Artificial Intelligence Adoption and Revenue Growth in European SMEs: Synergies with IoT and Big Data Analytics

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Abstract

Purpose - The conventional notion that adopting Artificial Intelligence (AI) positively affects firm performance is often confronted with various examples of failures. In this context, large-scale empirical evidence of the economic performance implications of adopting AI is poor, especially in the context of Small and Medium Sized Enterprises (SMEs). Drawing upon the Resource-Based View and the Digital Complementary Asset literature, we assessed whether the adoption of AI affects SMEs' revenue growth.

Design/methodology/approach - First, we examine the relationship between the adoption of AI and SMEs' revenue growth. Second, we assess whether AI complements the Internet of Things (IoT) and Big Data Analytics (BDA). We use firm-level data gathered by the European Commission in 2020 on 11,429 European SMEs (Flash Eurobarometer 486).

Findings - Among the key findings, we found that *ceteris paribus*, the adoption of AI positively affects SMEs' revenue growth (by more than 30%) and, in conjunction with IoT and BDA, appears to be even more beneficial.

Originality/value. Our results suggest that AI fosters SME growth, especially in combination with IoT and BDA. Thus, SME managers should be aware of the positive impacts of investments in AI and make decisions accordingly. Likewise, policymakers are aware of the positive effects of SMEs' reliance on AI, so they may design policies and funding schemes to push this digitalization of SMEs further.

Keywords

Artificial Intelligence; Revenue growth; Small and Medium Sized Enterprises; Europe; Big Data Analytics; Internet of Things.

1. Introduction

Small and Medium-Sized Enterprises (SMEs) account for the large majority of companies and the largest portion of jobs worldwide (Di Bella *et al.*, 2023). Scholars view digitalization as an opportunity for SMEs' growth (e.g. Gurbaxani and Dunkle, 2019; Habibi and Zabardast, 2020; Hausberg *et al.*, 2019). Nonetheless, while the digital transformation has continued apace across sectors in recent years, smaller organizations are involved to a lesser extent (OECD, 2019; Piccoli *et al.*, 2024).

Scholars have sought to understand the barriers and enablers of SMEs' digitalization (Hansen and Bøgh, 2021; Li *et al.*, 2018; Rialti and Filieri, 2024). Conversely, evidence on the impacts of the adoption of specific digital technologies on SMEs' revenue growth is scant (Skare *et al.*, 2023). This is true specifically for the impact of the adoption of Artificial Intelligence (AI), which is defined as a system's ability to correctly interpret external data, learn from such data, and use those learnings to achieve specific goals and tasks through flexible adaptation (Kaplan and Haenlein, 2019).

Despite AI being considered a herald for revenue growth among the digitalization options (Grashof and Kopka, 2023; OECD, 2019), there is little research on its impact on SMEs' revenue growth (Akter *et al.*, 2021; Rahman *et al.*, 2023). The relevance of this gap recalls a vivid debate about the readiness and capabilities of SMEs to take advantage of AI. On one side, Hansen and Bøgh (2021) literature review work shows that SMEs lack the required Information Technology knowledge, expertise, and resources even though the benefits are known. Likewise, the OECD (2021) and Bhalerao *et al.* (2022) identified, among other constraints, a lack of data culture, AI technical competencies of human resources, and awareness about what benefits AI could bring. On the other side, it remains an open question whether and to what extent those SMEs that have adopted AI have experienced revenue growth.

Initial insights have been provided by Baabdullah *et al.* (2021), who, however, focused on business-to-business SMEs. Also, among the few studies interested in the financial returns of SMEs' digital transformation, the focus is primarily on potential opportunities and perceived benefits rather than actual performance (Li *et al.*, 2018; Enholm *et al.*, 2022). At best, intermediate performance outcomes were considered, such as SMEs' innovation performance (e.g. Kiel *et al.*, 2017), marketing performance, and operational performance (Abrokwah-Larbi and Awuku-Larbi, 2024; Basri, 2020; Chen *et al.*, 2016). Hence, further investigation is required to shed light on the relationship between AI adoption and SME growth. Hence, the first research question that this study aims to answer is the following: *Does SME's AI adoption lead to revenue growth?*

Some studies consider complementary assets, such as complementary digital technologies, that facilitate the use of digital innovation and increase the value of its output (Steinhauser, Doblinger, and Hüsig, 2020). Thus, complementary digital technologies are required to get the most out of digital transformation, especially with regard to AI (Mikalef *et al.*, 2021; OECD, 2021). Therefore, we investigate the complementary contribution of the Internet of Things (IoT) and Big

Data Analytics (BDA) to SME revenue growth. We base our decision on the fact that AI is often used with other technologies to create comprehensive solutions. For example, AI can be combined with IoT devices to enable smart and connected systems. Yet, AI is different from IoT and BDA, albeit connected. AI aims to replicate human cognitive abilities such as learning, reasoning, problem-solving, perception, and language understanding, whereas IoT refers to everyday objects equipped with the ability to gather data, connect to networks, and process information (Côrte-Real *et al.*, 2020). IoT allows these objects to communicate with other devices and online services (Côrte-Real *et al.*, 2020), eventually allowing the acquisition of data to be used as input for further analysis, also through AI (Hansen and Bøgh, 2021). Moreover, the core IoT functionality focuses on connectivity and data transfer from different technologies through sensor hardware/firmware, cloud computing, data modelling, storing, reasoning, processing, and communication technologies (Botta *et al.*, 2016; Perera *et al.*, 2013), excluding tasks related to data processing, as AI does. BDA involves examining large and varied datasets (i.e., big data) to uncover hidden patterns, correlations, market trends, and other valuable business information (Zakir *et al.*, 2015). Thus, BDA involves sophisticated tools and techniques to exploit big data's volume, velocity, variety, variability, veracity, visualization, and value (Mayer-Schönberger and Cukier, 2013; Naeem *et al.*, 2022). While Big Data Analytics (BDA) and Artificial Intelligence (AI) are related, they serve different purposes. BDA focuses on analyzing large datasets to uncover patterns and insights, but it does not create autonomous decision-making systems as AI does. However, BDA can incorporate AI techniques to improve its analytical capabilities, resulting in more efficient and meaningful data analysis (Awan *et al.*, 2021).

Given the inherent differences among AI, IoT, and BDA, but recognizing their interconnections, we study the complementary role of IoT and BDA for AI. Complementary assets contribute to the success of innovations and the appropriation of their economic value (Teece, 2018; Steinhauser et al., 2020). In our study, IoT and BDA are supposed to sustain the contribution of AI to SMEs' revenue growth by creating a synergistic data ecosystem that enhances the decision-making process. IoT provides vast amounts of real-time data from diverse sources in the physical world (i.e., smart objects), BDA offers tools to process and analyze this data efficiently, whereas AI algorithms can then use this processed data to make intelligent decisions and predictions. Studying their complementarity can reveal how these digital technologies create a powerful data ecosystem that can sustain firms' growth. Furthermore, IoT enables data collection at an unprecedented scale, and BDA provides methods to handle this volume efficiently. AI can scale its learning and adaptation based on this processed data (Akter *et al.*, 2021). To the best of our knowledge (Table I), there is no empirical study that measures AI complementary assets and their joint effects on SMEs' revenue growth. Hence, the second research question of the study is the following*: Are IoT and BDA complementary to AI for SMEs' revenue growth?*

INSERT **TABLE I** ABOUT HERE

To answer the proposed questions, we draw upon the Resource-Based View of the firm (Wernerfelt, 1984; Barney, 2001) and the Complementary Asset concept (Teece, 2000), and we used a sample of 11,429 European SMEs whose data were gathered from the Flash Eurobarometer 486 survey (European Commission, 2020), to conduct an econometric analysis. The results of the study reveal that *ceteris paribus* the adoption of AI positively affects SMEs' revenue growth (> 30%). The implementation of AI alongside IoT and BDA, respectively, further enhances SMEs' revenue growth. Hence, IoT and BDA are complementary assets for AI when it comes to SMEs' growth options.

2. Theoretical background

Our investigation is grounded on two main theories: the Resource-Based View theory of the firm (Wernerfelt, 1984) and the Complementary Asset concept (Teece, 2000). The Resource-Based View justifies why AI could contribute to revenue growth, while the Complementary Asset concept supports the synergistic effect of digital complementary technologies such as IoT and BDA. The Resource-Based View of the firm posits that companies should be analyzed primarily through their unique bundle of resources and capabilities rather than just their product market position (Wernerfelt, 1984). These resources, which can be tangible or intangible, are the primary determinants of a firm's strategic options and potential for competitive advantage (Wernerfelt, 1984). Resources that provide sustained competitive advantage should be valuable, rare, inimitable, and non-substitutable (Barney, 1991).

The Resource-Based View has been applied to understand whether investments in digital technologies enable firms to increase efficiency performance (Liang *et al.*, 2010), financial performance (Wu *et al.*, 2006), and propensity to undertake digital export (Elia *et al.*, 2021). The Resource-Based View (RBV) offers three key insights that are particularly valuable when studying how digital transformation affects firm performance. First, it helps identify and define the specific technological resources a firm possesses. Second, it allows for a clear distinction between technical resources (like AI or data analytics tools) and non-technical resources (such as human skills or organizational processes), enabling research across different business functions. Third, it provides a framework for researchers to methodically examine how these various resources contribute to a firm's overall performance (Gupta and George, 2016).

Scholars highlight that ***in the data-driven revolution (McAfee and Brynjolfsson, 2012), digital technologies that allow acquiring, managing and taking advantage of data (i.e., resources like digital data technologies) are considered the most suited resources to improve firm performance. Accordingly***, digital data technologies have been shown to provide SMEs with new resources, instruments, and approaches to expand globally (Elia *et al.*, 2021), and develop new ways to organize business operations (Denicolai *et al.*, 2021). Digital data technologies also offer SMEs the possibility to increase productivity and efficiency, doing more but with fewer financial resources (Moeuf *et al.*, 2020). Additionally, SMEs can employ digital data technologies to access and manage knowledge resources more easily, both beyond (e.g., with customers, stakeholders, or suppliers) and within organizational boundaries (Ardito *et al.*, 2021).

Based on this, we suggest that firms leveraging digital data technologies, such as AI, are likely to obtain a revenue growth advantage out of the acquisition, elaboration, and exploitation of data (Ardito *et al.*, 2021). According to the Digital Complementary Asset theory, ***technological complementarity occurs when the value of an innovation depends on other technologies, either already existing technologies or new ones. Said otherwise, two assets (i.e., resources, in line with the*** Resource-Based View ***theory) are complementary if they result in improvements in the marginal value of both (Milgrom and Roberts, 1995). Consequently, the full benefit of this innovation cannot be achieved without such complementary technology (Teece, 2018). According to*** Steinhauser et al. (2020), complementary digital technologies are digital assets that facilitate the use of digital innovation and increase the value of its output. This technological complementarity expands our understanding of the conditions that enable innovative companies to reap the financial benefits of their inventions. ***Such a perspective seeks to examine if and what combination of information technologies drives performance gains (e.g. Mikalef*** *et al.*, 2021)***. Three building blocks contribute to profitability: the appropriability regime, the dominant design paradigm, and the role of complementary assets (***Holgersson, Granstrand, and Bogers, 2018***). Complementary assets could be of different types: production, consumption, asset price, input oligopoly, and innovational and technological complementarities. In the era of digital transformation, the concept of complementarity has become crucial for creating and capturing value (***Steinhauser *et al.*, 2020)***. This is largely due to the modular nature of digital resources, which allows them to be easily separated and recombined.*** AI, IoT, and BDA can be viewed as distinct digital building blocks that organizations can synergistically combine into larger, more complex systems to enhance value creation (Piccoli *et al.*, 2022; Schilling, 2000). These combinatorial opportunities are driven by the growing availability and diversity of digital components. However, leveraging these modular resources requires a robust digital infrastructure. This infrastructure provides the necessary foundation for envisioning, deploying, and integrating these digital modules into more sophisticated systems. From this perspective, AI, IoT and BDA are distinct digital resources for organizations that can be synergistically combined into larger systems for better value creation and appropriation. These building blocks can be modules that, when combined, form higher-order components for more complex systems (Arthur, 2010). The digital infrastructure provides the facilities and foundations to envision and deploy these modules and combine them into higher-order systems (Tilson *et al.*, 2010). Furthermore, the trend of servitization is reshaping both digital infrastructure and resources (Favoretto *et al.*, 2022). Digital components are increasingly being offered as services, not only within organizations but also to external companies (Tronvoll *et al.*, 2020). This shift expands the potential for combinatorial innovation beyond organizational boundaries, allowing businesses to incorporate external digital services into their systems. In essence, the modular design of digital resources, supported by appropriate infrastructure and embracing servitization, opens up new avenues for organizations to create unique, value-adding combinations of AI, IoT, and BDA technologies. Organizations can strategically exploit their digital resources most effectively when they build a business environment with infrastructural, combinatorial, and servitized characteristics (Piccoli *et al.*, 2022). This makes it particularly relevant to focus on firms that have concurrently adopted multiple digital data technologies internally. While each digital data technology could deliver certain advantages, their combination would especially benefit SMEs' organizational performance by enhancing their capacity for decision-making, automation, internationalization, access to resources, and collaboration with supply chain members (Contractor *et al.*, 2010).

3. Hypotheses development

3.1 The role of AI for SMEs' revenue growth

Among the different digital data technologies, AI technology is seen as a key driver of growth, being positively associated with productivity and employment (Yang, 2022). AI technology has valuable applications from human resource management to new product development. This versatility comes from integrating into many heterogeneous systems, such as robotics, autonomous vehicles, computer vision, language, and virtual agents. This integration of AI into many systems is eased by the degree of modularity of the AI as a digital resource, the digital infrastructure and the servitization of the adopting firm and its business environment (Piccoli *et al.*, 2022).

In this study, we argue that AI is likely to support SMEs' revenue growth for various reasons. First, AI may alleviate some of the liabilities characterizing SMEs by enabling the automation of organizational processes (Raisch and Krakowski, 2021) and increasing operational efficiency (Huang *et al.*, 2020). AI can lead to efficiency gains, which is especially valuable for SMEs that often have limited financial resources. Through automation, AI allows SMEs to accomplish more tasks without increasing their existing assets or workforce. As a result, SMEs can expand their business operations and increase revenue without the need for significant additional investments in other resources.

Second, AI may also support SMEs' revenue growth through augmentation (Raisch and Krakowski, 2021), which means AI may improve a person's productivity (Tong *et al.*, 2021) while reducing potential mistakes. This is an advantage because SMEs have fewer slack resources to cope with failures (Damanpour, 2010). Their smaller workforce often lacks the expertise found in larger corporations, as highly skilled professionals tend to be attracted to more established, well-known companies. This combination of resource constraints and potential skill gaps can put SMEs at a disadvantage. Augmentation is not only relevant at the operational level, but also at the managerial level or when innovation comes into play. Notably, SME managers and R&D personnel are usually involved in multiple tasks that can lead to attention allocation issues and creativity constraints (Miric *et al.*, 2023). Augmentation may relax those issues, thus benefiting decision-making and innovation in the SME context (Dwivedi *et al.*, 2021).

Third, unlike other (digital) technologies, AI is characterized by flexibility and adaptability, so SMEs are not locked into a rigid technological path. Unlike some specialized technologies, AI can adapt to changing business needs, reducing the risk of costly technological shifts in the future (Wei and Pardo, 2022). SMEs can adopt AI through service-based resources provided by external companies, digital platforms, and ecosystems. This approach can help alleviate the financial burdens typically associated with developing in-house digital infrastructure (Morgan-Thomas, 2016) or establishing a proprietary digital ecosystem (Brock and Von Wangenheim, 2019).

Fourth, as compared to their larger counterparts, SMEs face more difficulties in gaining customer knowledge, interacting with distant customers, and providing customized products in a timely manner. AI, instead, is deemed to ease such tasks through chatbots, image-generation applications, personalized marketing, and resource optimization. The implementation of these AI solutions can drive potential positive returns to SMEs' business development and internationalization (Denicolai *et al.*, 2021).

Fifth, AI improves predictive capabilities (e.g., customer demands or supply chain risks), making firms more resilient (Chen *et al.*, 2021). This is especially beneficial for SMEs that, contrary to large firms, fail to survive after important failures (Damanpour, 2010). Finally, customized AI solutions tailored to specific business needs can create unique knowledge, processes, and offerings that are hard to replicate even from large firms, thus giving SMEs a competitive advantage. Moreover, AI technologies enable a faster and more precise segmentation of customers, enabling the development of more effective marketing strategies (Filieri *et al.*, 2021). Given the potential of artificial intelligence to enhance operational efficiency and decision-making processes, we propose the following hypothesis:

Hypothesis 1. Ceteris paribus, the adoption of AI will positively affect SMEs' revenue growth.

3.2 Technological complementary of AI with IoT and BDA

According to the Digital Complementary Asset concept (Steinhauser et al. 2020), if AI is considered the herald for growth, IoT and BDA could be important complementary digital assets. On one side, we acknowledge that adopting multiple digital data technologies may come with a price and that one of the main barriers SMEs face still relates to financial constraints. Nonetheless, digital data technologies are increasingly modular, encapsulate objects of value, assets, and/or capabilities and are accessible through a programmatic interface (Piccoli *et al.*, 2022). This makes AI less expensive and more easily available also for SMEs (Baur and Wee, 2015). Still, the cost associated with each digital data technology may have decreased, but the overall cost associated with the adoption and integration of multiple digital data technologies cannot be underestimated. This adds to the fact that returns on investments in digital data technologies by SMEs may not compensate for high integration costs. On the other side, this can be true for short-term financial performance rather than revenue growth-rate over more years. Second, in the hypothesis that SMEs can afford digital data technology integration costs, they may not be able to attain its benefits and become victims of the digital age. Digital data technologies are quite different, and each digital data technology requires dedicated human resources - SMEs may lack (Quigley and Burke, 2013) - to assess, implement, and effectively integrate each digital data technology with the others. Said otherwise, SMEs could not efficiently combine these digital resources as modules in higher-order systems. Consequently, they often struggle to integrate cutting-edge digital and data-driven technologies into their operations. This challenge hinders their ability to fully leverage their competitive advantages and explore innovative business opportunities (Pwc, 2018). Finally, studies reveal that digitalization may fail due to the tendency to maintain the stability of existing resources and routines despite environmental change (Radicic and Petković, 2023), even though this effect is expected to be lower in SMEs without internal R&D activities thanks to their flatter organizational structure.

In today's economic landscape, businesses that fail to embrace the data-driven revolution and digitalization can be at a disadvantage. Large corporations are already leveraging the benefits of digital data technologies, and SMEs must keep pace to avoid being marginalized in rapidly evolving markets. However, it is important to note that while AI adoption generally leads to positive outcomes, these results are often suboptimal (Radicic and Petković, 2023). This is because AI, although necessary in the current business environment, is not sufficient on its own to deliver its full potential benefits. To maximize the advantages of AI, companies need to integrate it effectively with other resources and capabilities. In this vein, it is argued that to fully benefit from their AI investments, companies must also allocate resources to supporting technologies and capabilities (Mikalef *et al.*, 2021). Consequently, we posit that the adoption of multiple digital data technologies, even considering its drawbacks, provides SMEs with more opportunities to grow. Indeed, we consider that SMEs are well suited to envision and deploy value-creating digital strategic initiatives combining different digital data technologies as building blocks of innovative systems, thanks to the already cited characteristics of the digital resources: modularity, encapsulation and access via programmatic interfaces (Piccoli *et al.*, 2022).

In our study, BDA and IoT would be the digital complementarities of AI. IoT solutions have the role of the vehicle to generate internally and acquire externally the data to feed AI. That is, environmental data is gathered and processed by an array of sensors and devices, which then send this information to cloud-based centres via the Internet. These centres analyze the data and return insights. However, this system faces challenges in efficiently handling large volumes of diverse data, interpreting complex situations, and making quick, intelligent choices. This is where AI becomes crucial. By integrating AI, the IoT can be enhanced to operate more rapidly, intelligently, sustainably, and securely (Zhang and Tao, 2020). Following this rationale, many studies show how the IoT solutions that connect things, sensors, actuators, and other smart technologies allow companies, especially SMEs (Hansen and Bøgh, 2021), to collect valuable data that can be converted into knowledge (Uden and He, 2017) and improve customer-level understanding (e.g. Lo and Campos, 2018) and SMEs innovation (Suciu *et al.*, 2021). AI is likely to become a relevant tool to support complex decision-making in SMEs by exploiting these big data. Thanks to servitization, IoT does not need to be fully developed inside the organizations because SMEs can benefit from servitized external resources to fill their technological gaps (Piccoli *et al.*, 2022) and reduce investment costs. Hence, we advance that:

Hypothesis 2. IoT is complementary to AI in fostering SMEs' revenue growth.

BDAs elaborate data, transform data into information and generate knowledge and wisdom for effective human decision-making where AI is not satisfactory, hence complementing AI (e.g. Côrte-Real *et al.*, 2020; Enholm *et al.*, 2022). For instance, AI and BDA have been combined within mobile health to provide the healthcare system, where statistical data analysis tools feed AI reporting to improve decision-making (Khan and Alotaibi, 2020). The synergy between BDA and AI is bidirectional. While big data and BDA can provide valuable input for AI systems, AI can also significantly enrich BDA capabilities (Rahman *et al.*, 2023). This creates a virtuous cycle where each technology enhances the other, leading to continuous improvement and innovation. For SMEs, this presents a unique opportunity to leverage servitized external resources to initiate and maintain this virtuous cycle, even with limited internal capabilities. Furthermore, the complementarity of BDA and AI can address the limitations of each technology when used in isolation. BDA can provide context and nuanced insights that AI might miss, while AI can process vast amounts of data at speeds impossible for traditional BDA methods. This combination can lead to more robust, accurate, and timely decision-making, which is crucial for SMEs operating in competitive markets. The integration of BDA and AI can help SMEs in various aspects of their operations, from customer relationship management to supply chain optimization. By harnessing the power of both technologies, SMEs can gain a competitive edge, identify new market opportunities, and streamline their operations, all of which can contribute to revenue growth. Given these arguments supporting the synergistic relationship between BDA and AI and their potential impact on SME performance, we propose the following hypothesis:

Hypothesis 3. BDA is complementary to AI in fostering SMEs' revenue growth.

4 Methodology

4.1 Sample and data collection

This study adopted the Flash Eurobarometer 486 questionnaire, coordinated by the European Commission in 2020 (European Commission, 2020). The questionnaire was composed of several sections. The first and second sections contained information about the demographic of the company and the SMEs' revenue growth and other innovation-related questions, respectively. The third section contains information about the business environment, while the fourth section includes questions about the problems and barriers encountered by the company. Finally, the fifth section was about the approach of the company towards the adoption of digital technologies, such as digital data technologies, while the last section contained questions about sustainability issues.

The survey encompassed several European countries and multiple sectors, focusing on enterprises with 1 to 250 employees, thus ensuring broad data coverage. Data was collected through telephone interviews with key personnel most knowledgeable about the survey topics, typically top and middle managers. This approach minimized question misinterpretation and enhanced response reliability. The survey gathered data from 11,429 European SMEs, forming the basis for testing our hypotheses.

4.2 Variable operationalization

4.2.1 Dependent variable

SMEs' revenue growth. This variable refers to an increase or decrease in SMEs' turnover in the last three years. It is a four-level ordinal variable (Stoian and Gilman, 2017) equal to one in case it has decreased, two in case it has remained stable, three in case it has grown by less than 30%, and four in case it has grown by at least 30%.

4.2.2 Independent variables

We built three distinct dummies reflecting the adoption of digital data technologies by the sample firms (Müller *et al.*, 2018) as indicated in the survey: 1) AI; 2) IoT, e.g., smart sensors; and 3) BDA, e.g. data mining and predictive analytics. AI is used as an independent variable to test Hypothesis 1, while IoT and BDA serve to test the complementary effects, i.e., Hypotheses 2 and 3. In the definition of the independent variables, while recognizing that some disagreements exist, insights from relevant academic and practitioner studies support the way AI, IoT, and BDA have been distinguished. In detail, technologies such as machine learning, neural networks (Benbya *et al.*, 2020; McKinsey, 2024) and technologies identifying objects or persons (Simeth *et al.*, 2022) fall into the AI domain. Technologies, including smart devices, smart sensors, and smart thermostats (Baali *et al.*, 2017; Channi and Kumar, 2021; Gupta, 2021) fall within the IoT domain. Technologies including data mining and predictive analysis (Tummala and Kalluri, 2018; Wlodarczyk and Hacker, 2014) fall within the BDA domain. The survey indicates which technologies fall within each main category. Thus, even though overlaps exist, the survey guides the respondents to indicate the most appropriate category to select.

4.2.3 Instrumental variables

To address the concern of the reverse causality and the endogeneity of investments in digital technologies, we treat the AI, IoT and BDA variables as endogenous (e.g., Aral *et al.*, 2006; Lee *et al.*, 1997). For each endogenous variable, we used as an instrumental variable the average diffusion rates for the given digital data technology in a company's industry to correct for potential biases following previous studies (e.g. Müller *et al.*, 2018). Specifically, instrumental variables are as follows:

Industry AI adoption: indicates the level of diffusion of AI in an industry (expressed in percentage).

Industry BDA adoption: indicates the level of diffusion of BDA in an industry (expressed in percentage).

Industry IoT adoption: indicates the level of diffusion of IoT in an industry (expressed in percentage).

4.2.4 Control variables

To improve the reliability of the analysis, several control variables were included in the model.

Patent ownership: We assessed each company's patent ownership (Acs et al., 2002) using a dummy variable based on the response to the survey question: "Does the company have a patent or patent application?"

Global value chain: We determined each company's participation in a global value chain (Reddy et al., 2021) using a dummy variable based on the response to the survey question: "Is the company part of a global value chain?"

Industry cluster: We evaluated each company's membership in a cluster (Grimpe and Sofka, 2009) using a dummy variable based on the response to the survey question: "Is the company a member of an industry cluster or another SME business support organization in the region?"

Industrial area: We identified whether each company is located in an industrial area based on demographic data. This is represented by a dummy variable equal to 1 if the company is in an industrial area and 0 otherwise.

Rural area: We determined whether each company is located in a rural area based on demographic data. This is represented by a dummy variable equal to 1 if the company is in a rural area and 0 otherwise.

Industry: We categorized each firm's industry using a dummy variable equal to 1 if the company is in the manufacturing industry and 0 otherwise.

Countries: We identified the country of each firm by creating a set of dummy variables, one for each European country, based on the company's demographic data.

5 Results

We computed pairwise correlations. All values were below the 0.70 threshold, indicating multicollinearity was not a problem.[1]We also computed the variance inflation factors (VIFs) to further exclude potential multicollinearity problems. Since the variables had adequate VIFs, that is, well below the suggested threshold of 10 (Kleinbaum *et al.*, 1988), multicollinearity was not a problem.

We used two-stage regressions with cluster-robust standard errors and instrumental variables to avoid potential endogeneity issues to test the hypothesis of this study. Specifically, the second stage is an ordered probit, given the nature of our dependent variable (Table II). As discussed by Müller *et al.* (2018), reverse causality is often an issue when studying the business impact of digital technology and occurs when, for example, a company's success leads to increased technology adoption, rather than the technology driving the success. For example, firms with high economic growth can build up slack resources that they may decide to invest in acquiring new, innovative technologies, such as BDA, AI and IoT. Moreover, Müller *et al.* (2018) contend that another potential source of bias in these studies is the simultaneity bias, which occurs when unseen factors influence both the adoption of technology and business performance simultaneously, making it difficult to determine which is truly causing the other. For instance, if unobserved positive external shocks to a firm's output occur during an observation period, they may simultaneously increase the economic growth of the firm and its investments in digital data technologies. To address the concern of the reverse causality and the endogeneity of investments in digital technologies, as anticipated earlier, we treated the AI, IoT and BDA variables as endogenous (e.g. Aral *et al.*, 2006; Lee *et al.*, 1997) and we used instrumental variables as defined in Section 4.2.3. To assess the appropriateness of our chosen instruments, we conducted endogeneity tests.

We tested the null hypothesis (H0) that the instrumental variables are exogenous. The results of the endogeneity tests allowed us to reject this null hypothesis, indicating that the instrumental

[1] Correlation values are available upon request. Descriptive statistics about the sample firms (e.g., distribution of firms per sector and country, adoption of each digital data technology per industry and country, tendency to adopt multiple digital data technologies, correlations) are also available upon request.

variables are indeed endogenous. To assess the validity of our instruments, we employed the Sargan test, which is an overidentification test (Sargan, 1958). In this test, the null hypothesis states that the instruments are valid, meaning they are uncorrelated with the error term. For the instruments to be considered valid, the test should not reject this null hypothesis. In our analysis, the Sargan test yielded a p-value greater than 5%, thus failing to reject the null hypothesis. This result supports the validity of our chosen instruments, as it suggests they are not correlated with the error term in the main equation.

INSERT **TABLE II** ABOUT HERE

Model 1 (Table II) tests Hypothesis 1, showing a positive effect of AI on SMEs' revenue growth, in line with Hypothesis 1. This result is corroborated by the estimation of the marginal effects of AI on each of the four levels of the dependent variable (reported at the bottom of Table II). Specifically, we found that firms adopting AI have 12.6% lower chances of reducing their turnover, 7.8% lower chances of maintaining stable their turnover, 5.3% higher chances of experiencing an economic growth of less than 30%, and 15.1% higher chances of experiencing an economic growth at least of the 30% (maximum level considered). That is, adopting AI leads to higher chances of economic growth, especially for higher growth rates.

To test Hypothesis 2 and Hypothesis 3, we tested the complementarity effect of every couple of digital data technologies on SMEs' revenue growth by estimating two separate models (Model 2 and Model 3 in Table II, respectively). These two separate models link SMEs' revenue growth with four exclusive dummy variables that depict the four possible states stemming from combining the adoption or not of every digital data technology in every couple of digital data technologies. In Model 2, the four states are *AI & IoT*, *Only AI no IoT*, *Only IoT no AI*, *no AI & no IoT*. In Model 3, the four states are *AI & BDA*, *Only AI no BDA*, *Only BDA no AI*, *no AI & no*. Specifically, in Model 2, the variable *AI & IoT* means that the company adopts both the technologies, *Only AI no IoT* means that the company adopts only AI, *Only IoT no AI* means that the company adopts only IoT, and *no AI & no IoT* means that the company does not adopt both the technologies. Since the four variables are linearly combined, in the models there are just three of them. The same explanation can be given for Model 3.

That is, to understand the complementary effects of digital data technologies on SMEs' revenue growth, we included: (a) in Model 2 the three dummy exclusives in case the company adopts AI and IoT while controlling for those that do not adopt any of these two digital data technologies and for the adoption of BDA; (b) in Model 3 the three dummy exclusives in case the company adopt AI and BDA while controlling for those that not adopt any of these two digital data technologies and for the adoption of IoT. In this way, we were able to observe whether the adoption of AI with one of the other two digital data technologies in conjunction, while controlling for the adoption of the remaining one, had any effect on SMEs' revenue growth. If two digital data technologies are complementary, we expect the coefficient estimate of *AI & IoT* and *AI & BDA* to be positive, significant, and higher than the parameter estimates of the dummies representing the remaining states of digital data technology adoption, as discussed above. Moreover, we expect Milgrom and Roberts's (1995) test of complementarity to be satisfied.

According to Models 2 and 3, coefficient estimates of *AI & IoT* and *AI & BDA*, respectively, were positive, significant, and higher than the other exclusive dummies included in the models, in line with Hypotheses 2 and 3. The test of complementarity provides additional confirmation of the complementarity effects supposed in the two hypotheses, as the Wald Chi2 statistic is significant in both cases (Table III). Thus Hypotheses 2 and 3 were supported.

INSERT **TABLE III** ABOUT HERE

The positive effects of having both AI and IoT technologies on the dependent variable are more deeply explained by the marginal effects of *AI & IoT* on the four levels of the dependent variable (Model 2). Specifically, we found that firms adopting AI and IoT concurrently have 17.8% lower chances of reducing their turnover, 11.1% lower chances of maintaining stable their turnover, 7.6% higher chances of experiencing an economic growth of less than 30%, and 21.3% higher chances of experiencing an economic growth at least of the 30% (the maximum level considered). In essence, adopting AI and IoT leads to higher chances of economic growth, especially for the higher growth rates.

Likewise, the marginal effects of *AI and BDA* on the four levels of the dependent variable (Model 3) reveal a similar pattern. Firms adopting AI and BDA concurrently have 17.5% lower chances of reducing their turnover, 11.0% lower chances of maintaining stable their turnover, 7.5% higher chances of experiencing an economic growth of less than 30%, and 21.0% higher chances of experiencing an economic growth at least 30% (the maximum level considered). This indicates that similar to AI and IoT, adopting AI and BDA leads to higher chances of economic growth, particularly for higher growth rates.

6 Discussion and conclusion

6.1 Theoretical contributions

Drawing on the Resource-Based View of the firm and the Complementary Asset concept and using a sample of 11,429 European SMEs, this study sheds light on the influence of the adoption of digital data technologies on SMEs' revenue growth. This study makes significant contributions to the growing body of literature on SMEs' revenue growth (e.g. Ingley *et al.*, 2017), and specifically on the impact of digital technologies on SME growth (Foroudi *et al.*, 2017; Radicic and Petković, 2023; Urbano *et al.*, 2024).

Our research represents one of the pioneering empirical investigations into the relationship between AI adoption and economic growth, specifically in the SME context (Abrokwah-Larbi and Awuku-Larbi, 2024; Baabdullah *et al.*, 2021). This focus on SMEs distinguishes our work from previous studies, which have predominantly examined these dynamics in large corporations (Eller *et al.*, 2020).

Our findings demonstrate that all else being equal, AI adoption has a positive impact on SMEs' revenue growth. This study contributes to the Resource-Based View theory by reinforcing the notion of AI as a valuable, rare, inimitable, and non-substitutable resource for SMEs (Olan *et al.*, 2022). The unique characteristics of AI position it as a strategically crucial digital resource upon which SMEs can build their competitive advantage and drive growth.

We also investigate the complementary contribution of Internet of Things (IoT) and Big Data Analytics (BDA) to SME revenue growth by combining the arguments from the Resource-Based View (Barney, 1991) and Asset Complementary (Teece, 2000). Our findings further highlight the significant role of the combination of digital data technologies in driving SME performance. Specifically, IoT and BDA emerge as valuable digital resources that can substantially contribute to revenue growth for SMEs. This finding contributes to the literature on complementary digital technologies (Steinhauser *et al.*, 2020), showing the synergistic effect of digital technologies, filling an important gap in the literature (Enholm *et al.*, 2022).

While digital data technologies such as AI, IoT, and BDA have been empirically shown to be profitable for SMEs when adopted individually (Bag *et al.*, 2023), their greatest contribution is realized when implemented together. Our research demonstrates that AI, when adopted in complementarity with IoT and BDA, significantly enhances the economic growth of SMEs. In essence, the advantages of AI are amplified when combined with other digital data technologies.

This finding contributes to the Digital Complementary Asset theory by highlighting the complementarity of IoT and BDA to AI. We observed that substantial growth occurs, particularly when these digital data technologies are adopted concurrently. Our study advances prior research in two ways. First, it disentangles the effects of adopting digital data technologies from the adoption of other digital technologies, addressing a gap noted by Eller *et al.* (2020). Second, it moves beyond the focus on single technology adoption that characterized earlier studies (Mikalef *et al.*, 2019), providing a more comprehensive understanding of the interplay between these technologies in driving SME growth.

In the digital transformation context (Piccoli *et al.*, 2022), this complementarity can be explained by the modularity of the digital resources. AI, as a module of digital transformation, is enhanced in combination with other digital resources, such as IoT and BDA. AI combines synergically with IoT and BDA into larger systems that are even more valuable than each one adopted separately. Our results confirm that these digital data technologies can indeed be combined in different ways, without any clear priority in terms of adoption, such as Big Data first to power AI (Bag *et al.*, 2023). This flexibility is possible because SMEs, even if they are financially and resource constrained, can exploit external digital services when internal digital resources are lacking, thanks to the infinite combinatorial possibilities digital resources offer (Piccoli *et al.*, 2022).

6.2 Managerial and societal implications

In light of our findings on the positive impact of AI adoption on SMEs' revenue growth, particularly when combined with IoT and BDA, we advise managers that SMEs may have opportunities to grow by relying on AI. Still, SMEs should rely on the possibility of integrating and gaining returns from digital data technologies in conjunction with AI. As such, SME managers should be aware that if they adopt digital data technologies that work in synergy, they are more likely to attain the largest advantages. Our research underscores the complementary nature of AI, IoT, and BDA, and we stress the importance of viewing these as an interconnected ecosystem rather than isolated tools.

The study has implications for policymakers and society. Policymakers are advised that the digital transformation of SMEs can lead to positive outcomes in terms of economic growth. Thus, policymakers should further promote such transformation by investing in current and new actions particularly considering the benefits of complementarity effects. For instance, this study highlights the important benefits of AI for SMEs' economic growth, which form the backbone of many economies in industrialized countries. Our findings could inform policymakers to establish education programs for SMEs in disadvantaged economies where there is a low level of economic and technological development. Research shows that organizations sometimes 'leapfrog' innovation stages and, from laggards, become innovators (Chen and Filieri, 2024). Innovation is indeed another area where we see significant societal impact. SMEs are often more agile than larger corporations, allowing them to quickly adapt and innovate with new technologies. This study could set up the basis for SME technology leapfrogging in disadvantaged European regions. For instance, policymakers could facilitate AI adoption in conjunction with IoT and BDA by SMEs in rural Southern Italy. These companies could benefit from these policies by hiring new Information Technology specialists with the knowledge and skills required to use these technologies to reduce costs, reach new markets, improve operational efficiency, and acquire customer knowledge. This example illustrates how AI adoption can drive both business growth, innovation, and job creation, particularly in regions that may have been struggling economically.

6.3 Limitations and future research

As with most studies, some limitations and future research opportunities should be acknowledged. First, future research should address and investigate how the innovation cycle can influence the diffusion of digital data technologies and how the complementary adoption and the consequent impacts on SMEs' revenue growth are related to the time of adoption of these technologies. In other words, it could be useful to look at the time when this complementarity occurs. Future research could also understand if and how these technologies are conditional to each other.[2]. Moreover, the Flash Eurobarometer survey does not enable monitoring the evolution of the company's technology adoption over time. However, future research should aim for a longitudinal analysis, which could reveal the impacts of adoption of digital data technologies on SMEs revenues over time, as well as

[2]Preliminary statistics show that there is not necessarily conditional adoption among the technologies for the companies of the sample since there are some companies that adopt only BDA, only AI or only IoT. However, future research could go in the direction of investigating this aspect.

confounders issues. Second, independent variables do not allow for capturing the extent of investments in the adoption of each **digital data technology** or potential overlaps. Thus, future studies may refine this study with this in mind. Third, contingent factors at the firm level may affect the proposed relationships, hence opening new lines of inquiry. Fourth, we could not assess the effects of the joint adoption of AI, IoT and BDA since only a very small share of SMEs adopt all digital data technologies concurrently, hence postponing an analysis in this sense. Fifth, we need some robustness checks about another cut-off of revenue growth or more robust measures of revenue to address the self-reporting bias. However, exact revenues or other cut-offs were not included in the adopted survey, opening a further line of inquiry.

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TABLES

Table I. Literature review of the empirical studies exploring AI impact on organizations

Reference	**Key findings**	**Theoretical foundation**	**Research method**	**Focus on SMEs**	**Inclusion of organizational performance**
Our study	*AI adoption has a positive impact on financial performance and IoT and BDA are complementary to AI in fostering financial performance*	*Resource-based view of the firm and Complementary asset theory*	*Survey*	*Yes*	*Yes*
Abrokwah-Larbi and Awuku-Larbi, 2024	AI-based marketing has a positive impact on the financial performance, customer performance, internal business process performance and learning and growth performance	Resource-based view of the firm	Survey	Yes	Yes
Baabdullah *et al.*, 2021	Technology roadmapping, attitude, infrastructure and awareness have positive impact on organizational AI practices, which have a positive impact on joint planning, service experience, joint problem-solving, customer engagement, financial and non-financial performance	Technology-organization-environment framework	Survey	Yes	Yes
Basri, 2020	AI-assisted social media marketing has a positive impact on organizational performance and effective business management	Technology adoption	Survey	Yes	Yes
Sharma *et al.*, 2022	Relative advantage, top management support, financial resource, employee capability have a positive impact on AI chat implementation intention, while complexity and cost have a negative impact.	Technology-organization–environment framework	Survey	Yes	No
Ghobakhloo and Ching, 2019	Perceived costs, perceived value, perceived compatibility, and knowledge competency have an impact on AI adoption.	Technology-organization-environment framework	Survey	Yes	No
Lee *et al.*, 2021	Emotional, informational and esteem supports have a positive impact on the interactant satisfaction, which has a positive impact on affective attachment and purchase intention	Theory of social support	Survey	No	No
Olan *et al.*, 2022	AI-based knowledge sharing system has a positive impact on organizational performance	Resource-based view	Survey	No	Yes
Wijayati *et al.*, 2022	AI has a positive impact on employee performance and work engagement	Dynamic capability view	Survey	No	No

Chen *et al.*, 2023	Management support, innovativeness, competitive pressure, regulatory support have a positive impact on the performance of AI adoption, while perceived AI risk has a negative impact	Technology-organization-environment framework	Survey	No	Yes
Mikalef and Gupta, 2021	AI capability has a positive impact on organizational performance, through the positive mediation of decision-making speed and quality	Resource-based view	Survey	No	Yes
Fajimolu *et al.*, 2023	AI capability has a positive impact on organizational performance, through the positive mediation of organizational creativity	Resource orchestration theory	Survey	No	Yes
Dubey *et al.*, 2021	The dynamic capability in AI driven supply chain analytics has a positive impact on the operational and financial organizational performance	Dynamic capability view and contingency theory	Survey	No	Yes
Chatterjee *et al.*, 2021	AI-based Customer Relationship Management has a positive impact on employee experience, engagement and information processing, which have a positive impact on organizational performance and competitive advantage	Institutional theory and resource-based view	Survey	No	Yes
Bag *et al.*, 2023	Managerial factors, intra and inter-organizational big data analytics and AI factors, and prior related knowledge on BDA and AI have a positive impact on absorptive capacity, which has a positive impact on innovation, flexibility and, at the end, organizational performance	Absorptive capacity theory	Survey	No	Yes
Prentice *et al.*, 2020	AI service performance has a positive impact on AI system satisfaction and AI information satisfaction, which have a positive impact on customer engagement	Affordance theory and theory of planned behavior	Survey	No	No
Bag, Gupta, *et al.*, 2021	Big data powered AI has a positive impact on firm performance through the mediation of knowledge creation	Knowledge management theory	Survey	No	Yes
Kumar *et al.*, 2023	Responsible AI has a positive impact on instrumental value, cognitive engagement and terminal value, which improves market performance	Means-end theory	Survey	No	Yes
Matsunaga, 2022	AI-driven uncertainty has a negative impact on employee performance	Uncertainty management theory	Survey	No	No
Wu *et al.*, 2022	Techno-stress has a negative impact on employee well-being and employee engagement, which decreases employee performance	Person–environment fit theory	Survey	No	No
Bag,	Coercive pressures, normative pressures,	Institutional theory	Survey	No	Yes

Pretorius, *et al.*, 2021	mimetic pressures have a positive impact on tangible resources and workforce skills, which increases the adoption of big data analytics powered AI, which in turns increases sustainable manufacturing and circular economy capabilities	and resource-based view			
Cao *et al.*, 2021	Performance expectancy and effort expectancy have a positive impact on managers' attitudes towards AI, while personal well-being concern and perceived threat have a negative impact managers' attitudes towards AI. Attitude has a positive impact on intention to use, while personal development concern and personal well-being concern has a negative impact on intention to use.	Acceptance - avoidance model	Survey	No	No
Rahman *et al.*, 2023	AI adoption enhances the relationships between marketing analytics capability and holistic marketing decision-making, and marketing analytics capability and competitive marketing performance	Dynamic capability view	Survey	No	Yes
Maity, 2019	AI has a positive impact on training and development practices	Seamless-Intutive-Personalized (SIP) Model	Interviews	No	No
Wang *et al.*, 2021	Enterprise development needs, implementation cost, human resources, top management involvement, external market pressure, convenience of AI technology and policy support have a positive impact on intelligent transformation	Intelligent transformation	Interviews	Yes	No
Bedué and Fritzsche, 2021	Ability, integrity and benevolence have a positive impact on trust, which has a positive influence on perceived benefits, perceived risks and intention to use.	Valence framework	Interviews	No	No
Jöhnk *et al.*, 2021	18 AI readiness factors are gathered in five categories: strategic alignment, resources, knowledge, culture and data	Innovation and technology adaption and organizational readiness for change	Interviews	No	No
Battisti *et al.*, 2022	AI-based innovation, orchestrated by meta-organizations, has a positive impact on new business models and social innovation	Meta-organization orchestration	Case study	No	No
Nylund *et al.*, 2020	Open innovation and automation (eventually, but not necessarily through AI) has a positive impact on firm turnover	Knowledge-based view	Panel data	No	Yes

Table II. Regression analysis results

Model	(1)	(2)	(3)
Variables	*H1*	*H2*	*H3*
Control variables			
Patent ownership	0.181	0.185	0.182
	(0.047)	(0.047)	(0.047)
	[0.000]	[0.000]	[0.000]
Global value chain	0.028	0.028	0.028
	(0.038)	(0.038)	(0.038)
	[0.461]	[0.454]	[0.461]
Industry cluster	0.032	0.031	0.032
	(0.032)	(0.032)	(0.032)
	[0.000]	[0.323]	[0.000]
Industrial area	0.144	0.143	0.144
	(0.031)	(0.031)	(0.031)
	[0.000]	[0.000]	[0.000]
Rural area	-0.018	-0.020	-0.019
	(0.032)	(0.032)	(0.032)
	[0.568]	[0.526]	[0.553]
Independent variables			
AI (Hypothesis 1)	0.532	…	…
	(0.153)	…	…
	[0.001]		
AI & IoT (Hypothesis 2)	…	0.750	…
	…	(0.196)	…
		[0.000]	
Only AI no IoT	…	0.228	…
	…	(0.063)	…
		[0.000]	
Only IoT no AI	…	0.166	…
	…	(0.024)	…
		[0.000]	
AI & BDA (Hypothesis 3)	…	…	0.738
	…	…	(0.180)
			[0.000]
Only AI no BDA	…	…	0.137
	…	…	(0.053)
			[0.009]
Only BDA no AI	…	…	0.157
	…	…	(0.036)
			[0.000]
IoT	0.149	…	0.149
	(0.023)	…	(0.024)
	[0.000]		[0.000]
BDA	0.146	0.147	…
	(0.033)	(0.033)	…
	[0.000]	[0.000]	
Industry dummy	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes
Constant	-1.860	-2.432	-2.416
	(0.139)	(0.145)	(0.188)
	[0.000]	[0.000]	[0.000]
Wald chi2	731.23	604.63	705.33
	[0.000]	[0.000]	[0.000]
VIF	4.90	4.52	4.96

Marginal effects	AI	AI & IoT	AI & BDA
Prob. (SMEs' revenue growth = 1): Turnover decreased in the last three years	-0.126 (0.037) [0.001]	-0.178 (0.050) [0.000]	-0.175 (0.043) [0.000]
Prob. (SMEs' revenue growth = 2): Turnover stable in the last three years	-0.078 (0.021) [0.000]	-0.111 (0.027) [0.000]	-0.110 (0.026) [0.000]
Prob. (SMEs' revenue growth = 3): Turnover increased less than 30%	0.053 (0.015) [0.000]	0.076 (0.019) [0.000]	0.075 (0.018) [0.000]
Prob. (SMEs' revenue growth = 4): Turnover increased at least of the 30%	0.151 (0.043) [0.000]	0.213 (0.055) [0.000]	0.210 (0.051) [0.000]

Note: Robust standard errors in parentheses; p-values in brackets; All estimations use the average diffusion rates for the three digital data technologies in a company's industry as instrumental variables; Number of observations=11,429 companies.

Table III. Complementarity tests (third step)

Test of complementarity	Chi2
Model 2: SMEs' revenue growth (AI & IoT) – SMEs' revenue growth (Only AI) ≥ SMEs' revenue growth (Only IoT) – SMEs' revenue growth (No AI & No IoT)	2.89 [0.089]
Model 3: SMEs' revenue growth (AI & BDA) – SMEs' revenue growth (Only AI) ≥ SMEs' revenue growth (Only BDA) – SMEs' revenue growth (No AI & No BDA)	5.28 [0.022]

Note: p-values in brackets.