor, as I said, the profit margins. If we have bigger profit, we will be able to attract more and better talent, and if we have more profit and talent, we will be able to attract more and bigger clients.

5.4.2 Time

Alongside increased productivity, our interviewees expressed an **understanding of the economic value of AI in terms of saved time**. Interviewee 19 stated explicitly that saving time is the key metric of advantages afforded by AI:

> We honestly didn't think about the return on investment. It's more that it saves time. The development cycles have been reduced from months to days or from weeks to hours.

In a similar manner, interviewee 12 reports that:

> We are now at a point where one week of focused work by a senior staff member that is familiar enough with development and AI is able to lead to an entire ready-to-deploy product that, last year, would have taken us maybe an entire year to build.

This is a particularly excessive estimate. **In the absence of clear measurements of a productivity boost, interviewees construct their own ad hoc and rough estimates.** Describing a similarly remarkable improvement, interviewee 15 reports that:

> We have been experiencing that the activity we used to do took, for example, 3 days. Now you can do it in 1 hour. This is quite normal.

Interviewee 7 provides a more modest estimate saying that:

> It's just slightly decreasing the time that we used to spend before, probably 20–25% maximum.

For interviewee 17, saving time results from the automation of mundane tasks:

> By making the routine work that is happening automated, it saved us a lot of time.

Some interviewees made an effort to calculate time saved due to AI adoption and then, in some cases, translate this into money saved. Interviewee 2 went as far as to claim that:

> It all comes down to speed and time saved. I'd say that at this stage, I'm saving about one or two hours every day which for me means I have a hundred or two hundred euros a day in working hours [...]. I'd estimate somewhere between two thousand and four thousand euros monthly.

This calculation transformed the interviewee's own time into a potential labour cost, e.g. hiring an assistant, linking back to what was observed earlier. However, the economic return from saving time is not directly translated into benefits for the firm; the participant acknowledged that the advantage was not directly tangible but potentially enabled other activities.

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The difficulty of evaluating AI benefits in any form was recurrent across interviews. For example, interviewee 16 estimated that AI had freed about 10-15% of team time but stated that this had not been converted into tangible economic benefits:

> This hasn't been translated into cost-cutting or anything, because we use this 15% of time to do other things... But the fact that they [employees] are more happy, and they feel more fulfilled, for me, is a huge impact.

Across the interviews, time was the most typical way in which the economic appeal of AI was described. **Both explicitly and implicitly, time was frequently invoked to describe the benefits, both anticipated and actual, of adoption.** Time served as an experiential indicator which could stand in for the complex reality of adoption. The interviewees performed diverse acts of reasoning to calculate the economic viability of AI in terms of time; time could be converted into quality, resilience, employee satisfaction or work that had previously been postponed.

5.4.3 Improved quality of output

Improved quality of output was another benefit frequently associated with AI adoption by the interviewees. In this case as well, interviewees were cautious not to attribute these improvements exclusively to AI adoption, but nonetheless reported increased satisfaction with final products following the introduction of AI in their firms. As interviewee 7 reports:

> We noted that since 2024 and up to now, we have significant improvements in the quality of the projects that we are delivering.

Similarly, interviewee 13 involved in network management and telecommunications software noted that "I can actually do better testing now with the AI in place than I could half a year ago". For interviewee 16, representing a firm in accounting and ICT, AI adoption meant more reliable final output:

> We were able to create some Python scripts that would produce those invoices in a way that ensures there are no typos, everything is correct.

Interviewee 18 links together quality of output, speed and cost to demonstrate their high satisfaction with AI in their firm:

> Automated counting replaces manual or expensive survey based methods and runs continuously and in real time rather than in occasional batches. Edge processing gives us lower latency and lower operating cost. Those are concrete, measurable advantages in quality, speed and cost of the data we deliver.

5.4.4 Market signalling

Interviewees also **articulated the economic viability of AI in terms of explicitly performative functions as a way of signalling competitiveness in the market**. In some cases they reported that just being associated with the buzzword of AI has benefits. Interviewee 16, whose company had operationally embedded AI held that it:

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> Certainly improved the visibility. […] I can fairly safely say that it improved our presence in the social media world, in the network."

Interviewee 19, who also had operationally embedded AI, argues that AI "certainly" makes a company "more attractive" and suggests that even if a company has not actually adopted AI, they have an incentive to pretend they have:

> The hype train is still accelerating, and it's definitely not the last station. I believe AI is the only thing that is currently attractive for investors. I think a majority, maybe 80%, of companies are just signaling that they have AI.

This social imperative for firms to adopt was described as a "non-negotiable" for "every company" by interviewee 5. Because AI, understood as a general purpose technology, should be applicable anywhere and any firm not adopting it could be reasonably assumed to be non-competitive.

Indeed, **signalling AI adoption was described by several interviewees as having tangible effects in terms of market access, or the possibility to sell to new customers who specifically want AI, appeal to investors and other dimensions of competition**. Interviewee 12 described how adoption enabled them to "enhance [their] client base".

For interviewee 18, the economic appeal of adoption was primarily in terms of signalling: "AI today is more a condition of relevance than a measurable profit centre." They contend that AI adoption affords credibility to their company that has already drawn economic benefits:

> The market access benefit is very real and already realised: without AI capability we would not be eligible or credible for a large share of the projects we win […] Credibility is a real asset in forming consortia, attracting partners and being taken seriously by investors and public bodies. For a small firm competing against much larger players, that signalling value is not cosmetic, it is part of how we get access.

The same firm linked AI to higher-value analytics contracts and a turnover of EUR 1.2 million: AI "moved us from being perceived as an IoT and sensor integrator to being an urban data intelligence provider." This access to new higher-value markets was an important aspect of signalling, beyond merely being seen as relevant.

Interviewee 10 explained that:

> AI is something that helped us provide more services in different domains, because now we can also offer some basic capabilities in terms of data science, data analytics, and data processing for using AI. This helped us be in a more competitive position, generally speaking.

In sum, European SMEs are not passively affected by expectations circulating in business circles. On the contrary, they actively perform work on expectations; in a way, they construct expectations about their products and company value by drawing from the broader promissory narratives on AI.

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5.4.5 Limits to economic benefits

The interviews suggest that **improvements in speed, productivity and capacity do not automatically translate into economic returns.** Their value depends on whether customers are willing to pay for the resulting outcomes, whether those outcomes provide a lasting advantage over competitors, and whether firms can demonstrate that AI was responsible for the improvement. These conditions created a series of limits between the operational benefits of AI and their conversion into revenue or higher margins.

One limit concerned customer value. Interview 12 said the firm generally tried "not to sell AI" but to sell outcomes such as increased sales, lower costs or a more reliable service. Interview 18 likewise reported that public authorities valued accurate counts, reliable environmental data and usable dashboards more than the AI label. Interview 4 found that some customers appreciated AI features being off by default. AI could therefore increase value when it disappeared into a dependable service; prominent AI branding could be neutral or even counterproductive.

The boundary between internal productivity and market advantage was also contested. Interview 11 argued that, for an established company, AI improved delivery speed but did not change market positioning: “the use of AI is more towards productivity and less towards gaining a competitive advantage.” If competitors adopt similar tools, an early advantage may be temporary and productivity gains may ultimately appear as lower prices rather than higher margins. Interview 13 anticipated precisely this possibility, fearing that widespread adoption might push the cost of software development “too close to zero.” From this perspective, AI can simultaneously strengthen an individual firm’s capacity and erode the market value of the activity in which that capacity is deployed.

Measurement difficulties also emerged. AI adoption often takes place alongside other organisational and technological changes, making it difficult for SMEs to identify its concrete contribution to overall productivity. This challenge may be particularly difficult for SMEs, which have smaller samples of workers and outputs in order to systematically measure productivity. For example, interviewee 7 reported a significant increase in their company’s capacity:

> What we noted is that for the last operational year (2025), we have an increase of the number of requests that we received, and those requests were successfully accomplished, within 22% less time, compared to 2024.

Nonetheless, the participant avoided attributing the entire increase to AI, noting that new services, changing demand and organisational improvements also mattered.

Finally, in some cases interviewees **actively challenge AI hype**. Interview 8 rejected claims that AI made developers seven times more productive as "far-fetched," adding that a potential twofold increase would already be highly valuable.

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Section 6: Limitations

Several considerations shape the interpretation of the findings. First, interview accounts are not audited measures of firm performance. Participants can provide valuable knowledge of expenditure, time savings, productivity, revenue, margins and commercial outcomes, but the study does not independently verify financial data. The findings therefore distinguish reported outcomes from estimates and expectations and avoid presenting managerial assessments as objective profitability measurements.

Second, participants spoke as senior representatives of their organisations. Their accounts may serve several purposes at once: describing experience, promoting a company or product, demonstrating technological competence, protecting commercially sensitive knowledge, and advancing policy claims. This positioned character of the interviews is analytically relevant. Rather than attempting to separate a supposedly neutral account from all strategic presentation, the discourse-oriented approach examines how credibility, innovation, responsibility and vulnerability are constructed within the interviews. The sample does not include direct interviews with employees who lacked decision-making roles, customers, investors, regulators or technology providers. Claims concerning these groups are consequently interpreted as part of SME representatives' accounts. Further research could compare managerial narratives with employee experiences or triangulate reported economic benefits through organisational metrics and financial data.

Purposive network-based recruitment and the eligibility requirement of active AI use limit generalisability. The sample is likely to over-represent firms with relatively strong digital capabilities, European networks and an interest in AI-related policy discussions. It does not reveal why other SMEs reject AI, fail during early experimentation or remain excluded from adoption.

Section 7: Discussion

Overall, findings indicate that AI adoption is progressing across European SMEs which, generally speaking, intend to deepen their engagement with AI in the near future as they expect significant economic benefits for their companies. None of the interviewees stated an intention to pause their investments in AI and were generally inclined to either continue their existing spending or increase it. However, AI adoption was not reckoned as a smooth, linear or certain process. Several risks were identified as having the potential to undermine the economic viability of AI adoption by European SMEs. In broad terms, these risks pertain to:

- Vendor lock-in and technological dependence
- Data privacy and confidentiality risk
- Risk of rising costs of AI adoption
- Failure to convert productivity into financial return
- Lack of public funding

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- Risk of regulatory uncertainty and rising cost of compliance
- Employment-growth stagnation
- Deskilling and skills-pipeline risk

These risks carry both short-term and long-term implications and are not acknowledged universally, or emphasised to the same degree across our sample. The last two risks, relating to labour conditions, are not directly referenced by our interviewees but are part of the interpretation of findings, as will be shown below. These risks merit further exploration and need to be addressed in future research.

First of all, SMEs in our sample hold generally positive expectations on AI adoption. At the same time, they also express concern for being "left behind" and being perceived as "non competitive"; this is also a driving factor between AI implementation which should not be underestimated. Furthermore, interviewees are largely aware of being involved in an AI hype cycle and therefore are conscious to not uncritically accept all claims surrounding AI at face value. Therefore, they try to occupy an intermediate position, where acceptance of and investment in AI can proceed without rendering them vulnerable.

Their ambivalent position is further complicated by external factors shaping AI adoption. Interviewees identified three major challenges (limited public funding, the costs and uncertainty associated with regulatory compliance, and dependence on Big Tech companies) with the third considered to be of particular significance. As already noted in FORSEE research (Minotakis et al., 2026), issues of digital sovereignty serve as nexus points, tying together and amplifying different concerns around AI. For our interviewees, dependence on Big Tech further complicated regulatory compliance, raised issues of data privacy and, perhaps most importantly, rendered their companies vulnerable to fluctuations in AI costs in the future. These two risks have immediate implications, as SMEs are concerned about complying with EU regulation when adopting AI systems provided by companies based outside the EU. They are also uncertain about how best to protect their customers' data and have experimented with layered data-management strategies, keeping sensitive data internally while relying on external AI providers for less sensitive tasks. These arrangements reflect limited trust in the data protection practices of AI systems based in the US or in China. The issue of fluctuating costs concerns a less tangible future risk, as SMEs cannot anticipate when and if increases in AI costs will materialise.

European SMEs want to catch up with perceived advanced AI adopters in the USA and China, but they are wary that building their products around specific AI applications may have implications for the future and create risks of vendor lock-in. They recognise that AI applications, and LLMs in particular, are currently available at relatively low costs in order to recruit customers, and they are concerned about how future increases to cost of subscriptions and tokens could negatively impact their operations. This particular risk is indicative of the unpredictability that accompanies AI adoption by European SMEs.

Delving deeper into the question of economic benefits and viability of AI adoption, it is noteworthy that none of our interviewees reports a link between AI adoption and a rise in profitability. This is consistent with larger studies on Generative AI (Challapally et al., 2025; Yortzov et al., 2026); a 2025 MIT study, drawing on structured interviews across 52 organisations, survey responses from 153 senior leaders and an analysis of more than 300

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publicly disclosed AI initiatives, highlights a "GenAI Divide". The research found that 95% of organisations had yet to achieve measurable financial returns from their investments in GenAI (Challapally et al., 2025). Our data from European SMEs corroborate these findings. However, they do not preclude the possibility that, given more time, investment in AI may generate measurable returns. Further longitudinal research involving larger samples is necessary in this respect.

Furthermore, findings provide valuable insights into the perception of economic benefits associated with AI in European SMEs. Interviewees largely associate AI adoption with productivity gains, but are conscious of their inability to provide clear estimates of the magnitude of this productivity boost. Consequently, they construct ad hoc measures of productivity gains, which vary from exceptionally high to minor increases.

The gap between perceived increases in productivity or expanded capacity and the missing boost in profitability suggests two distinctive aspects of AI adoption for European digital SMEs. Firstly, it shows that European digital SMEs intend to persist with their AI investments while building internal capacity and waiting for clearer benefits to materialise. This is, among other things, a function of positive expectations about AI which circulate in popular, business and EU political discourse. These expectations about the future of AI are mobilising resources and investment and encouraging SMEs to anticipate future returns.

Secondly, this gap demonstrates how European SMEs themselves actively shape expectations about AI and are not merely passive recipients of circulating promissory narratives. The "market signalling" advantage reported in Section 5.4.4 is indicative in this respect. Even where AI has yet to yield clear gains in terms of profitability, SMEs may benefit from projecting an innovative and competitive image in the market, signalling their capacity to "stay ahead of the curve". More broadly, the articulation of various ad hoc measures of AI's economic value constitutes the creation of bespoke expectations about AI which can explain and justify investment in it in the absence of measurable increases in productivity.

The SoE theoretical framework is particularly useful here, as it argues that the boundaries between expectations about and impacts of new technologies are more blurred and significantly less clear-cut than often hypothesised (van Lente, 2012). Furthermore, this research suggests that the viability of AI adoption hinges, among other factors, on the capacity of SMEs to utilise and advance expectations and draw on future-oriented, promissory narratives about AI's economic benefits to mobilise investment and attract customers themselves (Geels and Smit, 2000). This does not imply that SMEs are acting deceptively. Rather, the value and utility of AI remain in flux and are still being negotiated through processes of adoption and experimentation. Expectations are part of this process as they contribute to how emerging technologies acquire more stable meanings and forms of economic value (Konrad et al., 2017).

Future concerns on the economic viability of AI adoption by SMEs

Yet, while expectations can act as a stabilising force in the present early days of AI adoption, our findings also cast doubt on the long term viability of this process.

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Interviewees were largely concerned that vendor lock-in could lead to increased subscription and token costs. There are already some indications, particularly among technology and ICT companies, that the "AI bill" is rapidly increasing (Landymore, 2026). Indeed, beyond price hikes, the capacities of free users of AI models are being downgraded, ads are being introduced and some features are being restricted unless premium tiers are paid for (Field 2026). Since the 2023 launch of ChatGPT, Generative AI has quietly been funded by robust internal subsidies, as Big Tech companies have burned cash to offer lower prices and gain market share, meaning that customers were "effectively being paid to adopt AI" (Garr 2026). As subsidies are diminished, the calculations required for AI adoption will likely involve very different magnitudes. The revealing of the true cost of AI will raise questions about the viability of AI adoption and will put to the test the expectations being developed by European SMEs. If measurable returns continue to remain elusive, the risks outlined above could place SMEs in an increasingly vulnerable position and render AI adoption a less viable proposition.

A distinct factor exacerbating the challenges outlined above relates to the lack of public funding or the significant difficulties SMEs face in accessing it. SMEs expect part of the costs associated with experimenting with AI adoption to be borne by member states and EU institutions as part of broader efforts to close the gap between European industry and its global counterparts and competitors. However, bureaucratic obstacles and lengthy funding cycles do not correspond to the needs imposed by the rapid pace of technological change. Furthermore, the preparation of funding applications itself involves considerable costs in terms of time and resources, creating an additional burden for SMEs, particularly when applications are unsuccessful.

Beyond the question of profitability and economic viability, our interviewees provided significant insights into the reorganisation of labour and transformation of skills underway amid AI adoption, although these insights are limited by the small number of personnel employed by firms in our sample. None of the interviewees reported job losses due to AI. There was a broad consensus that AI is being introduced to augment and assist workers rather than replace them. Similarly, the interviewees conceptualised AI adoption as both a precondition for, and a result of, upskilling and increasing digital maturity within their companies. Nonetheless, a significant proportion reported that AI adoption has resulted in a slowdown in hiring and expected this tendency to continue.

This suggests implications which may be significant for quality of work and along with it, workers' acceptance of AI in the workplace. Interviewees held that AI increased the capacity of existing personnel, allowing them to undertake a greater number of tasks. They reported no significant discontent among workers associated with this. However, recent reports from the tech industry describe the rise of "AI burnout" as routine tasks are automated, boosted productivity becomes the norm, and workers must operate at higher cognitive levels constantly (Ranganathan and Ye, 2026). It is not a given that AI adoption will increase productivity while simultaneously lowering the intensity of work. If this increase in work intensity persists alongside stagnant or reduced hiring, the dynamic of workers' acceptance of AI may change and SMEs could be confronted with rising workers' dissatisfaction. This could be exacerbated if expected productivity gains do not translate into gains for employees. Furthermore, stagnated hiring may limit the entry of junior

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workers and in so doing eliminate the possibility of such workers learning on the job. These points should, however, be understood as pointing towards a potential long-term risk rather than a position observed in our sample.

Section 8: Conclusion

AI adoption among European SMEs is uneven and complex, reflecting both a reality of dependence on Big Tech companies and driving factors where positive expectations are combined with the fear of being left behind. Vendor lock-in is associated with multiple concerns, potentially clashes with EU regulation on AI and data privacy and raises issues of economic viability as AI costs are not stable nor changing in a predictable manner SMEs are still in the early stages of adopting AI.

Thus far, AI adoption has not resulted in measurable gains in profitability for SMEs. Nonetheless, SMEs investing in AI report broader economic benefits while constructing ad hoc measures of productivity. The ad hoc measures of economic viability discussed by the interviewees serve to bridge the gap between these popular expectations and the less stark and much more uncertain reality of on the ground AI adoption.

Furthermore, working with limited resources, both internally and within the broader EU context, European SMEs develop expectations around AI that reflect the EU's relatively peripheral position in the AI landscape. Promises of revolutionising business models and upending entire industries are difficult to sustain. Nonetheless, reporting economic benefits and projecting an image of competitiveness and being "up to date" allow SMEs to strengthen their market position. Here too, a degree of fear acts as a driving force, as SMEs feel that failing to adopt AI may exclude them from future business opportunities.

In terms of labour, SMEs associate AI with human augmentation and the upskilling of existing workers, with no job losses reported in our sample. Nonetheless, the potential stagnation of hiring carries negative economic consequences, while an intensified workload for workers who are expected to take on more projects may generate tensions in the future.

Overall, AI adoption is progressing, but in a precarious manner. The "profitability paradox" and fluctuating costs reported by interviewees raise questions about the long-term economic viability of AI implementation. This results in a situation in which the economic benefits for SMEs remain uncertain, while, in contrast, the benefits accruing to Big Tech companies developing AI through growing dependence on their models appear considerably more ensured.

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Appendix 1. Semi-structured interview guide

The semi-structured interview guide was used flexibly, with questions selected and adapted according to each interviewee's role, organisational context and experience with AI adoption.

Background & context questions
When and why did you decide to adopt AI?
How does your company currently use AI? For what tasks, precisely?
When your company decided to adopt or develop AI, what economic benefits did you expect it to generate?
Where did these expectations mainly come from? (internal strategic projections, investor expectations, vendor or technology provider narratives, industry trends or policy initiatives)
To what extent have these expected economic benefits been realized so far?
What measurable benefits has AI generated for your business?
What types of investments were required to implement AI?
Which factors are most important when deciding whether to invest in AI?
How has AI affected revenues, margins, or cost structures?
What kinds of costs or challenges did you encounter when implementing AI? Were any of them unexpected?
What ongoing costs are associated with maintaining AI systems?
How has investing in AI affected the way your company allocates resources or prioritizes projects? (i.e. changes in subscriptions in favour of GenAI tools, cut-cancel outsourcing of services).
Has AI played a role in attracting funding, investment, or public support for your company?
Have you applied for or received public funding related to AI or digital innovation? Did the availability of such funding influence your decision to pursue AI projects?
How has using AI changed how your company positions itself in the market? (Has it, and if yes, how)?
Do customers explicitly value your AI capabilities?

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Would you say AI has produced measurable competitive advantage (e.g., performance, speed, quality)?
Or has it primarily helped with branding, credibility, or attracting partners/investors?
Compared to competitors without AI, where do you see concrete advantages or disadvantages?
What resources (time, money, expertise) does compliance require?
How does regulatory compliance requirements affect your ability to use AI?
Have regulatory expectations influenced whether you pursue or limit AI projects?
How is AI discussed internally (e.g., strategic priority, future growth engine, innovation signal, improve productivity)?
Do you have an AI use policy in the company?
How did staff respond to the decision to deploy AI?
What steps have you taken to support workers' ability to use AI tools?
How do worker attitudes affect your organisational decision making regarding AI?
If AI does succeed in making your firm more productive, how do you think this will affect headcount?
How has AI adoption affected work practices, roles, or workloads?

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