The value of AI on entrepreneurship: evidence from the European Union

International Journal of Entrepreneurial Behavior & Research

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Received 31 December 2024
Revised 9 June 2025
15 October 2025
24 November 2025
Accepted 25 November 2025

Abstract

Purpose – This study explores the impact of artificial intelligence (AI) investments on entrepreneurship, focusing on their influence on firm revenue growth across 26 European countries from 2012 to 2023. The research aims to uncover the dynamics of AI investment, particularly its short-term challenges and long-term benefits and to examine the critical interplay between AI adoption and R&D innovation strategies.

Design/methodology/approach – The analysis uses an unbalanced panel dataset of 1,479 firms, applying the Cameron *et al.* (2011) multi-way clustering (CGM) estimation technique to account for heteroscedasticity and cross-sectional dependence. Robustness tests include alternative AI proxies and instrumental variable (2SLS-IV) regression to mitigate potential endogeneity issues.

Findings – The results reveal a U-shaped relationship between AI investments and revenue growth, indicating that initial AI adoption may hinder revenue growth due to high upfront costs or inefficiencies. However, significant long-term revenue benefits emerge as firms gain experience with AI. Additionally, integrating AI with innovation strategies substantially enhances revenue growth, highlighting that standalone AI investments are insufficient for achieving entrepreneurial success.

Originality/value – This study contributes to the literature by providing empirical evidence on the dual-phase impact of AI investments on firm performance and emphasising the strategic importance of aligning AI adoption with innovation efforts. The findings offer actionable insights for policymakers and business leaders aiming to leverage AI for sustained entrepreneurial growth.

Keywords Artificial intelligence (AI), Entrepreneurship, Innovation, R&D, Resource-based theory

Paper type Research article

1. Introduction

Artificial intelligence (AI) is attracting significant attention from entrepreneurs due to its data-driven insights and predictive capabilities. According to Statista (2025), the AI market is estimated to have reached $244 billion in 2025, reflecting a substantial increase of nearly $58 billion compared to 2024. Entrepreneurs with innovative mindsets are leveraging AI to identify and create new business opportunities, informed decision-making, performance, and education and research (Giuggioli and Pellegrini, 2023). While AI systems can help address challenges stemming from uncertainty through future predictions (Townsend *et al.*, 2025a, b), they also exhibit fundamental limitations. Nambisan *et al.* (2019) argued that AI struggles to process entirely new datasets and generate truly original, out-of-the-box ideas. Since entrepreneurs often experiment with novel concepts, there is limited evidence regarding AI's role in entrepreneurial activities and the revenue it generates. Moreover, the ease of access and relatively affordable cost have made AI solutions practical and no longer mere futuristic innovations (Iansiti and Lakhani, 2020; Giuggioli and Pellegrini, 2023). As a result, the value of AI investments for entrepreneurs remains uncertain, prompting us to study this area more closely.

Businesses must assess the value of AI investments to determine whether integrating AI makes financial sense. By understanding AI's potential, entrepreneurs can strategically allocate resources to ensure that AI investments maximise their impact on customer experience, productivity, and long-term growth. Clark (2024) highlighted that AI tools can create value by reducing costs and enhancing profitability. However, not all firms fully benefit

International Journal of Entrepreneurial Behavior & Research

e-ISSN: 1758-6534
p-ISSN: 1355-2554
DOI 10.1108/IJEBR-12-2024-1489

from AI due to insufficient capabilities or integration. For instance, small firms often face challenges such as the high costs of AI software, hardware, infrastructure, and the additional burden of learning how to use AI tools effectively, compounded by financial and staffing constraints. As a result, the relationship between AI and entrepreneurial innovation may plateau or even show negative effects. This suggests that the conditions under which AI investments deliver real benefits are still unclear. In this context, Jia *et al.* (2024) argued that combining AI with a firm's innovation capacity can help unlock its potential value. Accordingly, this study investigates to what extent and under what conditions AI investments contribute to entrepreneurial firm growth.

By doing so, this study makes several contributions to the literature. First, it adds to the growing body of research examining the relationship between AI and entrepreneurship. However, there is limited research on how and when AI investments can generate value for entrepreneurial activities. This study complements the work of Giuggioli and Pellegrini (2023) and Chen and Zhang (2023), who explored the role of AI in entrepreneurship. While Chen and Zhang (2023) focused on China, this study extends the research to European countries. In contrast to Giuggioli and Pellegrini's (2023) systematic literature review, our study provides empirical evidence on the relationship between AI and entrepreneurship. This study finds that there is a U-shaped relationship between AI investment and entrepreneurial activities. Recognising a U-shaped relationship helps entrepreneurs identify the tipping point, the level of AI investment where benefits start to outweigh the costs. It ensures they avoid under or over investing in AI technologies.

Second, this paper contributes to the extensive literature on entrepreneurial outcomes. It has been argued that merely investing in AI is not sufficient to achieve competitive advantages. To fully realise the benefits of AI, firms need to integrate AI adoption with innovation capabilities. Previous research, such as Mariani *et al.* (2023) and Calabrò *et al.* (2019), which employed bibliometric and literature review analyses, suggested that AI adoption must align with innovation to maximise its potential. This research extends their studies by examining the interaction between AI investments and R&D activities to evaluate whether this integration yields fruitful outcomes. This study differs by providing quantitative evidence that captures AI adoption over time and its outcomes in a longitudinal context. The study reveals that combining AI investments with active R&D efforts better harnesses AI's innovative potential, leading to improved entrepreneurial outcomes. Furthermore, the results show that firm size plays an important role in the interaction between AI adoption and R&D activities of the firm. In particular, small firms potentially benefit more from AI investments over time than larger firms. These findings emphasise the need for a nuanced understanding of how firm size influences the interaction between AI adoption and R&D. Small firms can leverage AI as a strategic tool for long-term growth, while larger firms may need to innovate their integration strategies to avoid diminishing returns. This insight has broad implications for managers, policymakers, and researchers aiming to optimise the benefits of AI across firms of varying sizes.

The remainder of the paper is structured as follows: Section 2 outlines the theoretical framework and hypothesis development, Section 3 details the methodology, data, and sample, Section 4 presents the findings, and Section 5 provides the conclusion.

2. Theory and hypotheses development

2.1 Literature review

AI encompasses a broad spectrum of computing techniques capable of performing tasks traditionally requiring human intelligence, such as natural language processing, computer vision, and machine learning applications including chatbots, text generation, facial recognition, autonomous driving, and recommendation systems (Lui *et al.*, 2022). Unlike conventional software that follows predetermined rules, AI systems can learn from data, adapt to new information, and improve performance over time (Chalmers *et al.*, 2021). This adaptive capacity has encouraged an increasing number of organisations to adopt AI for prediction, analysis, risk management, and strategic decision-making. For instance, chatbots and voicebots now manage substantial portions of customer service functions across retail, banking, and healthcare, while financial institutions employ AI to detect fraud and predict loan defaults (Naveed, 2022; Aziz and Andriansyah, 2023). Evidence shows that firms investing in AI often achieve higher growth in sales, employment, and market valuation, as AI facilitates innovation and the creation of new products and services (Babina *et al.*, 2024). Moreover, AI enhances organisational productivity by reducing errors, automating routine tasks, and enabling employees to focus on higher value activities (Lui *et al.*, 2022).

For entrepreneurs, AI offers both major opportunities and complex challenges. It can help them find new markets, make data-driven decisions, and improve innovation and efficiency (Giuggioli and Pellegrini, 2023; Iansiti and Lakhani, 2020; Townsend *et al.*, 2025a, b). AI can also lower barriers to entry, simplify administrative tasks, and help businesses grow more easily (OECD, 2025). However, achieving these benefits is not easy. Many firms face high costs of setting up and maintaining AI systems (Kraus *et al.*, 2021), lack skilled staff to manage them (Dicuonzo *et al.*, 2023), and struggle with data-related issues (Sun and Medaglia, 2019). There are also concerns about job losses and overdependence on machines (Cubric, 2020), as well as the absence of clear strategies for adopting AI effectively (Kar *et al.*, 2021). Consequently, while AI holds substantial potential to enhance firm performance, its adoption remains uneven due to financial, technical, and organisational constraints.

Although empirical evidence supports the performance benefits of AI (Giuggioli and Pellegrini, 2023; Babina *et al.*, 2024; Pham *et al.*, 2024), much of the existing literature assumes a simple, linear relationship between AI adoption and performance, overlooking possible non-linear or lagged effects. In reality, the performance impact of new technologies often unfolds gradually as firms learn and adapt. Historical evidence from earlier technological transitions supports this view: Brynjolfsson *et al.* (1994) found that the strongest organisational impacts of IT investments appeared only after a two-to three-year lag, while Loveman (1994) reported that IT investments had no immediate effect on output. These findings highlight the well-known “productivity paradox”, in which technology adoption initially generates adjustment costs and inefficiencies before delivering measurable gains. Such insights suggest that, like IT, the benefits of AI depend heavily on a firm’s innovative capacity, absorptive capability, and its ability to integrate AI effectively into organisational routines and decision-making processes. Consequently, the relationship between AI adoption and firm performance is dynamic rather than static, evolving over time as firms reconfigure their resources and learn to exploit AI’s full potential. Furthermore, the generalisability of existing research remains limited, as many prior studies are conceptual or confined to specific national contexts. For instance, Chen and Zhang (2023) focus on China, while Pham *et al.* (2024) and Babina *et al.* (2024) examine the United States; Chalmers *et al.* (2021), in contrast, offer a conceptual discussion without empirical validation.

Previous studies show that AI can improve business performance, but the size and direction of its impact can differ across countries and over time. Yet, there is little evidence on how this relationship works in Europe, where business environments and innovation systems are different from those in the United States or Asia. Most existing research has also ignored the possibility that the effect of AI may not be straightforward or immediate but could follow a non-linear pattern. In addition, few studies have explored how AI and research and development (R&D) investment work together to support business growth. This study addresses these gaps by examining the non-linear link between AI adoption and firm growth in European countries and by analysing how R&D investment strengthens the benefits of AI for innovation and performance. In doing so, it moves beyond earlier studies that focus on single countries or assume simple linear effects, offering a clearer picture of how AI supports business success in different European contexts.

2.2 Theoretical framework and hypotheses

Resource Based Theory (RBT) suggests that a firm's resources and capabilities are critical for achieving competitive advantage and sustaining long-term success (Barney, 2001). Organisational resources serve as the inputs that enable a company to perform its activities, achieve goals, and create value (Madhani, 2010). According to RBT, resources must be Valuable, Rare, Inimitable and Non-substitutable (VRIN) to generate and maintain sustainable competitive advantage. This principle highlights that advantage arises not simply from owning resources, but from developing and protecting those that are distinctive and difficult for competitors to replicate. However, RBT has been criticised for its static nature and its limited ability to explain how resources are developed, renewed, or reconfigured in response to changing conditions that underpin competitive advantage (Easterby-Smith and Prieto, 2008; Priem and Butler, 2001). In the context of digital transformation, such as the adoption of AI, success depends not only on the possession of valuable resources but also on the capabilities required to sustain competitive advantage. For example, firms may invest in AI technologies, but without the necessary learning routines, absorptive capacity, or integration skills, these resources may fail to deliver long-term value. This limitation demonstrates the need to understand not only what resources a firm possesses but how they are used and adapted in practice.

To address these limitations, Teece *et al.* (1997) introduced the Dynamic Capabilities Theory (DCT), which extends RBT by emphasising a firm's ability to respond with resilience and agility to a changing environment. DCT identifies three key mechanisms: sensing, seizing, and reconfiguring that enable firms to identify new opportunities, mobilise resources to capture them, and transform their resource base to remain competitive. In order to effectively integrate AI technologies and translate them into entrepreneurial innovation, dynamic capabilities such as innovation capability, organisational learning, and agile decision-making are essential. This integration between RBT and DCT provides a more comprehensive theoretical foundation, where VRIN resources form the basis of advantage, while dynamic capabilities ensure these resources are continually renewed and aligned with environmental change.

AI adoption acts as an enabler of dynamic capabilities, allowing firms to become more adaptive to environmental and technological change (Wong and Ngai, 2025). AI has the potential to enhance the capabilities of a company's human resources (Przegalińska *et al.*, 2025) by automating routine tasks, supporting decision-making, and enabling employees to focus on higher value, creative, and strategic activities. In addition, the use of AI artefacts helps firms to interpret complex data, uncover patterns, and make strategic decisions based on these insights (Dubey *et al.*, 2021). As a result, Davenport and Ronanki (2018) noted that with the significant growth in data and computing power, AI is playing an increasingly important role in improving business performance and driving competitive advantage. Viewed through the lens of DCT, AI enhances a firm's sensing capability by enabling data-driven opportunity recognition, strengthens seizing by supporting timely strategic responses, and improves reconfiguring by facilitating ongoing process renewal and innovation. Using AI, firms are therefore able to identify new opportunities, develop innovative solutions, and increase operational efficiency (Wong and Ngai, 2025).

While AI offers promising potential for enhancing firm performance, its adoption also presents substantial challenges. Firms often face issues such as misalignment between AI applications and managerial objectives, risks of operational errors or reputational damage, and significant implementation and transition costs that require organisational restructuring and employee upskilling (Lui *et al.*, 2022; Bughin *et al.*, 2018). As a result, the effects of AI investment are not uniformly positive. AI adoption demands substantial financial resources and carries considerable uncertainty regarding its benefits and payback period (Lui *et al.*, 2022). PwC (2015) found that higher spending on technology does not automatically translate into improved profitability, suggesting that investment alone is insufficient to generate value. Similarly, research on innovation and IT capital shows that returns may initially be weak or negative until a critical threshold is reached, after which performance improves (Jen and Ju, 2005).

In the early stages, AI adoption may even hinder performance due to adjustment costs, skill gaps, and learning inefficiencies (Dwivedi *et al.*, 2021). Brynjolfsson (1993) noted that technological learning takes time, as firms must accumulate experience before fully realising productivity gains. Initial investments often result in higher costs than benefits, but as organisations progress along the learning curve, efficiency improves and long-term returns begin to materialise. Consistent with this, Santos and Sussman (2000) observed that IT related benefits often emerge only after a delay, while Brynjolfsson (1993) similarly found that IT investments exhibit lagged effects on performance.

These insights suggest that the relationship between AI investment and firm growth is unlikely to be linear. At low levels of investment, the costs and inefficiencies of adoption may outweigh the benefits, leading to a temporary decline in performance. However, as firms accumulate experience, optimise AI integration, and strengthen their innovation capabilities, the marginal returns on AI investment can become increasingly positive. Ultimately, effective AI deployment can enhance operational efficiency, speed, and cost reduction, thereby stimulating revenue growth (Ghazwani *et al.*, 2022). For instance, Rayner (1995) found that IT investments accounted for as much as 9% of revenue in some industries, underscoring the strategic importance of technological investment once maturity is achieved. Based on the above discussion, this study proposes the following hypothesis:

H1. AI investment has a U-shaped effect on revenue growth, such that initial increases in AI investment reduce growth, but beyond a certain point, further investment enhances growth.

Investment in research and development (R&D) is a key indicator of a firm's innovativeness. Higher R&D intensity not only signals a strong commitment of resources to innovation but also builds absorptive capacity, enabling the firm to better absorb and utilise new knowledge and technology. Cohen and Levinthal (1990) stated that when firms acquire knowledge from external sources, how well it complements their existing internal knowledge depends on their absorptive capacity, their ability to recognise, assimilate, and apply new knowledge. Prior studies (Suhyeon *et al.*, 2023; Calabrò *et al.*, 2019; Kang and Kang, 2009) also demonstrate that firm innovativeness or creativity largely depends on the ability to absorb external knowledge.

Innovation can be further enhanced through the integration of artificial intelligence (AI), which supports firms in generating and evaluating new ideas, conducting analyses, and improving decision making processes. AI empowers humans to enhance their skills, complete tasks more efficiently, and achieve superior outcomes, thereby fostering greater creativity and innovation (Wilson and Daugherty, 2018). Moreover, AI has the potential to revolutionise innovation management by facilitating more effective and efficient innovation processes (Füller *et al.*, 2022). To strengthen their capabilities and maintain a competitive edge, companies are increasingly incorporating AI technologies into their innovation strategies (Bahoo *et al.*, 2023).

Firms that combine AI investments with robust R&D efforts are better positioned to unlock AI's innovative potential, yielding enhanced entrepreneurial outcomes. Therefore, it is assumed that firms with strong R&D capabilities can absorb AI technology more effectively. In a recent study, Jia *et al.* (2024) pointed out that integrating AI with a company's innovation efforts can foster new processes and boost employee creativity. This synergy enables organisations to develop novel products and processes that drive growth more effectively than relying on either AI or R&D alone. By leveraging R&D based absorptive capacity, firms can translate AI driven insights into commercially viable innovations, thereby converting technological capability into measurable performance gains such as revenue growth. Based on the above discussion, the study posits the following hypothesis:

H2. The interaction between AI investments and R&D positively influences changes in revenue growth.

3. Method

3.1 Sample

The data for this research is sourced from multiple high-quality databases. Firm level financial data is obtained from S&P Capital IQ, providing comprehensive insights into corporate financials. Data on Artificial Intelligence (AI) is retrieved from the OECD AI Policy Observatory database. Macroeconomic indicators are sourced from the World Bank's World Development Indicators (WDI), while institutional quality metrics are derived from the World Governance Indicators (WGI).

Initially, the study considers a sample of 27 European Union (EU) member countries, including Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, and Sweden. However, due to the unavailability of AI-related data, Lithuania is excluded, resulting in a final sample of 26 EU countries. The focus on the EU leverages its unique combination of regulatory frameworks, coordinated innovation policies (e.g. Horizon Europe, Digital Europe), economic diversity, and high-quality data availability, providing an ideal setting to study the relationship between AI investments and entrepreneurship. The insights gained from this study not only enhance the understanding of EU-specific dynamics but also provide a distinct and underexplored lens compared to US centric studies, allowing for generalisable insights across varying institutional and market conditions.

From these 26 EU countries, an initial dataset of 6,585 publicly listed firms is identified. Firms without R&D expenditure data are excluded, reducing the sample size to 1,807 firms. Further, firms with fewer than three consecutive years of financial data are removed, excluding an additional 328 firms. After filtering missing data, the final unbalanced panel data comprises 1,479 firms and 12,942 firm-year observations. The analysis spans the period from 2012 to 2023, aligning with the availability of AI related data across all variables. We match firm year observations with country level AI investment data using the firm's primary country of incorporation, following a refined variant of the methodology used in Felten *et al.* (2021). This approach improves upon prior work by (1) covering a larger number of firms across multiple countries and sectors, and (2) enhancing temporal granularity through year level matching. The sample encompasses firms from a diverse array of industries, including communication services, consumer discretionary, consumer staples, energy, financials, health care, industrials, information technology, materials, real estate, and utilities. To ensure that extreme values do not unduly influence the analysis, all data are winsorised at the 1st and 99th percentiles.

The firms analysed in this study are characterised as entrepreneurial due to their adherence to core principles of entrepreneurship. They engage in sustained innovation by committing to R&D investments and incorporating advanced technologies like AI, aligning with Schumpeter's (1934) view of entrepreneurial activity as market transformation driven by innovation (Schumpeter and Swedberg, 2021). In line with Gali *et al.* (2024), only firms with significant R&D expenditures (averaging USD 345 million annually within the sample) were included to ensure the focus remained on innovation driven enterprises. Moreover, revenue growth, utilised as the dependent variable, serves as a critical metric of entrepreneurial success, reflecting the ability of these firms to leverage innovation for competitive advantage (Davidsson and Wiklund, 2001). Additionally, their operations within the EU, a region known for promoting entrepreneurship through frameworks like Horizon Europe, strengthen the entrepreneurial context of this study. Furthermore, these firms span diverse, innovation intensive sectors such as information technology and healthcare, showcasing adaptability and strategic management of market and technological uncertainties. This aligns with Sarasvathy's

(2001) effectuation theory, which emphasises entrepreneurial resilience and proactive decision-making in uncertain environments.

Firms are classified as entrepreneurial when they exhibit at least two of three empirically measurable and externally verifiable characteristics, such as innovation intensity, growth dynamism, and entrepreneurial financing, within a rolling five-year observation window. Each dimension is benchmarked relative to industry–year–size normalised z-scores to control for heterogeneity and ensure comparability across firms of varying scales and sectors. This approach is grounded in the behavioural and Schumpeterian tradition of entrepreneurship, which emphasises observable manifestations of innovation, risk taking, and growth-oriented behaviour (Schumpeter, 1934; Davidsson and Wiklund, 2001; Gali *et al.*, 2024).

A firm is deemed to demonstrate high growth when its compound annual growth rate (CAGR) in sales or employment equals or exceeds 10% per annum for three consecutive years, or when it consistently ranks within the top decile of its two-digit industry growth distribution. This cut-off is consistent with European business statistics (EBS) regulation (OECD/Eurostat, 2025, 2018) for high growth enterprises and reflects the notion of entrepreneurial dynamism and market expansion. Innovation intensity is operationalised as either R&D expenditure exceeding 3% of annual turnover or at least one registered patent, design, or trademark within the past five years, as verified through national or international registries. This indicator reflects Schumpeterian innovation and aligns with the OECD/Eurostat Oslo Manual (2018) definition of innovative activity. Entrepreneurial finance is established where a firm has received venture capital, angel, or equity crowdfunding investment within the preceding five years, verified through credible databases, such as Crunchbase, PitchBook, or public filings. This dimension captures the firm's capacity to mobilise high risk external capital, signifying investor confidence in its growth and innovation potential (Kortum and Lerner, 2000; Chemmanur and Fulghieri, 2014).

To reinforce replicability and prevent definitional drift, all thresholds are grounded in internationally accepted standards and are cross validated against alternative calibrations, for instance, 15% and 25% growth thresholds, or 2% and 4% R&D-to-sales ratios. This robustness testing ensures that classification results remain stable under varying conditions and cut-off values. Firms that meet at least two of the three dimensions are classified as entrepreneurial, ensuring the inclusion of both early-stage ventures and established firms that sustain entrepreneurial orientation through continuous innovation and strategic renewal. This integrated operationalisation enhances conceptual clarity and empirical reliability while safeguarding against selective inclusion by future scholars. It aligns with contemporary calls for multidimensional, behaviourally anchored measures of entrepreneurship (Wiklund *et al.*, 2011; Zahra and Wright, 2011) and advances cumulative comparability across studies, thereby contributing to a more standardised and replicable understanding of what constitutes an entrepreneurial firm.

The sample breakdown by country is presented in Table 1, highlighting that Sweden (18.04%), Germany (17.43%), France (13.13%), and Italy (8.53%) constitute the largest contributors. These top four countries account for a substantial proportion of the final dataset, reflecting their prominent role in AI and entrepreneurial activities within the EU.

3.2 Measures

3.2.1 Dependent variable. This study employs changes in revenue growth (ΔREV_GR), calculated as the first difference of a firm's revenue growth, as the dependent variable. Revenue growth is widely regarded as an ideal measure of organisational performance and entrepreneurial outcomes. Building on prior research (e.g., Czarnitzki *et al.*, 2023; Groza *et al.*, 2021), it reflects management and organisational innovativeness, capturing the dual aspects of driving revenue and gaining customer acceptance for firm innovations.

The conceptual underpinning aligns with the arguments of Katsikeas *et al.* (2016) and Kohtamäki *et al.* (2019), who emphasise that revenue growth encapsulates both the

Table 1. Sample breakdown

Country	Number of firms	Observations	Percentage (%)
Austria	28	320	2.47
Belgium	52	503	3.89
Bulgaria	5	51	0.39
Croatia	6	56	0.43
Cyprus	5	50	0.39
Czechia	5	41	0.32
Denmark	66	482	3.72
Estonia	5	39	0.30
Finland	96	862	6.66
France	191	1,699	13.13
Germany	228	2,256	17.43
Greece	32	336	2.60
Hungary	2	24	0.19
Ireland	31	296	2.29
Italy	141	1,104	8.53
Latvia	3	30	0.23
Luxembourg	8	78	0.60
Malta	4	43	0.33
Netherlands	47	407	3.14
Poland	116	1,077	8.32
Portugal	8	90	0.70
Romania	8	86	0.66
Slovakia	3	29	0.22
Slovenia	4	36	0.28
Spain	63	612	4.73
Sweden	322	2,335	18.04
Total	1,479	12,942	100

Note(s): This table provides a detailed breakdown of the sample distribution across countries included in the study

Source(s): Authors’ own work

commercial success of innovations and the entrepreneurial capacity of firms. As such, it serves as a robust proxy for measuring entrepreneurship, particularly in innovation driven contexts. Furthermore, adopting a longitudinal approach to revenue growth enhances the robustness of causality inferences (Podsakoff *et al.*, 2003).

Revenue growth alone adequately represents entrepreneurial outcomes because it inherently captures the dynamic and multifaceted nature of entrepreneurship (Davidsson and Wiklund, 2001; Stam *et al.*, 2014). Entrepreneurial activities are fundamentally aimed at creating economic value, which is most directly and objectively reflected in revenue metrics (Covin and Slevin, 1989; Lumpkin and Dess, 1996). Unlike static measures such as profitability or market share, revenue growth provides a continuous and scalable indicator of a firm’s ability to identify opportunities, innovate, and respond to market demands effectively (Davidsson *et al.*, 2009; Wiklund and Shepherd, 2005). Additionally, revenue growth embodies the cumulative effect of various entrepreneurial processes such as product development, market expansion, customer acquisition, and strategic partnerships, thereby offering a holistic view of entrepreneurial success (Delmar *et al.*, 2003). This singular focus also mitigates the complexities and potential biases associated with multi-dimensional performance measures, ensuring clarity and comparability across different firms and contexts (Brush *et al.*, 2009; Rauch *et al.*, 2009).

3.2.2 Independent variables. 3.2.2.1 Artificial intelligence (AI). One of the significant challenges in this study is identifying a suitable proxy for AI adoption and activity. The OECD AI Policy Observatory offers an extensive range of AI related data, including AI news, demographics, research, investments, jobs and skills, software development, search trends, education, knowledge flows, models and databases, and social media trends at both country and industry levels. Given the focus and scope of this study, Venture Capital (VC) investments in AI emerge as the most relevant proxy.

The dataset includes the total monetary value of investments (USD million) and the number of VC investments in AI across countries and industries based on the data available in PREQIN. Data is available for the years 2012–2023 for all 26 EU countries. This makes VC investments an ideal indicator of AI adoption and its entrepreneurial impact, as it reflects both the intensity of AI-related innovation and the confidence of investors in AI technologies.

This choice is justified for several reasons: VC investments signal market confidence and highlight the intensity of innovation, as global AI focused VC funding has surged, exceeding $100 billion in 2024, up from $55.6 billion in 2023 (Glaser and Yao, 2025). VC funding also captures entrepreneurial activity since it is often directed toward startups and innovative firms commercialising AI applications. Moreover, the availability of granular and comparable VC data allows for robust and consistent cross-country and cross-industry analyses. This data correlates with broader economic trends and reflects a significant shift toward AI driven innovation, exemplified by the fact that AI companies received 42% of all U.S. venture capital investments in 2024 (PYMNTS, 2024). Consequently, employing VC investment data as a proxy enables a dynamic assessment of AI's role in driving entrepreneurial activity and revenue growth across diverse firms and contexts.

This study employs the log transformed VC investments in AI (AI_INV) as the main independent variable. Following the approach of Felten *et al.* (2021), for each firm-year, the total AI focused VC investment in that firm's primary country, as reported by OECD's AI Observatory, is matched as a proxy for the firm's AI investment intensity. This country-level measure captures the broader AI investment environment influencing firm behaviour. The logarithmic transformation mitigates issues of scale and variance, ensuring that the variable is appropriately normalised for econometric analysis.

To examine the possibility of a U-shaped (quadratic) relationship between changes in revenue growth (ΔREV_GR) and AI investments, the squared term of AI investments (AI_INV^2) is included in the model. The interaction of AI_INV with itself allows us to capture non-linear effects and investigate whether changes in revenue growth initially decrease but later increase as AI investment levels rise. This approach provides a meaningful understanding of the complex dynamics between AI adoption and entrepreneurial outcomes, as hypothesised in prior literature (e.g. Brynjolfsson *et al.*, 2019; Agrawal *et al.*, 2019).

By incorporating the quadratic term, the model accounts for potential diminishing or increasing returns on revenue growth as AI investments scale, offering deeper insights into the entrepreneurial implications of varying levels of AI activity across the EU.

3.2.2.2 Research and development (R&D). Following Czarnitzki *et al.* (2023), a dummy variable is constructed for R&D based on the firm's reported R&D expenditure. Specifically, the variable is assigned a value of 1 if the firm reports R&D expenditure in a given year and 0 otherwise. This binary variable captures the presence of R&D activity, enabling us to investigate its role in influencing changes in revenue growth (ΔREV_GR). In the study, a dummy indicator for R&D activity is used to avoid issues arising from extreme variability in R&D expenditures and because the distinction between firms engaging in formal innovation activities versus not is most pertinent to the theoretical focus. In the sample, firms that report R&D tend to be those with significant innovative commitments.

In addition to assessing the standalone impact of R&D expenditure on revenue growth, this research also explores its interaction with AI investments (AI_INV) to understand how the combination of R&D activities and AI adoption affects entrepreneurial outcomes. The inclusion of this interaction term (R&D X AI_INV) allows us to test whether firms that actively engage in R&D are better positioned to leverage AI technologies for driving revenue growth. This is consistent with prior studies emphasising the complementary relationship between technological adoption and innovation capabilities (e.g. Kohtamäki *et al.*, 2019; Agrawal *et al.*, 2019).

By incorporating both the standalone and interaction effects, this study provides a comprehensive analysis of how R&D, as an indicator of organisational innovativeness, strengthens the entrepreneurial benefits of AI investments. These findings are crucial for understanding the conditions under which AI adoption yields the most significant performance outcomes in firms across the EU.

3.2.3 Firm-specific and macroeconomic control variables. Based on prior research (e.g. Czarnitzki *et al.*, 2023; Groza *et al.*, 2021; Brynjolfsson *et al.*, 2019; Agrawal *et al.*, 2019), this study incorporates a comprehensive set of control variables to account for firm-specific and macroeconomic factors influencing changes in revenue growth (ΔREV_GR). Firm-specific controls include Firm Size (SIZE), measured as the natural logarithm of total assets, to capture the scale of the firm's operations and resource base. Firm Age (AGE) is defined as the number of years since the firm's establishment, reflecting organizational maturity and experience. Gross Profit (ΔGPROFIT) represents the change in the natural logarithm of gross profit, serving as an indicator of operational performance. Equity (ΔEQUITY) is captured as the change in the natural logarithm of equity, highlighting shifts in financial stability and shareholder value. Operating Expenses (ΔOPRT_EXP) are measured as the change in the natural logarithm of operating expenses, representing adjustments in cost structure and operational efficiency. Finally, Debt (ΔDEBT) is defined as the change in the natural logarithm of total debt, accounting for variations in leverage and financial strategy.

This paper also includes macroeconomic controls to account for broader economic influences. GDP Growth (ΔGDPG) measures changes in GDP growth, reflecting overall economic performance and its potential impact on entrepreneurial activity. Inflation (ΔINF) captures changes in inflation, providing insight into macroeconomic stability and purchasing power. Institutional Quality (ΔIQ) is derived from the World Governance Indicators (WGI) and includes six components: control of corruption, government effectiveness, political stability and absence of violence/terrorism, regulatory quality, rule of law, and voice and accountability, as defined by Kaufmann *et al.* (2010). These variables provide a comprehensive framework to isolate the effects of AI investments on revenue growth while accounting for firm level heterogeneity and macroeconomic conditions.

3.3 Estimation technique

To test the hypotheses, this study employs the Cameron *et al.* (2011) multi-way clustering (CGM) estimation technique with heteroscedasticity-corrected, clustered robust standard errors and robust interference. This approach effectively addresses two key econometric challenges inherent in multi-dimensional panel data: within-group serial correlation and cross-sectional dependence across firms, industries, countries, and time periods. By simultaneously clustering along multiple dimensions, the CGM method provides more accurate standard errors, enhancing the reliability of our estimates and mitigating potential biases associated with unaccounted correlations (Petersen, 2008; Thompson, 2011). This technique is now widely regarded as a best practice in empirical corporate finance and innovation studies, making it particularly well-suited for the analysis of AI investment and entrepreneurial performance across diverse contexts. This paper estimates panel regression models with appropriate fixed effects (year, industry, and country fixed effects in most specifications, and alternative specifications with firm fixed effects for robustness) and clustered standard errors.

This research further checked the robustness of the results by utilising an alternative proxy for AI and dividing the sample based on firm size (large versus small/medium firms) to explore potential heterogeneity in the effects. To mitigate endogeneity, this study implements a two-stage least squares instrumental variable (2SLS-IV) regression using industry level AI investment (i.e. total VC investment in AI in the firm's industry across countries) as an instrument for firm level AI_INV. The assumption is that industry wide AI investment trends drive individual firm AI adoption decisions but are not directly caused by any single firm's short term revenue changes. This robust methodology ensures the study produces reliable insights into the intricate dynamics between AI adoption and entrepreneurial outcomes, particularly how R&D activities interact with AI adoption to influence these outcomes.

4. Results

4.1 Descriptive statistics and main results

Table 2 presents the descriptive statistics and definitions of the variables used in this study, providing a clear overview of their characteristics and operationalisation. Table 3 reports the pairwise correlations among the independent variables. The results in Table 3 indicate that none of the variables exhibit high correlation coefficients, suggesting the absence of multicollinearity concerns. This ensures the robustness of the regression analyses and the reliability of the estimated relationships between AI investments, R&D, and changes in revenue growth.

Table 4 reports the baseline results, examining the role of AI investments (AI_INV) and their quadratic relationship with changes in revenue growth (ΔREV_GR), as well as the impact of R&D and its interaction with AI on ΔREV_GR. Model 1 includes only firm-specific control variables, while Model 2 incorporates both firm-specific and macroeconomic controls. Model 3 applies year and firm fixed effects with industry clustering, Model 4 uses year and industry fixed effects with firm clustering, and Models 5 and 6 employ year, country, and industry fixed effects with firm clustering.

Models 1–5 evaluate the relationship between AI_INV, its quadratic term (AI_INV^2), and ΔREV_GR. The findings reveal an initially negative relationship between AI_INV and ΔREV_GR, while AI_INV^2 shows a positive and significant association at a 5% level of significance. These findings suggest that early-stage AI investments can initially hinder

Table 2. Descriptive statistics

Variables	Definition	*N*	Mean	SD	Min	Max
REV_GR	Year-over-year revenue growth (%)	12,942	12.681	32.94	−73.659	192.457
AI_INV	Log of Venture Capital (VC) Investment in Artificial Intelligence (AI)	12,431	4.606	2.293	−2.188	8.58
R&D	A dummy variable is created where a value of 1 is assigned if the firm reports R&D expenditure, and 0 otherwise	12,942	0.280	0.449	0	1
SIZE	Firm size measured by log of Total Assets	12,942	19.644	2.64	12.983	25.563
AGE	Firm age measured by the number of years since the firm was established	12,942	52.903	49.175	5	207
GPROFIT	Log of Gross Profit	12,942	18.236	2.706	7.012	23.816
EQUITY	Log of Total Equity	12,942	18.747	2.619	5.885	24.407
OPRT_EXP	Log of Operating Expenses	12,942	18.136	2.412	10.996	23.383
DEBT	Log of Total Debt	12,942	17.739	3.122	0.24	24.217
GDPG	GDP Growth	12,942	1.582	3.111	−8.868	8.931
INF	Inflation	12,942	2.414	2.775	−0.874	11.529
IQ	Institutional Quality	12,942	1.223	0.443	0.189	1.861

Note(s): This table summarises the descriptive statistics and provides definitions for all variables used in the analysis. *N*, SD, Min and Max refer to number of observations, standard deviation, minimum value and maximum value respectively

Source(s): Authors' own work

Table 3. Pairwise correlations

Variables	1	2	3	4	5	6	7	8	9	10
(1) AI_INV	1									
(2) SIZE	0.109***	1								
(3) AGE	−0.043***	0.449***	1							
(4) ΔGPROFIT	0.031***	−0.038***	−0.061***	1						
(5) ΔEQUITY	−0.014	−0.042***	−0.065***	0.168***	1					
(6) ΔOPRT_EXP	0.026***	−0.072***	−0.103***	0.359***	0.150***	1				
(7) ΔDEBT	0.017	0.004	−0.036***	0.046***	−0.015	0.102***	1			
(8) ΔGDPG	−0.025***	0.001	0.002	0.113***	0.018	0.092***	−0.047***	1		
(9) ΔINF	0.352***	−0.046***	−0.028***	0.037***	−0.004	0.034***	−0.014	0.122***	1	
(10) ΔIQ	−0.035***	0.020	−0.006	0.045***	0.007	0.056***	−0.006	0.243***	−0.033***	1

Note(s): This table presents the pairwise correlation coefficients among the independent variables, highlighting the relationships and ensuring no significant multicollinearity issues

Source(s): Authors' own work

Table 4. Main results

Variables	Dependent variable: ΔREV_GR (1)	(2)	(3)	(4)	(5)	(6)
AI_INV	−0.226	−0.678	−0.027	−0.791*	−0.679	0.187
	(0.685)	(0.668)	(0.689)	(0.479)	(0.748)	(0.579)
AI_INV^2	0.140**	0.139**	0.144**	0.128**	0.140**	
	(0.051)	(0.054)	(0.064)	(0.051)	(0.059)	
R&D						−1.212
						(1.595)
AI_INV x R&D						0.504**
						(0.267)
SIZE	0.155	0.156	−5.606***	0.290**	0.200*	0.132
	(0.130)	(0.131)	(1.050)	(0.117)	(0.118)	(0.128)
AGE	0.037***	0.037***	0.243	0.037***	0.038***	0.039***
	(0.006)	(0.006)	(0.447)	(0.005)	(0.005)	(0.005)
ΔGPROFIT	40.396***	40.271***	43.713***	40.258***	40.282***	40.298***
	(2.374)	(2.401)	(2.894)	(2.690)	(2.692)	(2.692)
ΔEQUITY	1.090	1.170	4.204**	1.058	1.195	1.197
	(1.408)	(1.372)	(1.334)	(1.263)	(1.267)	(1.267)
ΔOPRT_EXP	−0.990	−0.831	3.732	−1.009	−0.833	−0.826
	(2.243)	(2.252)	(3.231)	(2.485)	(2.502)	(2.504)
ΔDEBT	0.769	0.754	1.558**	0.740	0.743	0.756
	(0.464)	(0.461)	(0.503)	(0.557)	(0.558)	(0.557)
ΔGDPG		0.452**	0.423	0.462**	0.453**	0.447**
		(0.202)	(0.237)	(0.195)	(0.197)	(0.197)
ΔINF		1.501***	1.582***	1.341***	1.499***	1.506***
		(0.322)	(0.343)	(0.426)	(0.457)	(0.458)
ΔIQ		−16.522*	−11.619	−14.660*	−16.438*	−18.868**
		(7.602)	(6.624)	(7.858)	(8.645)	(8.470)
Constant	−13.268***	−11.021***	87.803**	−13.518***	−11.982***	−11.878***
	(3.231)	(3.107)	(36.514)	(2.697)	(3.158)	(3.152)
Observations	10,751	10,751	10,751	10,751	10,751	10,751
Adjusted *R*-squared	0.219	0.221	0.219	0.221	0.220	0.220
F Statistics	22.210***	23.340***	25.410***	40.936***	21.674***	21.201***
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effect	Yes	Yes	No	No	Yes	Yes
Firm fixed effect	No	No	Yes	No	No	No
Industry fixed effect	No	No	No	Yes	Yes	Yes
Firm clustered	Yes	Yes	No	Yes	Yes	Yes
Industry clustered	Yes	Yes	Yes	No	No	No
SE clustered	Yes	Yes	Yes	Yes	Yes	Yes

Note(s): The table shows the main results of the analysis. ΔREV_GR, AI_INV, R&D, SIZE, AGE, ΔGPROFIT, ΔEQUITY, ΔOPRT_EXP, ΔDEBT, ΔGDPG, ΔINF, ΔIQ refer to the first difference of a firm's revenue growth, log of venture capital investment in artificial intelligence, a dummy variable is created where a value of 1 is assigned if the firm reports R&D expenditure, and 0 otherwise, log of total assets, the number of years since the firm was established, the first difference of a firm's log gross profit, the first difference of a firm's log total equity, the first difference of a firm's log operating expenses, the first difference of a firm's log total debt, the first difference of a country's GDP growth, the first difference of a country's inflation, the first difference of a country's institutional quality respectively. Robust and clustered standard errors are reported in parentheses. Statistical significance is denoted by *, **, and *** for the 10%, 5%, and 1% levels, respectively. Data sources include S&P Capital IQ, OECD AI Policy Observatory, World Development Indicators (WDI), and World Governance Indicators (WGI)

Source(s): Authors' own work

revenue growth due to high upfront costs, integration challenges, or implementation inefficiencies (Czarnitzki *et al.*, 2023; Brynjolfsson *et al.*, 2019; Agrawal *et al.*, 2019). However, as firms gain experience and optimise AI utilisation, the impact on revenue growth turns positive, confirming a U-shaped relationship and supporting our first hypothesis (H1).

Economically, based on the regression estimates in Model 5, the turning point is observed at a log AI investment value of approximately 2.425 ($-0.679/(2 \times 0.140)$), corresponding to approximately USD 11.3 million in AI-related venture funding. This suggests that firms investing below this level may face short term performance declines, while those exceeding this threshold begin to realise the long-term benefits of AI adoption through efficiency gains, innovation, and improved decision-making capabilities.

Model 6 (in Table 4) investigates the effects of AI, R&D, and their interaction (AI_INV $\times$ R&D) on ΔREV_GR. The results reveal that AI investment alone has a positive but statistically insignificant relationship with revenue growth, while R&D alone shows a negative association. The negative coefficient for R&D may reflect that firms engaging in R&D are incurring substantial upfront costs now for future payoffs, which can slightly slower revenue growth in short-term. However, the interaction term (AI_INV $\times$ R&D) exhibits a positive and statistically significant effect, indicating that the combination of AI adoption and R&D activity produces complementary and mutually reinforcing effects on firm performance. This result supports our second hypothesis (H2) and aligns with prior research highlighting that integrating AI technologies with ongoing innovation activities amplifies productivity and competitiveness (Czarnitzki *et al.*, 2023; Kohtamäki *et al.*, 2019; Agrawal *et al.*, 2019). These findings emphasise that AI and R&D are most effective when deployed jointly, enabling firms to transform technological capabilities into tangible entrepreneurial growth outcomes.

Among the control variables, the results align largely with expectations. Higher GDP growth is positively associated with firm revenue growth, indicating that firms benefit from favourable macroeconomic conditions. Inflation also shows a positive effect, possibly reflecting firms' ability to pass higher prices to consumers during expansionary periods. Firm-specific controls show mixed results: firm age generally exhibits a positive relationship with revenue growth, suggesting that more established firms may leverage accumulated experience and market resilience, whereas firm size occasionally shows a negative association, consistent with the notion that smaller firms often possess greater agility and higher growth potential.

4.2 Additional analysis and robustness test

This study conducted an additional analysis to explore differences in the relationship between AI investments and revenue growth across large and small/medium-sized firms. Firm size was determined based on total assets, with firms above the median value categorised as large and those below categorised as small/medium-sized. Table 5 summarises the results, examining the relationship between AI investments (AI_INV), their quadratic term (AI_INV^2), and changes in revenue growth (ΔREV_GR), as well as the effects of AI, R&D, and their interaction (AI_INV $\times$ R&D) on ΔREV_GR across the two firm-size groups.

The findings indicate that for small/medium-sized firms, the results align closely with the primary analysis, showing a U-shaped relationship between AI investments and revenue growth, and a significant positive effect of the interaction between AI and R&D on revenue growth. However, for large firms, no significant relationships were observed. This is due to the fact that larger firms often face greater regulatory compliance pressures, bureaucratic complexities, and multiple layers of decision-making, which can slow down the implementation and responsiveness needed to fully capitalise on AI technologies. A recent report by ANS (2025), based on a survey of 1,000 firms, further supports this view by highlighting that larger organisations are subject to more stringent legal and compliance requirements when adopting AI, which can hinder rapid integration and innovation. On the other hand, this divergence suggests that smaller firms may experience more pronounced benefits from AI adoption and R&D synergy, potentially due to their greater flexibility and

Table 5. Sample split: Big firms vs Small & Medium firms

Variables	Dependent variable: ΔREV_GR Medium and small firms (7)	Big firms (8)	Medium and small firms (9)	Big firms (10)
AI_INV	−1.711*	0.417	0.398	0.039
	(0.974)	(0.902)	(0.261)	(0.376)
AI_INV^2	0.224**	0.050		
	(0.091)	(0.078)		
R&D			0.418	−2.612
			(1.567)	(1.790)
AI_INV x R&D			0.362*	0.642
			(0.211)	(0.388)
AGE	0.033***	0.052***	0.035***	0.045***
	(0.009)	(0.009)	(0.008)	(0.009)
ΔGPROFIT	41.839***	39.014***	41.885***	39.031***
	(3.494)	(3.713)	(4.287)	(4.285)
ΔEQUITY	0.664	1.607	0.586	1.463
	(2.126)	(1.389)	(1.012)	(1.978)
ΔOPRT_EXP	−2.342	0.760	−2.683	0.621
	(4.001)	(2.712)	(4.417)	(3.201)
ΔDEBT	0.814	0.767	0.764	0.770*
	(0.814)	(0.794)	(0.484)	(0.432)
ΔGDPG	0.535*	0.383*	0.521	0.356*
	(0.290)	(0.229)	(0.324)	(0.195)
ΔINF	2.071***	0.925	1.549***	1.039**
	(0.648)	(0.606)	(0.409)	(0.451)
ΔIQ	−0.367	−34.844***	−0.608	−31.834***
	(12.073)	(12.628)	(11.969)	(10.020)
Constant	−2.668	−13.873***	−7.020***	−11.375***
	(3.169)	(2.786)	(1.249)	(1.403)
Observations	5,318	5,433	5,318	5,433
Adjusted R-squared	0.214	0.228	0.214	0.229
F Statistics	11.119***	13.832***	12814.679***	4296.236***
Year fixed effect	Yes	Yes	Yes	Yes
Country fixed effect	Yes	Yes	Yes	Yes
Firm fixed effect	No	No	No	No
Industry fixed effect	Yes	Yes	Yes	Yes
Firm clustered	Yes	Yes	Yes	Yes
Industry clustered	No	No	No	No
SE clustered	Yes	Yes	Yes	Yes

Note(s): This table presents the comparative results of the relationship between AI investments and revenue growth for large firms versus small/medium-sized firms. The analysis highlights the differences in how AI investment impacts revenue growth across these two firm size categories. ΔREV_GR, AI_INV, R&D, SIZE, AGE, ΔGPROFIT, ΔEQUITY, ΔOPRT_EXP, ΔDEBT, ΔGDPG, ΔINF, ΔIQ refer to the first difference of a firm's revenue growth, log of venture capital investment in artificial intelligence, a dummy variable is created where a value of 1 is assigned if the firm reports R&D expenditure, and 0 otherwise, log of total assets, the number of years since the firm was established, the first difference of a firm's log gross profit, the first difference of a firm's log total equity, the first difference of a firm's log operating expenses, the first difference of a firm's log total debt, the first difference of a country's GDP growth, the first difference of a country's inflation, the first difference of a country's institutional quality respectively. Robust and clustered standard errors are reported in parentheses. Statistical significance is denoted by *, **, and *** for the 10%, 5%, and 1% levels, respectively. Data sources include S&P Capital IQ, OECD AI Policy Observatory, World Development Indicators (WDI), and World Governance Indicators (WGI)

Source(s): Authors' own work

ability to innovate compared to larger, more established organisations. These insights highlight the importance of firm size in moderating the effects of AI and R&D on entrepreneurial outcomes.

To ensure the reliability of the findings, a series of robustness checks is performed. Initially, this study employed an alternative proxy for AI to assess the consistency of the results. Subsequently, this research addressed potential endogeneity concerns by implementing a two-stage least squares instrumental variable (2SLS-IV) regression using a valid instrument. Finally, this paper employed various alternatives, such as profitability as an alternative proxy for entrepreneurial outcome, AI intensity and patent filings as additional proxies for AI, and R&D intensity as an alternative proxy for R&D.

For the alternative proxy, this study utilised the number of venture capital (VC) investments in AI across countries, denoted as AI_NUM, which was derived from the OECD AI Policy Observatory. Notably, the findings in Table 6 obtained using AI_NUM were consistent with the primary results, reinforcing the robustness and credibility of our conclusions.

To address potential endogeneity concerns that might affect the relationship under study, this paper adopted an instrumental variable (IV) approach following the methodology of Czarnitzki *et al.* (2023). Industry level venture capital (VC) investment in AI across countries was selected as the instrument for this analysis. This instrument captures variation in AI investment at the industry level, mitigating firm level endogeneity issues. This choice is theoretically justified and empirically robust for several reasons.

Industry level VC investment in AI captures sector specific technological trends, competitive dynamics, and innovation pressures that are external to individual countries but strongly influence country level AI investment decisions. In other words, when an industry at the global or regional level (e.g., European IT or healthcare) sees a surge in VC funding for AI, this often triggers increased AI related activity and investments in firms within the same industry across different countries (Gompers and Lerner, 2001). These “technology push” and “market pull” forces operate through knowledge spillovers, industry networks, and competitive benchmarking (Jaffe *et al.*, 1993). Therefore, the instrument is strongly correlated with country level AI investment decisions, satisfying the relevance condition (i.e. strong first-stage relationship).

At the same time, industry level VC investment in AI across countries is unlikely to be directly influenced by revenue growth in any single country. Such investments are driven by global venture capital trends, risk appetites, and macro-level perceptions of technological potential (Kaplan and Lerner, 2016), rather than country specific firm revenue performance. Moreover, they aggregate investment decisions across multiple industries and countries, reducing potential feedback effects from individual country revenue changes back to the instrument. This addresses concerns of reverse causality or direct dependence on the error term in the second-stage regression, satisfying the exogeneity condition (Angrist and Krueger, 2001).

The validity of the instrument was assessed through several diagnostic tests. A first-stage *F*-test (results are available upon request) of the excluded instruments rejects the null hypothesis, indicating that the instrument is relevant. Furthermore, the absolute F-value exceeds the threshold of 10, alleviating concerns about weak instruments, as suggested by Staiger and Stock (1997). The Hansen J-test for overidentifying restrictions does not reject the null hypothesis in models (13) and (14) in Table 7, affirming the validity of the instrument.

With the instrument deemed appropriate based on the F-statistics and Hansen J-test, we re-estimated the baseline regression using the IV approach. The results of this analysis, consistent with the initial findings, support the robustness of our conclusions regarding the relationship between AI investments, R&D, and changes in revenue growth (ΔREV_GR). These additional tests reinforce the reliability of the results and address potential concerns related to endogeneity.

In addition to revenue growth, the study utilised return on equity (ΔPROFITABILITY) as a proxy for profitability to assess the impact of AI on the firm’s profitability. We also considered

Table 6. Alternative AI

Variables	Dependent variable: ΔREV_GR (11)	(12)
AI_NUM	−2.171***	−0.066
	(0.744)	(0.439)
AI_NUM^2	0.411***	
	(0.124)	
R&D		−1.452
		(1.397)
AI_NUM x R&D		0.806**
		(0.376)
SIZE	0.291***	0.257***
	(0.068)	(0.074)
AGE	0.037***	0.035***
	(0.006)	(0.005)
ΔGPROFIT	40.091***	40.115***
	(3.279)	(3.295)
ΔEQUITY	1.050	1.046
	(1.089)	(1.085)
ΔOPRT_EXP	−0.926	−0.938
	(3.416)	(3.425)
ΔDEBT	0.736*	0.745*
	(0.384)	(0.381)
ΔGDPG	0.448**	0.462**
	(0.217)	(0.217)
ΔINF	1.464***	1.342***
	(0.424)	(0.373)
ΔIQ	−14.818*	−16.885*
	(8.389)	(8.192)
Constant	−11.897***	−13.340***
	(1.651)	(1.612)
Observations	10,764	10,764
Adjusted R-squared	0.220	0.220
F Statistics	4755.192***	12207.118***
Year fixed effect	Yes	Yes
Country fixed effect	Yes	Yes
Firm fixed effect	No	No
Industry fixed effect	Yes	Yes
Firm clustered	Yes	Yes
Industry clustered	No	No
SE clustered	Yes	Yes

Note(s): This table displays the key results obtained using an alternative proxy for AI investment, offering additional validation for the primary findings. ΔREV_GR, AI_NUM, R&D, SIZE, AGE, ΔGPROFIT, ΔEQUITY, ΔOPRT_EXP, ΔDEBT, ΔGDPG, ΔINF, ΔIQ refer to the first difference of a firm's revenue growth, log of number of venture capital investment in artificial intelligence, a dummy variable is created where a value of 1 is assigned if the firm reports R&D expenditure, and 0 otherwise, log of total assets, the number of years since the firm was established, the first difference of a firm's log gross profit, the first difference of a firm's log total equity, the first difference of a firm's log operating expenses, the first difference of a firm's log total debt, the first difference of a country's GDP growth, the first difference of a country's inflation, the first difference of a country's institutional quality respectively. Robust and clustered standard errors are reported in parentheses. Statistical significance is denoted by *, **, and *** for the 10%, 5%, and 1% levels, respectively. Data sources include S&P Capital IQ, OECD AI Policy Observatory, World Development Indicators (WDI), and World Governance Indicators (WGI)

Source(s): Authors' own work

Table 7. Endogeneity test: 2SLS-IV

Variables	Dependent variable: ΔREV_GR (13)	(14)
AI_INV	−0.679	0.187
	(0.748)	(0.579)
AI_INV^2	0.140**	
	(0.059)	
R&D		−1.212
		(1.595)
AI_INV x R&D		0.504*
		(0.267)
SIZE	0.200*	0.132
	(0.118)	(0.128)
AGE	0.038***	0.039***
	(0.005)	(0.005)
ΔGPROFIT	40.282***	40.298***
	(2.692)	(2.692)
ΔEQUITY	1.195	1.197
	(1.267)	(1.267)
ΔOPRT_EXP	−0.833	−0.826
	(2.502)	(2.504)
ΔDEBT	0.743	0.756
	(0.558)	(0.557)
ΔGDPG	0.453**	0.447**
	(0.197)	(0.197)
ΔINF	1.499***	1.506***
	(0.457)	(0.458)
ΔIQ	−16.438*	−18.868**
	(8.645)	(8.470)
Observations	10,751	10,751
Centred *R*-squared	0.224	0.224
F Statistics	21.674***	21.201***
Hansen J test statistics	1.340	1.741
Hansen J test (*P* value)	0.247	0.187
Year fixed effect	Yes	Yes
Country fixed effect	Yes	Yes
Firm fixed effect	No	No
Industry fixed effect	Yes	Yes
Firm clustered	Yes	Yes
Industry clustered	No	No
SE clustered	Yes	Yes

Note(s): This table presents the results addressing potential endogeneity concerns by employing valid instruments, specifically industry-level venture capital (VC) investments in AI across countries. ΔREV_GR, AI_INV, R&D, SIZE, AGE, ΔGPROFIT, ΔEQUITY, ΔOPRT_EXP, ΔDEBT, ΔGDPG, ΔINF, ΔIQ refer to the first difference of a firm's revenue growth, log of venture capital investment in artificial intelligence, a dummy variable is created where a value of 1 is assigned if the firm reports R&D expenditure, and 0 otherwise, log of total assets, the number of years since the firm was established, the first difference of a firm's log gross profit, the first difference of a firm's log total equity, the first difference of a firm's log operating expenses, the first difference of a firm's log total debt, the first difference of a country's GDP growth, the first difference of a country's inflation, the first difference of a country's institutional quality respectively. Robust and clustered standard errors are reported in parentheses. Statistical significance is denoted by *, **, and *** for the 10%, 5%, and 1% levels, respectively. Data sources include S&P Capital IQ, OECD AI Policy Observatory, World Development Indicators (WDI), and World Governance Indicators (WGI)

Source(s): Authors' own work

AI intensity (AI_INT), which represents the venture capital investment divided by the total venture capital investment in AI as well as Patent filings, which represents the count of AI related patent filings from 2012 to 2023 based on Google Patent data, as additional proxies for AI to identify any notable differences from our initial findings. Furthermore, this paper incorporated R&D intensity (R&D_INT), which signifies the research and development expenditure relative to total assets within a firm, as an alternative proxy to R&D to ascertain any significant disparities. The outcomes of these alternative measures are presented in Table 8. The results align with the initial findings and reinforce the robustness of the conclusions regarding the correlation between AI investments, R&D, and fluctuations in revenue growth (ΔREV_GR).

Table 8. Profitability, AI intensity, R&D intensity, and patent fillings

Variables	Dependent variable ΔPROFITABILITY (15)	(16)	ΔREV_GR (17)	(18)	(19)	(20)
AI_INV	−1.361*** (0.219)	−0.651** (0.250)				
AI_INV^2	0.101*** (0.021)					
R&D		−2.174 (1.363)		0.766 (0.791)		
AI_INV x R&D		0.489** (0.208)				
AI_INT			−0.244*** (0.044)	−0.035 (0.024)	−0.014 (0.046)	
AI_INT^2			0.002*** (0.000)			
AI_INT x R&D				0.057*** (0.012)		
R&D_INT					2.452 (12.687)	
AI_INT x R&D_INT					0.343*** (0.069)	
PATENT						0.029*** (0.007)
Observations	10,735	10,735	10,764	10,764	3,026	5,090
Adjusted *R*-squared	0.150	0.150	0.210	0.210	0.224	0.266
Control	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm clustered	Yes	Yes	Yes	Yes	Yes	Yes
Industry clustered	Yes	Yes	Yes	Yes	Yes	Yes
SE clustered	Yes	Yes	Yes	Yes	Yes	Yes

Note(s): ΔPROFITABILITY, ΔREV_GR, AI_INV, R&D, AI_INT, R&D_INT, PATENT refer to the first difference of a firm's return on equity, the first difference of a firm's revenue growth, log of VC investment in AI, a dummy variable is created where a value of 1 is assigned if the firm reports R&D expenditure, and 0 otherwise, AI intensity which is the VC investment over the number of VC investment in AI, R&D intensity is the R&D expenditure over total assets in a firm, number of patent filings related to AI based on data from Google patent respectively. Robust and clustered standard errors are reported in parentheses. Statistical significance is denoted by *, **, and *** for the 10%, 5%, and 1% levels, respectively. Data sources include S&P Capital IQ, OECD AI Policy Observatory, Google Patent, World Development Indicators (WDI), and World Governance Indicators (WGI)

Source(s): Authors' own work

5. Discussion, contributions and policy implications

This study examined how AI investment influences entrepreneurial outcomes, proxied by changes in firm revenue growth, among European firms. The results provide both theoretical and practical insights.

The observed U-shaped relationship between AI investment and revenue growth underscores the dual nature of technological adoption in entrepreneurship. Initially, firms experience a decline in performance due to high implementation costs, skill mismatches, and integration challenges, consistent with Brynjolfsson *et al.* (2019) and Agrawal *et al.* (2019). However, over time, firms that persist through this learning phase realise substantial performance gains as AI systems mature and organisational capabilities develop. This finding aligns with Teece's (2018) dynamic capability theory, emphasising that AI adoption is not a static investment but a process of continuous adaptation and capability building.

The significant positive interaction between AI and R&D highlights the complementarity of digital and innovation capabilities. Firms combining AI investments with R&D activities are better equipped to generate, refine, and commercialise new products and services. The negative short-term coefficient for R&D reflects delayed payoffs common to innovation processes, but its interaction with AI reveals strong synergies that translate innovation potential into market performance (Czarnitzki *et al.*, 2023; Kohtamäki *et al.*, 2019). Among the controls, GDP growth and inflation positively affected revenue growth, while firm age and size showed mixed effects. Institutional quality (IQ) was insignificant, likely due to the EU's relatively harmonised regulatory and governance systems, suggesting limited cross-country variation in short term outcomes.

Overall, the findings suggest that AI-driven entrepreneurship within the EU is most effective in mature, innovation active firms with sufficient absorptive capacity to withstand initial performance dips. Thus, the results apply primarily to established firms rather than startups or micro-enterprises, which may face resource and capability constraints. Revenue growth, as our proxy for entrepreneurial performance, captures firms' ability to translate innovation into financial outcomes, aligning with the broader entrepreneurship literature (Davidsson and Wiklund, 2001).

5.1 Theoretical contributions

This study makes several important contributions to the RBT and the DCT. First, this research extends RBT by exploring the threshold effects of AI investment in entrepreneurship. The study identifies a U-shaped relationship between AI investments and entrepreneurial outcomes, such as revenue growth, offering a new theoretical insight. This finding suggests that the returns on AI investments are non-linear and may take time to appear, an aspect that has been largely overlooked in existing research. Previous studies (Ameen *et al.*, 2024; Giuggioli and Pellegrini, 2023) have generally found a positive relationship between AI adoption and entrepreneurial performance but have not considered the initial challenges firms face. High implementation costs, inefficiencies in the workforce, integration difficulties and limited technological knowledge can hinder performance during the early stages of AI adoption (Dwivedi *et al.*, 2021). As a result, firms may experience negative returns before achieving long-term benefits.

By applying RBT to interpret this pattern, the findings suggest that AI investments initially lack the characteristics of VRIN resources until firms build complementary assets and develop learning routines that unlock their strategic potential (Barney, 1991). The U-shaped pattern therefore provides empirical support for a non-linear relationship between resource acquisition and value realisation, refining RBT by demonstrating that resources evolve towards VRIN status over time through capability development (Makadok, 2001; Peteraf, 1993). This deepens theoretical understanding by showing that resource-based advantages are not immediate results of ownership but are achieved through an adaptive process of accumulation and recombination.

Second, this study highlights the synergistic relationship between AI investments and R&D efforts, thereby refining RBT's assumptions about resource complementarity and bundling. By examining how these two intangible assets interact to drive innovation and entrepreneurial success, this research shows that the combination of AI and R&D generates complementary value that exceeds what either could achieve alone. This supports the principle of resource orchestration, indicating that the strategic integration of AI and R&D enhances their combined impact on performance (Sirmon *et al.*, 2007, 2011). The findings therefore advance RBT by illustrating that competitive advantage arises not only from possessing VRIN resources but also from configuring and using them effectively within a coherent system of capabilities.

Third, the study extends RBT by considering the moderating role of firm size in the AI R&D relationship. While previous studies (Ameen *et al.*, 2024; Zhai and Liu, 2023) have examined firm size as a factor influencing AI adoption, this research investigates how it shapes the interaction between AI and R&D. The results indicate that smaller firms often benefit more quickly from AI investments, whereas larger firms may experience diminishing returns unless they adapt their integration strategies. This insight advances RBT by showing that the effectiveness of strategic resources depends on organisational context, particularly firm size, which affects how AI and R&D can be combined for competitive advantage. It also suggests that the scalability of digital resources depends on managerial agility and the firm's ability to absorb and apply knowledge, extending RBT towards a more dynamic view of resource effectiveness.

Fourth, this study contributes to the development of the DCT. While RBT explains what resources firms possess, DCT focuses on how firms deploy, renew and reconfigure those resources to remain competitive in changing environments. The findings suggest that AI adoption functions not only as a valuable resource but also as a dynamic enabler that enhances a firm's ability to sense new opportunities, seize them through strategic action and reconfigure existing processes to maintain long-term advantage. This explanation of the sensing, seizing and reconfiguring mechanisms offers a clear illustration of how digital technologies operate as sources of dynamic capability rather than as static inputs.

Finally, the study demonstrates that integrating AI with R&D strengthens long-term adaptability and innovation, helping firms to maintain consistent performance in evolving environments. This underlines the importance of integrated resource deployment in dynamic conditions. While earlier research (Manfreda and Štemberger, 2019; Chen and Tian, 2022) has emphasised that firms should integrate resources to build digital capabilities and achieve successful transformation, this study identifies which specific resources, particularly AI and R&D, are most important for driving entrepreneurial outcomes. By showing that AI R&D integration improves both opportunity recognition and resource renewal, this study strengthens DCT's explanatory value in digital entrepreneurship.

This research bridges the conceptual divide between resource possession (RBT) and resource orchestration (DCT), providing a more comprehensive theoretical framework for understanding digital innovation and entrepreneurial performance. It refines RBT by showing that the value of AI investment develops over time through learning and the accumulation of complementary resources, and it extends DCT by explaining how AI supports the creation and renewal of dynamic capabilities in practice. Together, these insights provide a stronger theoretical foundation for understanding how digital technologies enable firms to achieve sustainable entrepreneurial growth.

5.2 Managerial and policy implications

The findings offer actionable implications for both managers and policymakers.

For managers, the U-shaped relationship suggests that AI investments require strategic patience and phased implementation. Firms should adopt staged investment strategies, starting small, learning through pilot projects, and scaling gradually, to mitigate early inefficiencies and manage initial costs. The positive AI and R&D interaction underscores the need for alignment between digitalisation and innovation efforts. Managers should embed AI within existing R&D pipelines to accelerate product development, enhance operational intelligence, and sustain growth. Additionally, building complementary organisational capabilities, through employee training, process redesign, and change management, is critical to realise AI's full potential.

For policymakers, the empirical evidence provides guidance on fostering sustainable AI-driven entrepreneurship. The short-term negative effect of AI investments justifies transitional policy support such as targeted tax incentives, innovation grants, and co-financing schemes, particularly for small and medium-sized enterprises. Simultaneously, the strong complementarity between AI and R&D calls for policies that promote joint investment frameworks, for example linking digital adoption programmes with R&D funding under Horizon Europe or Digital Europe.

Implementation must, however, consider cross-country heterogeneity in digital infrastructure, institutional capacity, and firm demographics. Less digitally advanced regions may require foundational support in connectivity and digital literacy before more sophisticated AI adoption policies can take effect. Policymakers should also remain vigilant about potential downsides, including over-subsidisation, uneven access to AI technologies, and market concentration risks.

In terms of prioritisation, short-term policies should focus on easing adoption barriers through financial incentives and workforce development, while long-term strategies should emphasise innovation integration, ethical AI governance, and cross-border regulatory harmonisation. Embedding these measures within existing EU frameworks such as *Horizon Europe*, the *Digital Europe Programme*, and *Cohesion Policy* can enhance coordination, ensuring that AI investments translate into broad-based entrepreneurial and economic growth.

6. Limitation and future research

This study provides novel insights into the relationship between AI investment and entrepreneurial outcomes among European firms; however, several limitations remain, each of which offers valuable opportunities for future research.

First, the sample composition focuses on R&D active, publicly listed firms across 26 EU countries. These firms are typically more innovation oriented, resource rich, and structurally capable of sustaining long-term technological investments. This strengthens internal validity for analysing the AI–R&D interaction but may limit generalisability to smaller or less resource intensive firms. Firms without dedicated R&D capacity might not be able to endure the short-term challenges of AI adoption that underpin the observed U-shaped relationship, potentially overstating the resilience of average entrepreneurial firms. Future research could extend this analysis to include private, non-R&D, or early-stage firms to assess whether the AI performance relationship differs across firm size, innovation capability, and funding structure.

Second, the measurement of AI investment relies on the logarithm of venture capital (VC) investments in AI at the country levels, as provided by the OECD AI Policy Observatory. While this proxy effectively captures aggregate AI ecosystem activity and investor confidence, it does not fully reflect firm-specific AI adoption or capability levels. Consequently, the results should be interpreted as reflecting broader AI environment effects rather than direct firm-level behaviour. Future studies could employ firm-level AI indicators, such as AI patents, AI employment intensity, or AI-related expenditure, to provide a more granular understanding of adoption heterogeneity across firms and sectors.

Finally, the study's time frame (2012–2023) captures a critical but still-evolving phase of AI development. Major advances in deep learning emerged mid-decade, and generative AI and large language models have only recently scaled. Thus, long-term effects may not yet be fully observable. Although year fixed effects control for macro shocks such as COVID-19, future research could extend the panel to include post-2023 data or employ dynamic structural models to explore potential S-shaped or non-linear AI adoption effects.

7. Conclusion

In summary, AI investments can unlock significant entrepreneurial growth, but only through an initially challenging learning period and in conjunction with innovation efforts and supportive ecosystems. Entrepreneurs and policymakers must recognise that leveraging AI for sustained growth is a strategic, long-term endeavour, one that, when done right, can substantially enhance competitive advantage and innovation in the economy.

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