

The bright and dark sides of AI-driven transformation: evidence from Italian firms

Syed Muhammad Ali Shah

*Department of Economics and Social Sciences, Università Politecnica delle Marche,
Ancona, Italy*

Michele Cincera

*Solvay Brussels School of Economics and Management, Université Libre de
Bruxelles, Brussels, Belgium, and*

Marco Cucculelli

*Department of Economics and Social Sciences, Università Politecnica delle Marche,
Ancona, Italy*

Abstract

Purpose – This study examines how firm-level Artificial Intelligence (AI) capabilities are associated with innovation trajectories and firm performance, with particular attention to sustainability-oriented (green) and efficiency-oriented (brown) innovation outcomes. It further investigates how government support relates to these innovation trajectories across firms with different capability profiles and whether AI capabilities are associated with subsequent AI adoption patterns.

Design/methodology/approach – The study combines large-scale survey data from 6,732 Italian firms with LinkedIn-based information on AI-skilled employees. We construct a multidimensional AI Capability Index capturing tangible, human, and intangible knowledge sources and estimate a two-stage CDM-inspired empirical model linking capabilities, innovation outcomes, firm performance and AI adoption over a four-year horizon.

Findings – Stronger AI capabilities are associated with a higher likelihood of both brown and green innovation, although with different performance profiles over time. Brown innovation is associated with short-term efficiency and revenue gains, whereas green innovation is associated with more persistent productivity and growth effects. Government support is positively associated with green innovation among firms with stronger AI capabilities, but more closely associated with brown innovation in low AI capability settings. AI capabilities are also strongly associated with subsequent AI adoption, consistent with path-dependent capability dynamics.

Research limitations/implications – The analysis focuses on Italian firms, which may limit generalizability to other institutional contexts. AI capabilities are measured cross-sectionally, constraining direct observation of capability evolution over time. Although LinkedIn data enables longitudinal tracking of AI adoption, adoption may be undercounted for micro firms or firms with limited online presence. Future research using panel data and cross-country settings could further strengthen causal inference and external validity.

Practical implications – For managers, the results highlight the importance of developing balanced AI capabilities rather than focusing solely on technology acquisition. Firms with stronger capabilities appear better positioned to align AI-related innovation with long-term sustainability and growth objectives. For policymakers, the findings suggest that broad AI support mechanisms may be associated with different innovation trajectories depending on firms' underlying capabilities, underscoring the importance of capability-sensitive policy design.

Social implications – By showing that AI capabilities are associated with different innovation orientations, the study highlights the societal importance of capability development in shaping the broader implications of AI adoption. Policy support aimed at strengthening firms' absorptive and organizational capacity may help align AI-enabled innovation with environmental and societal objectives, reducing the risk that public support becomes associated primarily with short-term efficiency-oriented innovation paths.

Originality/value – The study contributes to research on AI and innovation by introducing a multidimensional measure of AI capabilities and by empirically examining how firm capabilities and public support are jointly



associated with AI-enabled innovation. Conceptually, the study develops the Triple Helix Twin as a capability-contingent analytical lens for understanding heterogeneous innovation trajectories under shared institutional conditions. The findings contribute to debates on AI adoption, industrial policy, sustainable innovation and the organizational implications of AI-driven transformation.

Keywords AI capability, AI adoption, Green innovation, brown innovation, Government support, Firm performance, Sustainability

Paper type Research article

1. Introduction

Artificial Intelligence (AI) is widely portrayed as a hallmark of the Fourth Industrial Revolution (4IR) (World Economic Forum, 2025), with the potential to transform economies and societies (Festa *et al.*, 2026). Yet, despite rapid deployment across industries, many organizations continue to struggle to translate AI investments into meaningful business value. Earlier evidence indicated that many firms reported limited business outcomes from AI initiatives, with more recent discussions similarly suggesting that organizations often approach AI as a stand-alone technological solution rather than as a broader organizational transformation requiring complementary capabilities, strategic alignment, governance structures, and changes in work processes (Ransbotham *et al.*, 2019; Stackpole, 2026). This paradox highlights a persistent gap between technological adoption and realized business impact, raising questions about the organizational conditions under which AI is associated with innovation and performance.

Prior research emphasizes the roles of complementary resources associated with AI-related outcomes, including technical infrastructure (Deepa *et al.*, 2024; Mikalef and Gupta, 2021), managerial skills (Iansiti and Lakhani, 2020), and policy frameworks supporting digital transformation (Fedyunina and Radosevic, 2022; Wang *et al.*, 2025). By contrast, relatively few studies systematically examine how tangible, intangible, and human knowledge resources interact to form firm-level AI capabilities, and how these capabilities relate to the direction of innovation. Addressing this gap is particularly important because AI adoption may give rise to both “bright” outcomes, such as green and sustainability-oriented innovation, and “dark” outcomes such as brown innovation, focused on efficiency gains without explicit environmental objectives, as well as broader concerns related to resource misallocation, and inequality [1]. Beyond performance considerations, concerns have also been raised regarding internal stakeholder perceptions and ethical risks associated with data-intensive AI systems (Randolph-Seng *et al.*, 2024).

In this study, we adopt a configurational perspective inspired by the Triple Helix tradition (Etzkowitz and Leydesdorff, 1995, 2000) to examine how firm-level AI capabilities interact with public support in relation to innovation pathways. Rather than proposing a new theory, we draw on the Triple Helix Twin perspective as a capability-contingent analytical lens to explain why similar policy support may be associated with different innovation orientation across firms with different capability endowments. Specifically, this lens allows us to examine how firm-level AI capabilities, reflecting the knowledge dimensions of the university–industry nexus, interact with government support in relation to different innovation trajectories, including green and brown innovation pathways, and their associated performance dynamics over time.

Consistent with recent research on the “bright” and “dark” sides of AI innovation (Canhoto and Clear, 2020; Mancuso *et al.*, 2025), we conceptualize the “dark side” not as economic failure, but as a potential misalignment between short-term efficiency gains and long-term sustainability objectives. This distinction is particularly relevant in policy-driven environments where similar support instruments may be associated with different innovation trajectories depending on firms’ underlying capabilities.

Against this background, we address two research questions. *First, how do firm-level AI capabilities, built from tangible, human, and intangible knowledge sources, relate to AI*

adoption and innovation direction (green vs brown)? Second, how are these innovation pathways associated with firm performance, productivity, and growth over time, and how are these relationships conditioned by government support?

Methodologically, we advance the literature in several ways. First, we construct a firm-level AI Capability Index using factor analysis on survey data from 6,732 Italian firms, a step which extends existing measurement approaches (Mikalef and Gupta, 2021). Second, we combine this Capability Index with LinkedIn-based information on AI-skilled employees to capture AI adoption at the firm level. Finally, we estimate a two-stage model inspired by Crépon *et al.* (1998), which links capabilities, innovation, and performance while distinguishing brown and green innovation trajectories.

This study makes four contributions. First, we provide a validated, multidimensional measure of AI capabilities which addresses a methodological gap in the empirical literature. Second, we show that government support is associated with differences in how AI capabilities relate to innovation direction: specifically, we find that government support is more strongly associated with green innovation among AI-capable firms, and with brown innovation in low-capability contexts. Third, we demonstrate that green innovation is associated with persistent productivity and revenue growth, thus contributing to the ongoing debate related to the Porter Hypothesis (Porter and van der Linde, 1995). Fourth, we document the path-dependent nature of AI adoption: firms with stronger AI capabilities in 2019 were more likely to report AI adoption by 2023 [2].

The remainder of the paper is structured as follows. Section 2 develops the theoretical background. Section 3 presents the hypotheses development. Section 4 describes the data sources and measurement strategy. Section 5 presents the descriptive statistics and research model. Section 6 reports the regression results and discussion. Section 7 concludes with theoretical and managerial implications. Section 8 outlines directions for future research, and Section 9 discusses the study's limitations.

2. Theoretical background

This study builds on the resource-based view (RBV) and the knowledge-based view (KBV) to conceptualize how firms develop AI-related capabilities and the natural RBV (NRBV) to distinguish between alternative innovation directions and their sustainability impacts. The firm-level mechanisms are embedded in an institutional context shaped by public policy, which we conceptualize through a refined Triple Helix perspective.

Rather than treating these frameworks as competing explanations, we adopt a layered approach. RBV and KBV provide micro-foundations of AI capabilities, NRBV offers a lens to assess the sustainability orientation of innovation outcomes, and the Triple Helix framework captures how government support may condition the association between capabilities and innovation trajectories. Together, this structure provides a basis for examining both the bright and the dark sides of AI-driven transformation.

2.1 AI capabilities

AI capabilities refer to a firm's ability to mobilize, integrate, and deploy AI-related resources in ways that support innovation and performance. Consistent with RBV and KBV, these capabilities do not reside in isolated assets but emerge from the interaction of complementary knowledge sources. The effectiveness of any individual capability dimension therefore depends partly on the presence and coordination of the others, implying potential complementarities as well as bottlenecks in firms' AI capability development. In line with prior work, we conceptualize AI capabilities along three interrelated pillars: tangible, human, and intangible knowledge. These pillars shape not only firms' innovation capacity, but also the organizational conditions under which AI-related knowledge is deployed: recent evidence further suggests that AI-related capabilities and AI-driven decision-making processes are

positively associated with firm performance, particularly when supported by data-intensive infrastructures and organizational alignment (Giachino *et al.*, 2025).

2.1.1 Tangible knowledge. Tangible knowledge includes data, technology, and basic resources that constitute the material foundation of AI capabilities (Sjödin *et al.*, 2021). Prior research shows that access to high-quality data, and scalable digital infrastructure is essential for extracting value from AI (Mikalef *et al.*, 2019; Al Halbusi *et al.*, 2025). These tangible assets include hardware, software, and structured or unstructured data (Almheiri *et al.*, 2024). When effectively governed, tangible resources may enable advanced applications such as predictive maintenance, energy optimization, and eco-design, which support green innovation. Conversely, poorly governed data, legacy IT systems, or biased datasets may be associated with narrow efficiency-oriented AI uses and brown innovation paths. Tangible knowledge is therefore a necessary but not sufficient condition: its innovation effects depend on complementarities with human and intangible resources.

2.1.2 Human knowledge. Human knowledge represents the second pillar of AI capabilities, encompassing technical, managerial, and relational skills required to design, adopt, and integrate AI into organizational processes. The AI era increasingly demands hybrid skill sets combining data science expertise with business understanding and collaborative capabilities (Iansiti and Lakhani, 2020; Babashahi *et al.*, 2024; Bobitan *et al.*, 2024). Technical and business skills help align AI applications with strategic objectives (Chowdhury *et al.*, 2023; Verma *et al.*, 2022), while soft skills such as adaptability and critical thinking enable effective human–AI collaboration (Du, 2024). Investment in upskilling may be associated with more inclusive innovation trajectories, whereas skill shortages and uneven access to training may increase automation risks and bias firms toward short-term efficiency solutions. Human knowledge is therefore central to how tangible resources are associated with green or brown innovation outcomes. Recent experimental evidence further shows that AI-supported decision-making enhances analytical depth but may reduce novelty unless complemented by domain expertise, underscoring the importance of sector-specific knowledge in shaping AI outcomes (Cristofaro *et al.*, 2025).

2.1.3 Intangible knowledge. Intangible knowledge constitutes the third pillar of AI capabilities and includes organizational routines, coordination mechanisms, change capacity, and risk proclivity. These elements are associated with how firms absorb, recombine, and scale AI-driven solutions (Kafourous and Aliyev, 2016; Nonnis *et al.*, 2023). Strong coordination and change capacity may support cross-functional integration and long-term innovation (Brown *et al.*, 2019; Leemann and Kanbach, 2022), while a balanced risk orientation facilitates opportunity recognition without excessive short-termism (Sallah and Caesar, 2020). In contrast, weak organizational alignment or cultures focused on short-term returns may coincide with incremental, brown innovation and undermine trust in automated systems. Intangible knowledge therefore conditions the extent to which AI capabilities are associated with sustainability-oriented transformation rather than efficiency-oriented trajectories. Recent studies show that AI-enabled transformation depends on integration and organizational agility (Ma and Chang, 2025), while the effective use of AI-generated insights is shaped by organizational routines and autonomy configurations (Cristofaro and Bañón-Gomis, 2025).

2.2 Innovation: green and brown trajectories

Innovation refers to the creation and implementation of new products and processes that enhance firm competitiveness. Building on NRBV, we distinguish between green and brown innovation to capture differences in sustainability-oriented and temporal performance effects. Green and brown innovation are not treated as strictly mutually exclusive categories, as firms may simultaneously engage in both sustainability-oriented and efficiency-oriented innovation activities. Accordingly, the empirical analysis distinguishes dominant innovation orientations while robustness checks additionally exclude overlapping cases to ensure that the main results are not driven by firms reporting both innovation types.

2.2.1 Green innovation. Green innovation involves products, processes, and practices that reduce environmental impact while maintaining or enhancing economic performance (Castellacci and Lie, 2017; Li *et al.*, 2022; Block *et al.*, 2025). Such innovation often relies on collaboration, knowledge sharing, and supportive regulatory frameworks (Lisi *et al.*, 2020; Wang *et al.*, 2022). Evidence from sustainability-oriented firms further indicates that business model innovation plays a critical role in translating sustainability intent into measurable environmental performance (Girma *et al.*, 2025). In this study, green innovation captures sustainability-oriented transformation associated with long-term environmental and organizational objectives.

2.2.2 Brown innovation. Brown innovation refers to technological or process improvements aimed primarily at efficiency and cost reduction without explicit environmental objectives (De Marchi, 2012). While innovation can generate short-term economic benefits, it may reinforce unsustainable development paths under weak regulatory or capability conditions (Edgeman *et al.*, 2013). Brown innovation is not treated as economically undesirable *per se* [3]. Rather, it reflects innovation trajectories primarily oriented toward short-term efficiency gains without explicit sustainability objectives.

2.3 Triple helix twin as an analytical lens

The Triple Helix framework emphasizes how interactions between universities, industry, and government shape innovation dynamics and knowledge diffusion (Zhou and Etzkowitz, 2021) [4]. Recent developments in this literature increasingly suggest that these interactions do not generate uniform outcomes, but instead depend on institutional openness, governance quality, organizational capabilities, and the structure of knowledge spillovers (El Quadghiri *et al.*, 2026; Liu *et al.*, 2026; Wu *et al.*, 2026). Building on this emerging perspective, we introduce the Triple Helix Twin as a capability-contingent analytical lens that distinguishes between innovation generation and innovation direction.

In our operationalization, firm-level AI capabilities capture the university-industry dimension through knowledge inputs and absorptive capacity, while government support represents the institutional helix. Government support is not uniformly associated with sustainability-oriented outcomes. Its relationship with innovation direction depends on firms' underlying AI capabilities. Strong capabilities may allow firms to absorb public support and align it with sustainability-oriented innovation, whereas weak capabilities may redirect the same support toward efficiency-oriented, brown innovation.

This conditional perspective aligns with recent Triple Helix research showing that institutional support, governance structures, and collaborative openness shape innovation outcomes differently depending on organizational and ecosystem conditions (Luengo-Valderrey *et al.*, 2020; Noya *et al.*, 2023; Liu *et al.*, 2026). The Triple Helix Twin therefore highlights how similar policy interventions may coincide with divergent innovation trajectories across firms with different capability endowments. More broadly, the Triple Helix Twin is intended as a portable analytical mechanism for explaining heterogeneous innovation outcomes under shared institutional conditions. Its relevance extends beyond AI and the Italian context when three conditions are present: (1) policy interventions are relatively broad rather than narrowly prescriptive; (2) firms differ meaningfully in absorptive and technological capabilities; (3) innovation can evolve along multiple strategic directions. Under such conditions, identical forms of public support may coincide with sustainability-oriented, efficiency-oriented, or structurally reconfiguring innovation trajectories depending on firms' capability foundations. The framework is therefore applicable to a wider set of digital and sustainability transitions, including Industry 4.0, clean-technology adoption, platform ecosystems, and AI-enabled supply-chain restructuring (Wu *et al.*, 2026). Conversely, the framework is less applicable where innovation pathways are tightly mandated by regulation, where firms are relatively homogeneous, or where organizational capabilities play only a limited role in shaping responses to institutional incentives. Figure 1 summarizes the

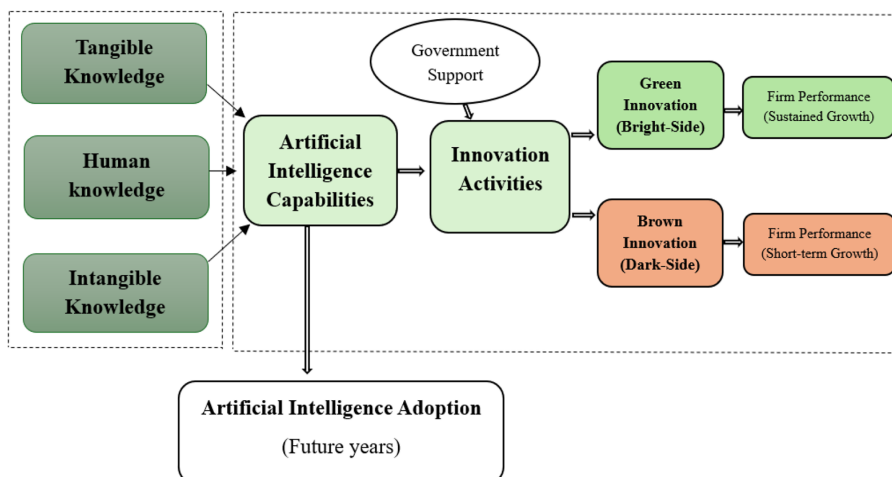


Figure 1. Conceptual framework. Note: The Triple Helix Twin framework conceptualizes how AI capabilities rooted in tangible, human, and intangible knowledge (university–industry dimensions) interact with government support (policy dimension) in relation to firms’ innovation trajectories. The framework distinguishes between sustainability-oriented (green) and efficiency-oriented (brown) innovation pathways and their potential implications for firm performance over time. It also reflects the possibility that firms with stronger AI capabilities are more likely to adopt AI in the future, consistent with capability accumulation and path-dependent technology development

conceptual framework, showing how AI capabilities and government support are linked to green and brown innovation trajectories and their performance implications over time.

3. Hypotheses development

3.1 Firm-level AI capabilities and innovation direction

AI capabilities are associated not only with firms’ propensity to innovate but also with differences in innovation orientation. Strong capabilities may allow firms to deploy AI across a wider set of applications, ranging from process optimization to sustainability-oriented solutions (Secundo *et al.*, 2025; Dai, 2024). However, when capabilities are limited or narrowly configured, AI use may be more concentrated on incremental efficiency gains and be associated with brown innovation paths (Bughin, 2023).

Importantly, because AI is a general-purpose technology, its application is directionally neutral *ex ante*. We therefore expect AI capabilities to be positively associated with both green and brown innovation, while recognizing that these effects differ in their strategic and sustainability implications. Accordingly, we test the following hypotheses:

- H1. Firm AI capabilities are positively associated with firms’ overall innovation propensity.
- H1a. Firm AI capabilities are positively associated with brown innovation.
- H1b. Firm AI capabilities are positively associated with green innovation.

3.2 Government support, AI capabilities, and innovation direction

Government support is closely associated with firms’ innovation choices through incentives and risk reduction mechanisms (Luengo-Valderrey *et al.*, 2020). However, its associations are

MD
64,13

conditional on firms’ absorptive capacity and AI capabilities. Within the Triple Helix Twin framework, government support is more likely to be associated with sustainability-oriented innovation when firms possess sufficient AI capabilities to leverage it effectively. Accordingly, we test the following hypotheses:

- 740
- H2a. Government support is positively associated with green innovation.

H2b. Government support is not expected to be systematically associated with brown innovation.

H2c. AI capabilities positively moderate the association between government support and green innovation.

H2d. AI capabilities negatively moderate the association between government support and brown innovation.

3.3 Innovation and firm performance

Both green and brown innovation may contribute to firm performance, but their temporal performance profiles differ. Brown innovation typically delivers short-term efficiency gains, while green innovation is more closely associated with longer-term productivity and growth through alignment with regulatory trends and stakeholder expectations. Accordingly, we test the following hypotheses:

- H3. AI-enabled innovation is positively associated with firm performance.

H3a. Brown innovation is positively associated with short-term performance but not sustained long-term growth.

H3b. Green innovation is positively associated with both short-term performance and long-term growth.

3.4 AI capabilities and AI adoption

A recent systematic review of AI adoption highlights the role of organizational, technological, and environmental factors in shaping AI implementation decisions (Khanfar et al., 2025), reinforcing the importance of firm-level capabilities in enabling sustained AI engagement. Moreover, AI capabilities are positively associated with firms’ likelihood of adopting AI technologies over time. Firms with stronger capabilities face lower uncertainty, higher readiness, and greater strategic alignment and are therefore more likely to exhibit higher AI adoption probabilities (Horvat et al., 2023). Accordingly, we test the following hypothesis:

- H4. Firms with higher AI capabilities are more likely to adopt AI technologies.

4. Data sources

This study combines a large-scale survey of Italian firms with LinkedIn data to examine how AI capabilities relate to innovation outcomes, firm performance, and AI adoption over time. The survey provides detailed information on firms’ tangible, human, and intangible knowledge resources, which we used to construct the AI Capability Index. These firm-level capabilities capture the university–industry dimensions of the Triple Helix framework, while government support is incorporated separately as the policy dimension.

The survey was developed in several stages. First, we used the Bureau van Dijk (Orbis/AIDA) database to identify 64,872 micro, small, and medium-sized enterprises (MSMEs) in manufacturing, services, and utilities (e.g., gas and electricity). Between May 2019 and February 2020, firms were invited to complete an online questionnaire on innovation activities

and knowledge resources. To improve response reliability and identify appropriate respondents, firms with 50 or more employees were first contacted by telephone by a trained survey team and subsequently invited to complete the questionnaire electronically, while smaller firms were primarily contacted via email with follow-up reminders. In total, 6,732 fully usable responses were obtained (response rate: 10.3%), comparable to other large-scale firm-level innovation surveys [5].

To capture AI adoption over time, we matched the survey data to LinkedIn data covering employee profiles associated with Italian firms. This integration allows us to track AI-related human capital dynamics between 2020 and 2023, providing a longitudinal perspective that complements the cross-sectional survey. Following recent calls for reflexive rigor in international management research (Abatecola *et al.*, 2025), we carefully aligned survey design, measurement, and data integration procedures to ensure construct consistency. For transparency, Appendix Table A6 provides a concise overview of data sources, variable operationalization, and measurement approaches used in the empirical analysis. Because LinkedIn coverage is generally higher among larger and more digitally active firms, the matched sample may underrepresent firms with limited online professional presence. We address this issue further in the limitations section.

4.1 AI capability index

The AI Capability Index builds on the framework proposed by Mikalef and Gupta (2021) but departs from equal-weighting approaches through the use of factor analysis. Survey items are grouped into three conceptual pillars: tangible, human, and intangible knowledge—consistent with the theoretical framework developed in Section 2. Within each pillar, related items are compressed into latent factor scores, rescaled to the [0,1] interval, and then aggregated into a composite index. The aggregation strategy reflects the view that AI capabilities operate as an interdependent system of complementary organizational resources rather than as isolated inputs. Tangible infrastructure, human expertise, and intangible organizational routines jointly support firms' ability to absorb, coordinate, and deploy AI-related knowledge. The composite index therefore serves as a parsimonious empirical proxy for the overall capability architecture supporting AI-driven transformation. Importantly, this approach does not assume that the three pillars are equally important, linearly additive, or fully substitutable. Rather, it captures the combined presence of mutually reinforcing resources that, taken together, condition firms' innovation potential.

At the same time, aggregation necessarily abstracts from more complex configurational dynamics. In particular, the index cannot fully capture bottlenecks, threshold effects, or asymmetric complementarities whereby weaknesses in one capability dimension constrain the effectiveness of others. While the aggregate specification is appropriate for identifying broad capability patterns across a large firm sample, future research could unpack these interdependencies more directly using configurational approaches, interaction models, or longitudinal designs examining capability co-evolution over time.

Exploratory factor analyses were conducted separately for each pillar using principal-component factor extraction; in all cases, a dominant factor emerged with satisfactory loadings (see Appendix A1). To address potential concerns regarding measurement robustness and missing data, we construct both a strict index (requiring non-missing information on all three pillars) and a lenient index (allowing index construction when at least two pillars are observed). Results are robust across both specifications (see Table 1).

4.2 Data on tangible sources of knowledge

Tangible sources of knowledge capture the material foundations of AI capabilities and include data generation, data sources, and technology-related practices. Firms indicated whether they generate data across core functional domains such as accounting, sales, production, human

Table 1. Components of the artificial intelligence (AI) capability index

Tangible sources of knowledge	Human sources of knowledge	Intangible sources of knowledge
•Data •Technology •Basic Resources	•Technical Skills •Business Skills	•Interdepartmental Coordination •Organizational change capacity •Risk proclivity
Note(s): Tangible, human, and intangible pillars are measured using survey items. Pillar scores are derived via factor analysis and rescaled to [0,1]. The AI Capability Index is computed as the average of the three rescaled pillar scores, serving as a parsimonious proxy for the joint presence of tangible, human, and intangible AI-related capabilities. Strict and lenient versions differ in their tolerance for missing values (see Section 4)		

resources, supply chain management, web or social media activities, and service provision. They also reported the use of external data sources including customer interactions, competitor monitoring, demand and technology forecasts, suppliers, publications, government reports, and market research. All items were coded as binary indicators. In addition, firms reported the adoption of technology- and resource-related practices, including dedicated digital budgets, business models (e.g. pay-per-use, licensing), product–service integration, market expansion strategies, and the use of specific technologies such as IoT, analytics, cloud computing, CRM systems, IT security, modular systems, robots, additive manufacturing, wearables, and augmented reality. These items were combined through factor analysis to extract a latent tangible knowledge score, rescaled to the [0,1] interval.

4.3 Data on human sources of knowledge

Human knowledge reflects firms’ AI and data-related skills and the use of data in business decision making. Firms reported whether they employed AI- and data-oriented professionals including data analysts, chief data officers, data scientists, architects, content or communication specialists, and social-mining specialists. They also reported how data are used within the firm for performance measurement, planning, predictive analytics, and customer management. All variables were coded as binary indicators. A latent human-knowledge factor was extracted using factor analysis and rescaled to [0,1]. This measure captures the presence of AI-related skills and data-driven practices that facilitate the effective development of AI technologies within the firm.

4.4 Data on intangible sources of knowledge

Intangible knowledge encompasses organizational attributes that support the integration and scaling of AI capabilities, including interdepartmental coordination, organizational change capacity, and risk proclivity [6]. Coordination was measured using binary indicators for capturing the introduction of new sales channels (e-commerce or digital platforms), modifications to indirect channels, and the establishment of new partnerships with customers, suppliers, or competitors. Organizational change capacity was measured through indicators capturing adjustments to job functions, skills requirements, training provision, process reorganization, and hierarchy changes. Risk proclivity was assessed using four continuous items reflecting firms’ willingness to invest under uncertainty and tolerance for delayed return. These items were combined into a single risk factor score. Factor analysis was used to extract a latent intangible-knowledge factor, rescaled to [0,1], and included as the third pillar of the AI Capability Index. The use of latent-factor methods for survey-based constructs follows recent advances in composite index construction in management research (Ferrigno *et al.*, 2025; Brenner *et al.*, 2019; Sha, 2024).

4.5 Data on innovation outcomes

Innovation outcomes were measured using survey questions asking whether firms had introduced: (1) a new product, (2) a green product, (3) green production processes, or (4) a circular or sustainability-oriented project. Multiple responses were allowed. Firms reporting sustainability-oriented product, process, or circular economy innovation were classified as engaging in green innovation. Firms reporting product innovation without explicit sustainability orientation were classified as engaging in brown innovation. This operationalization distinguishes sustainability-oriented innovation from efficiency-oriented innovation while recognizing that firms may engage in broader innovation activity. The classification is consistent with the conceptual distinction developed in [Section 2](#) between sustainability-oriented and efficiency-oriented innovation trajectories.

4.6 Data on AI adoption

AI adoption was measured using LinkedIn data on employee skills. Employee profiles were classified into soft, technical, and AI-specific skill categories based on documented competencies. To ensure classification accuracy, a BERT-based machine-learning model was trained on a manually labeled dataset of 600 skill terms spanning AI, technical, and soft-skill categories and achieved over 90% out-of-sample classification accuracy [7].

A firm was classified as an AI adopter if it employed at least one individual with AI-specific skills between 2020 and 2023. This approach provides a longitudinal and externally observable proxy for AI adoption that is less exposed to self-reported bias. At the same time, the measure should be interpreted cautiously, as the presence of AI-skilled employees may also reflect emerging capability development rather than fully implemented AI deployment. Moreover, LinkedIn-based measures may underrepresent smaller or less digitally visible firms, reflecting a broader digital divide.

4.7 Variables and controls

To test the hypotheses developed in [Section 3](#), we construct dependent, independent, and control variables. Innovation outcomes are binary indicators for overall innovation, brown innovation, and green innovation. Firm performance is measured using labor productivity (log value added per employee), revenue per employee (log), and four-year growth rates for both measures. AI adoption is coded as a binary variable indicating the presence of AI-skilled employees between 2020 and 2023.

The AI Capability Index aggregates tangible, human, and intangible knowledge pillars as described above. Government support is captured by a binary indicator equal to one if the firm received tax incentives, subsidies, or public grants. This specification focuses on access to policy instruments rather than their intensity, consistent with prior firm-level innovation studies and helping reduce, though not eliminate, endogeneity concerns. Control variables include firm size (log employment), firm age (log years since establishment), export orientation (log export turnover), and capital intensity (log capital stock). Industry fixed effects (2-digit NACE ATECO code) and regional fixed effects are included to account for sectoral and spatial heterogeneity.

5. Descriptive statistics and research model

5.1 Descriptive statistics

[Table 2](#) reports summary statistics for 6,732 Italian firms included in the analysis. The mean value of the AI Capability Index is relatively low, indicating that, on average, firms are still at an early stage in the development of AI-related capabilities. AI adoption remains limited, consistent with well-documented cost, skill, and organizational barriers. At the same time, firms with stronger AI capabilities are more likely to report AI adoption in subsequent years. Nearly half of firms report some form of innovation activity (mean = 0.48); among these, 25% engage in brown innovation, while 32% report green innovation. Government support is

Table 2. Summary statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
AI Capability Index	6,732	0.1725	0.1421	0	0.6839
AI adoption	6,713	0.0810	0.2729	0	1
Innovation	6,126	0.4823	0.4997	0	1
Brown innovation	6,713	0.2514	0.4338	0	1
Green innovation	6,732	0.3183	0.4658	0	1
Green product innovation	6,732	0.0779	0.2681	0	1
Green process innovation	6,732	0.0947	0.2929	0	1
Circular green economy project	6,732	0.1056	0.3073	0	1
Government support	6,732	0.2275	0.4192	0	1
Log export turnover	6,713	1.4156	1.6750	0	4.6151
Log revenue	6,572	7.0633	1.6103	0	13.683
Log value added	6,459	6.0098	1.5978	0	12.924
ROA	6,594	6.1061	21.951	−14.4	64.521
Firm size (log Employment)	6,302	2.2578	1.2486	0	9.6
Firm age (years)	6,540	20.178	14.247	2	120

Note(s): Observations vary due to data linkage and missing values. ROA is measured in percentage points. AI adoption is defined based on LinkedIn data (see [Section 4](#)). Full variable definitions are provided in [Section 4](#)

received by 23% of firms, primarily through tax incentives, subsidies, and grants, with notable variation across industries and regions.

[Table 3](#) shows pairwise correlations. AI capabilities are positively correlated with innovation outcomes, government support, export orientation, and later AI adoption, while correlations among explanatory variables remain moderate, suggesting no immediate multicollinearity concerns.

5.2 Research model

Our empirical strategy follows a two-stage structural approach inspired by the Crépon–Duguet–Mairesse (CDM) framework ([Crépon et al., 1998](#)), adapted to examine the relationships between AI capabilities, innovation outcomes, and firm performance [\[8\]](#). While the traditional CDM framework focuses on R&D inputs, innovation outputs, and productivity, our framework places AI capabilities at the core of the innovation process and explicitly distinguishes between green and brown innovation pathways.

In the first stage, we estimate the probability that a firm engages in innovation (overall, green, and brown) as a function of AI capabilities and government support:

$$Innovation_i = \beta_0 + \beta_1 AI\ Capability_i + \beta_2 Government\ Support_i + \sum_k \beta_k^{(c)} Controls_{ik} + u_{2i} \tag{1}$$

Innovation is treated as a latent variable observed through binary innovation indicators. [Equation \(1\)](#) is estimated using a probit model. AI capabilities enter the model as a latent composite index constructed through factor analysis of tangible, human, and intangible knowledge pillars, rather than as a simple equally weighted score.

In the second stage, we relate the predicted innovation probabilities from [Equation \(1\)](#) to firm performance outcomes:

$$Y_i = \beta_0 + \beta_3 Predicted\ Innovation_i + \sum_k \beta_k^{(c)} Controls_{ik} + u_{3i} \tag{2}$$

Table 3. Correlation matrix and VIFs

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	VIF	1/VIF
(1) AI Capability Index	1.00															1.32	0.75
(2) AI adoption	0.38	1.00														1.17	0.85
(3) Innovation	0.28	0.14	1.00													3.16	0.31
(4) Brown innovation	0.02	0.01	0.64	1.00												1.90	0.52
(5) Green innovation	0.30	0.13	0.15	−0.45	1.00											2.67	0.37
(6) Green product innovation	0.18	0.09	0.16	−0.19	0.41	1.00										1.29	0.77
(7) Green process innovation	0.21	0.10	0.09	−0.21	0.47	0.27	1.00									1.27	0.78
(8) Circular green economy project	0.22	0.10	0.08	−0.22	0.49	0.17	0.19	1.00								1.28	0.78
(9) Government support	0.17	0.06	0.15	0.02	0.14	0.08	0.12	0.09	1.00							1.11	0.90
(10) Log export turnover	0.09	0.03	0.23	0.07	0.15	0.11	0.06	0.07	0.13	1.00						1.21	0.83
(11) Log revenue	0.09	0.04	0.08	−0.04	0.13	0.06	0.07	0.08	0.19	0.28	1.00					3.04	0.32
(12) Log value added	0.08	0.04	0.05	−0.05	0.12	0.04	0.08	0.08	0.23	0.22	0.89	1.00				1.31	0.76
(13) ROA	0.02	0.03	0.02	0.02	−0.03	−0.02	−0.03	−0.02	0.03	0.01	0.08	0.15	1.00			1.05	0.94
(14) Firm size (log Employment)	0.07	0.04	0.02	−0.07	0.11	0.03	0.07	0.07	0.20	0.17	0.80	0.89	−0.04	1.00		1.63	0.61
(15) Firm age	−0.03	−0.02	0.01	−0.05	0.06	0.02	0.05	0.01	0.11	0.14	0.43	0.42	−0.08	0.37	1.00	1.38	0.72

Note(s): Correlations are pairwise and based on the matched estimation sample. VIFs are computed from the baseline performance specification including the full set of control variables. Values below 10 indicate no problematic multicollinearity

Where Y_i denotes firm performance, measured as log value added per employee or log revenue per employee; β represents the estimated parameters; and u_{2i} and u_{3i} are the disturbance terms. Equation (2) is estimated using ordinary least squares.

This procedure follows the logic of the CDM framework by modeling the sequential relationship between capabilities, innovation, and performance. While it does not provide causal identification, the use of predicted innovation probabilities helps mitigate concerns related to simultaneity and selection that arise when innovation outcomes are directly included in performance regressions. The framework is consistent with the Triple Helix Twin perspective, in which firm-level AI capabilities and government support are jointly associated with different innovation trajectories and performance patterns.

6. Regression results and discussion

6.1 AI capabilities, government support, and innovation

Table 4 shows results for overall innovation. Across all specifications, AI capabilities are positively associated with innovation (coefficients approximately 0.92–1.08, $p < 0.01$). Government support is positively associated with innovation, suggesting that firms receiving policy incentives or grants are more likely to report innovation activity. Among control variables, export-oriented firms exhibit a higher propensity to innovate, while firm size shows a negative association, consistent with coordination and organizational complexity in larger firms.

Table 5 focuses on brown innovation. AI capabilities are positively associated with efficiency-oriented innovation. Government support is not significantly associated with brown innovation, indicating that policy support is not systematically correlated with firms' engagement in traditional efficiency-focused innovation.

Table 6 shows results for green innovation. Both AI capabilities and government support display strong positive associations with sustainability-oriented innovation. Notably, the coefficient of the AI-capability index is larger for green than for brown innovation, indicating that firms with more developed capabilities are more likely to engage in environmentally oriented innovation activities. The positive association between government support and

Table 4. AI Capabilities, Government support and overall innovation (marginal effects)

Variables	(1) Overall innovation	(2)	(3)	(4)
AI Capability Index	1.078*** (0.0399)	0.937*** (0.0400)	1.050*** (0.0432)	0.918*** (0.0442)
Government support	0.0656*** (0.0148)	0.0524*** (0.0146)	0.0640*** (0.0151)	0.0584*** (0.0150)
Log export turnover	–	–	0.0519*** (0.00373)	0.0356*** (0.00417)
Log employment	–	–	–0.0409*** (0.00577)	–0.0262*** (0.00596)
Log firm age	–	–	0.0103 (0.00919)	0.00571 (0.00917)
Industry FE	NO	YES	NO	YES
Region FE	NO	YES	NO	YES
Observations	5,705	5,683	5,181	5,160
Pseudo R^2	0.0926	0.1644	0.1239	0.1815

Note(s): Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Probit marginal effects reported; SEs (Standard errors); p levels shown; Industry (2-digit ATECO) and region FEs as indicated; Number of observations vary due to missing values

Table 5. AI Capabilities, Government support and brown innovation (Marginal effects)

Variables	(1) Brown innovation	(2)	(3)	(4)
AI Capability Index	0.202*** (0.0384)	0.0905** (0.0388)	0.233*** (0.0416)	0.0980** (0.0424)
Government support	−0.00894 (0.0140)	−0.00408 (0.0140)	0.00710 (0.0146)	0.00498 (0.0146)
Log export turnover	–	–	0.0168*** (0.00370)	0.0139*** (0.00402)
Log employment	–	–	−0.0337*** (0.00547)	−0.0179*** (0.00581)
Log firm age	–	–	−0.0118 (0.00861)	−0.00860 (0.00881)
Industry FE	NO	YES	NO	YES
Region FE	NO	YES	NO	YES
Observations	5,705	5,683	5,181	5,162
Pseudo R^2	0.0039	0.0571	0.0153	0.0659

Note(s): Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Probit marginal effects reported; SEs (Standard errors); p levels shown; Industry (2-digit ATECO) and region FEs as indicated; Number of observations vary due to missing values

Table 6. AI Capabilities, government support and green innovation (marginal effects)

Variables	(1) Green innovation	(2)	(3)	(4)
AI Capability Index	0.901*** (0.0381)	0.940*** (0.0379)	0.850*** (0.0418)	0.930*** (0.0423)
Government support	0.0708*** (0.0141)	0.0529*** (0.0142)	0.0512*** (0.0149)	0.0489*** (0.0149)
Log export turnover	–	–	0.0259*** (0.00380)	0.0197*** (0.00425)
Log employment	–	–	0.00417 (0.00580)	−0.00781 (0.00614)
Log firm age	–	–	0.0147 (0.00918)	0.0118 (0.00923)
Industry FE	NO	YES	NO	YES
Region FE	NO	YES	NO	YES
Observations	5,705	5,702	5,181	5,178
Pseudo R^2	0.0770	0.1202	0.0838	0.1243

Note(s): Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Probit marginal effects reported; SEs (Standard errors); p levels shown; Industry (2-digit ATECO) and region FEs as indicated; Number of observations vary due to missing values

green innovation is consistent with arguments in the directed technological change literature (Acemoglu *et al.*, 2016).

Taken together, the results do not reject H1, H1a, H1b, H2a, and H2b and extend prior research on AI capabilities by showing that AI-related resources are associated not only with firms' propensity to innovate, but also with the direction of innovation trajectories. Existing studies have largely focused on AI adoption, digital transformation, or innovation intensity

(Mikalef and Gupta, 2021; Iansiti and Lakhani, 2020), whereas our findings indicate that AI capabilities may simultaneously support both sustainability-oriented and efficiency-oriented innovation pathways. This distinction contributes to emerging debates on the heterogeneous organizational consequences of AI and may help explain why many firms continue to struggle to translate AI investments into meaningful business outcomes despite rapid technological adoption (Ransbotham *et al.*, 2019).

6.2 Moderation effects and the Triple Helix Twin

We next examine whether the relationship between government support and innovation differs depending on firms' AI capability level. Because interaction coefficients in nonlinear models are not directly interpretable, we assess moderation effects using predicted probabilities [9]. Figure 2 shows the interaction effect for brown innovation. Among firms with weaker AI capabilities, government support is associated with a higher likelihood of brown innovation. In contrast, as AI capabilities increase, this association diminishes and eventually turns negative. This pattern is consistent with a substitution effect, whereby AI-capable firms appear less likely to associate policy support with efficiency-oriented innovation.

Figure 3 shows the corresponding relationship for green innovation. Firms with stronger AI capabilities already exhibit a substantially higher baseline propensity to engage in green innovation, and government support is associated with a further increase across the capability distribution. Although the interaction term is not statistically significant, the predicted probabilities suggest that firms with stronger AI capabilities and government support tend to exhibit higher propensities for green innovation. Accordingly, the results should be interpreted as descriptive patterns rather than conclusive evidence of moderation.

Taken together, these findings provide empirical support for the Triple Helix Twin perspective developed in this study. Rather than exerting uniform effects, government support appears to operate conditionally through firms' underlying capability structures. The results therefore suggest that similar policy interventions may coincide with different innovation trajectories depending on firms' absorptive and organizational capacities. This extends conventional Triple Helix interpretations (Etzkowitz and Leydesdorff, 2000; Zhou and Etzkowitz, 2021), which often emphasize institutional interaction and collaboration intensity,

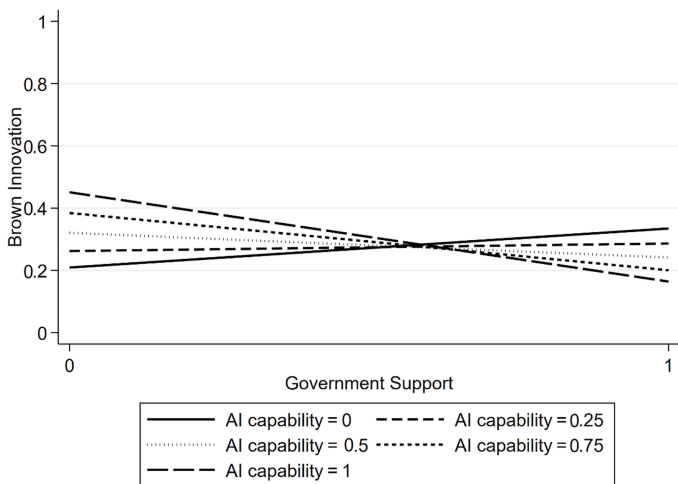


Figure 2. Predicted probability of brown innovation by government support, conditional on AI capability (probit marginal effects). Note: Predicted probabilities are derived from probit models with industry and region fixed effects. Lines represent different levels of the AI Capability Index

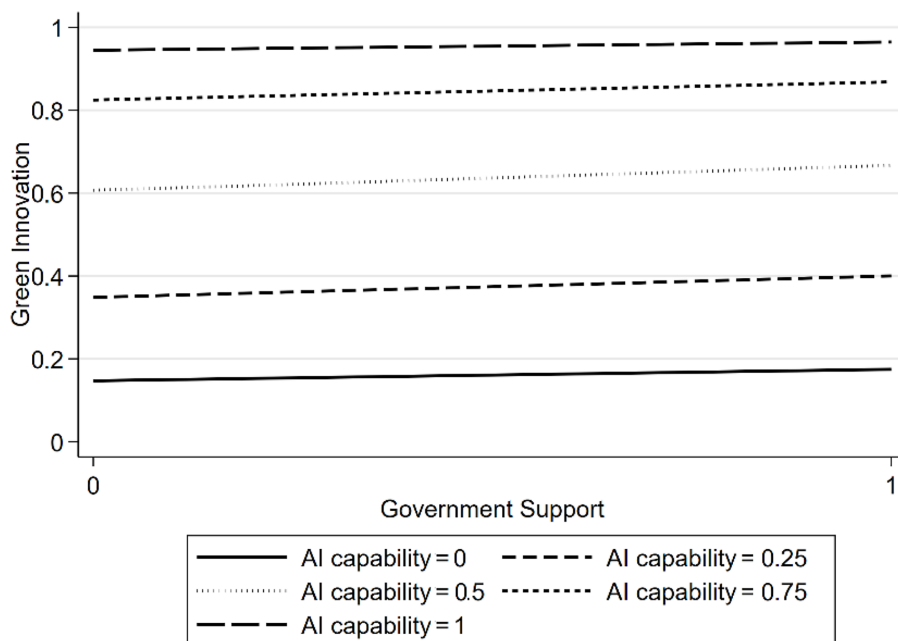


Figure 3. Predicted probability of green innovation by government support, conditional on AI capability (probit marginal effects). Note: Predicted probabilities are derived from probit models with industry and region fixed effects. Lines represent different levels of the AI capability index

by highlighting capability heterogeneity as an important mechanism shaping the direction of innovation outcomes. Overall, the moderation results provide partial support for H2c and clearer support for H2d, indicating that the relationship between policy support and innovation direction is capability contingent rather than uniform across firms.

6.3 Innovation and firm performance

Table 7 (and Appendix Table A2) shows the second-stage results linking overall innovation to firm performance. Innovation is positively associated with both productivity and revenue per employee in the current year and up to four years ahead. Although the magnitude of the coefficient decreases over time, the association remains economically meaningful. Capital intensity is positively associated with performance, while firm size is negatively associated with revenue per employee.

Table 8 (and Appendix Table A3) shows results for brown innovation. Brown innovation is associated with substantial contemporaneous and medium-term gains in productivity and revenue, with particularly large effects on the revenue per employee. These results indicate that efficiency-oriented innovation is strongly correlated with near-to-medium-run performance gains. These findings extend prior work on AI-enabled productivity and digital transformation (Brynjolfsson *et al.*, 2021; Mikalef *et al.*, 2019) by suggesting that the performance implications of innovation differ not only in magnitude, but also in temporal structure. Brown innovation appears more closely associated with immediate efficiency extraction and operational optimization, whereas green innovation is more strongly associated with broader organizational adaptation and sustainability-oriented transformation. This distinction helps explain why firms may continue to prioritize efficiency-oriented AI

Table 7. Second-stage results: overall Innovation and firm productivity

Variables	(1) Log value added per employee (t)	(2) Log value added per employee (t+1)	(3) (t+2)	(4) (t+3)	(5) (t+4)
Overall innovation (t)	0.0897*** (0.0179)	0.0849*** (0.0202)	0.0961*** (0.0203)	0.0874*** (0.0209)	0.0775*** (0.0225)
Log capital (t)	0.124*** (0.00719)	0.107*** (0.00810)	0.115*** (0.00771)	0.105*** (0.00810)	0.0984*** (0.00889)
Log employment (t)	−0.0285*** (0.0107)	0.0135 (0.0122)	−0.0119 (0.0124)	−0.00875 (0.0116)	0.00194 (0.0135)
Industry FE	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES
Observations	5,023	4,819	4,810	4,654	3,433
R-squared	0.239	0.215	0.221	0.217	0.212

Note(s): Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Predicted overall innovation probabilities from the first-stage probit are included as generated regressors following the CDM framework. Industry and region fixed effects included. Robust standard errors reported

Table 8. Second-stage results: Brown Innovation and firm productivity

Variables	(1) Log value added per employee (t)	(2) Log value added per employee (t+1)	(3) (t+2)	(4) (t+3)	(5) (t+4)
Brown innovation (t)	0.345*** (0.0979)	0.280** (0.116)	0.386*** (0.114)	0.338*** (0.113)	0.380*** (0.122)
Log capital (t)	0.126*** (0.00721)	0.109*** (0.00808)	0.117*** (0.00770)	0.107*** (0.00807)	0.0993*** (0.00890)
Log employment (t)	−0.00949 (0.0113)	0.0289** (0.0128)	0.00942 (0.0130)	0.00958 (0.0127)	0.0220 (0.0140)
Industry FE	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES
Observations	5,025	4,820	4,812	4,655	3,435
R-squared	0.238	0.214	0.219	0.215	0.211

Note(s): Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Predicted brown innovation probabilities from the first-stage probit are included as generated regressors following the CDM framework. Industry and region fixed effects included. Robust standard errors reported

investments despite the more persistent long-term benefits associated with green innovation pathways.

Table 9 (and Appendix Table A4) shows results for green innovation. Green innovation is positively associated with both productivity and revenue per employee, with coefficients that are smaller in magnitude than for brown innovation but notably stable over time. This pattern is consistent with the view that sustainability-oriented innovation is linked to more persistent performance benefits.

Overall, these results do not reject H3, H3a and H3b and are consistent with distinct performance dynamics. Brown innovation is associated with larger immediate gains, whereas green innovation is associated with steadier improvements that persist over time. Importantly, these differences in short- and medium-term performance effects should not be interpreted as purely technological superiority of one innovation type over another. Larger immediate gains

Table 9. Second-stage results: Green Innovation and firm productivity

Variables	(1) Log value added per employee (t)	(2) Log value added per employee (t+1)	(3) (t+2)	(4) (t+3)	(5) (t+4)
Green Innovation (t)	0.0905*** (0.0193)	0.0884*** (0.0217)	0.0986*** (0.0220)	0.0902*** (0.0226)	0.0743*** (0.0245)
Log capital (t)	0.124*** (0.00718)	0.107*** (0.00809)	0.115*** (0.00770)	0.105*** (0.00809)	0.0985*** (0.00889)
Log employment (t)	−0.0332*** (0.0109)	0.00875 (0.0124)	−0.0167 (0.0125)	−0.0139 (0.0117)	−0.00170 (0.0137)
Constant	3.037*** (0.136)	2.681*** (0.204)	2.867*** (0.180)	2.906*** (0.151)	2.998*** (0.265)
Industry FE	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES
Observations	5,041	4,836	4,828	4,671	3,444
R-squared	0.239	0.216	0.221	0.217	0.212

Note(s): Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Predicted green innovation probabilities from the first-stage probit are included as generated regressors following the CDM framework. Industry and region fixed effects included. Robust standard errors reported

from brown innovation may reflect capital-deepening, process optimization, demand conditions, or industry-specific production structures, rather than sustainable efficiency improvements *per se*. While our models control capital intensity, firm size, industry, and region fixed effects, unobserved heterogeneity related to sectoral composition or market conditions may still contribute to the magnitude of short-run effects. At the same time, several features of the results are more consistent with a capability-based interpretation than with a purely sectoral or compositional explanation. First, the association between AI capabilities and innovation direction remains robust after controlling for industry and regional fixed effects, suggesting that the observed patterns are not reducible to sector-specific structures alone. Second, the stronger and more persistent association between green innovation and long-term growth is concentrated among firms with higher underlying AI capabilities, which is less consistent with explanations based solely on industry composition or capital intensity. If sectoral structure were the dominant mechanism, one would expect performance dynamics to converge more strongly within industries once controls are introduced. Instead, the results point to firm-level capability heterogeneity as an important differentiating factor shaping how innovation trajectories are associated with performance over time. While these patterns cannot establish causality, they are consistent with the interpretation that AI capabilities may operate as an important organizational conditioning mechanism rather than merely reflecting sectoral composition.

More broadly, these findings contribute to the emerging literature on the bright and dark sides of AI-driven transformation (Canhoto and Clear, 2020; Mancuso *et al.*, 2025) by showing that the consequences of AI-related innovation depend not only on technology adoption itself, but also on the capability structures through which AI is integrated into organizational processes. In doing so, the study moves beyond binary views of AI as either beneficial or harmful and instead highlights how organizational capabilities shape the sustainability orientation and temporal performance dynamics of AI-enabled innovation.

6.4 Innovation and long-term growth

Table 10 (and Appendix Table A5) presents four-year growth regressions. Overall innovation is positively associated with productivity and revenue growth. When disaggregated, green

Table 10. Second-stage results: Innovation types and four-year firm growth (4-year productivity growth)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Four-year growth rate (firm productivity)								
Innovation	0.0236*	0.0948***	0.0275*	–	–	–	–	–	–
	(0.0125)	(0.0195)	(0.0161)						
Brown Innovation	–	–	–	–0.0111	0.488***	0.110	–	–	–
				(0.0234)	(0.102)	(0.0843)			
Green Innovation	–	–	–				0.0571***	0.0917***	0.0294*
							(0.0146)	(0.0200)	(0.0166)
Change in log capital (t_4 - t)	–	–	0.0584***	–	–	0.0600***	–	–	0.0586***
			(0.0158)			(0.0159)			(0.0158)
Change in log employment (t_4 - t)	–	–	0.612***	–	–	0.610***	–	–	0.613***
			(0.0346)			(0.0349)			(0.0344)
Constant	0.162***	–0.00978	–0.00916	0.153***	0.379***	0.0848	0.180***	0.0490	0.0121
	(0.00917)	(0.0941)	(0.0889)	(0.0196)	(0.118)	(0.106)	(0.00972)	(0.0920)	(0.0886)
Industry FE	NO	YES	YES	NO	YES	YES	NO	YES	YES
Region FE	NO	YES	YES	NO	YES	YES	NO	YES	YES
Observations	4,765	4,765	4,610	4,766	4,766	4,611	4,782	4,782	4,627
R-squared	0.001	0.040	0.258	0.001	0.041	0.258	0.003	0.039	0.259

Note(s): Robust standard errors in parentheses*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ Dependent variable: Δ 4-year log value added per employee; industry and region FEs; robust SEs; “ Δ capital” and “ Δ employment” are ($t+4 - t$). Specifications reported separately for overall, brown, and green innovation

innovation is consistently and positively related to long-term growth in both productivity and revenue, whereas brown innovation is not statistically associated with growth once controls and fixed effects are included.

These findings sharpen the dynamic interpretation of the results: sustainability-oriented innovation is associated with longer-term expansion, while efficiency-oriented innovation, despite its short-run performance benefits, is not associated with sustained growth. This pattern is consistent with arguments in the Porter Hypothesis literature (Porter and van der Linde, 1995) but should be interpreted with caution. Rather than providing a direct test of regulatory efficiency effects, our results suggest that sustainability-oriented innovation is more likely to translate into sustained growth when supported by firm-level AI capabilities and complementary organizational resources. This interpretation is reinforced by the fact that the persistence of growth effects is more strongly associated with firms' capability intensity than with observable industry characteristics alone, pointing toward organizational capability heterogeneity as a key differentiating mechanism.

These findings also extend sustainability-transition and capability-based innovation research (Porter and van der Linde, 1995; Castellacci and Lie, 2017) by suggesting that the long-run benefits of AI-enabled innovation depend less on AI adoption alone and more on the capability configurations through which AI is embedded within firms. In this sense, the results support a capability-based interpretation of sustainable digital transformation rather than a purely technology-centric explanation of innovation and growth dynamics.

6.5 AI capabilities and subsequent AI adoption

Finally, Table 11 examines whether baseline AI capabilities are associated with subsequent AI adoption between 2020 and 2023. Across specifications, the marginal effect of AI capabilities on the adoption probability is large and highly significant (approximately 0.53–0.56, $p < 0.01$). This result is consistent with path-dependence dynamics: firms with more developed AI capabilities are substantially more likely to adopt AI technologies in subsequent years. The findings further extend prior AI-adoption research (Horvat et al., 2023; Khanfar et al., 2025)

Table 11. AI Capability and subsequent AI adoption (Marginal effects)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	AI adoption in four years					
AI Capability Index	0.525*** (0.0237)	0.534*** (0.0250)	0.539*** (0.0251)	0.561*** (0.0277)	0.549*** (0.0278)	0.548*** (0.0278)
Log capital (t)	–	–	–	0.00259 (0.00279)	–	–
Log employment (t)	–	–	–	0.00992** (0.00403)	–	–
Change in log capital ($t_4 - t$)	–	–	–	–	–0.00690 (0.00816)	–0.00712 (0.00822)
Change in log employment ($t_4 - t$)	–	–	–	–	0.00130 (0.00901)	–0.00202 (0.0102)
Change in log revenue ($t_4 - t$)	–	–	–	–	–	0.00526 (0.00817)
Industry FE	NO	YES	YES	YES	YES	YES
Region FE	NO	NO	YES	YES	YES	YES
Observations	5,705	5,487	5,477	5,054	4,672	4,658
Pseudo R^2	0.1558	0.1721	0.1775	0.1819	0.1806	0.1808

Note(s): Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Note: AI adoption = 1 if firm employs ≥ 1 AI-skilled worker in 2020–2023 (LinkedIn); SEs (standard error); different combinations of industry and region FEs as indicated

by suggesting that AI diffusion is not merely a discrete technological decision, but part of a cumulative organizational trajectory shaped by pre-existing knowledge structures and absorptive capacities. Firms with stronger initial AI capabilities appear substantially better positioned to sustain subsequent AI adoption, reinforcing the view that digital transformation evolves through path-dependent organizational learning processes. Accordingly, the results provide strong support for [H4](#).

6.6 Robustness check

We conducted a series of robustness checks addressing measurement, specification, and sample heterogeneity. First, we replicated the analyses using alternative constructions of the AI capability index, including a strict and a lenient version. Results were highly consistent across specifications.

Second, we tested alternative definitions of green innovation, focusing separately on green products, green processes, and circular green projects, and excluded firms reporting overlapping innovation types. The main patterns remained unchanged.

Third, all main specifications were estimated with industry and regional fixed effects to account for sectoral and geographic heterogeneity. We additionally examined overlaps between AI capability and government support and found satisfactory common support. Variance inflation factors (VIF) were below conventional thresholds, indicating no problematic multicollinearity. Finally, we replicated performance regressions using log revenue per employee as an alternative outcome measure. These results closely mirror those reported for value-added per employee.

Taken together, these checks indicate that the central patterns documented in the analysis are robust: AI capabilities and government support are jointly associated with firms' innovation trajectories, green innovation is linked to more persistent performance and growth effects, and brown innovation is associated primarily with short-to-medium-term gains. Nevertheless, the robustness analyses should not be interpreted as evidence that the three capability pillars operate independently or symmetrically. The aggregate index is designed to capture broad capability intensity rather than fine-grained configurational effects. More complex complementarities or bottleneck dynamics across tangible, human, and intangible knowledge may still shape firms' innovation trajectories in ways that are not directly observable within the present specification.

7. Conclusion

This study contributes to research on artificial intelligence (AI), innovation, and firm performance by examining how firm-level AI capabilities are associated with firms' innovation trajectories and performance implications. Drawing on the resource-based view, the knowledge-based view, and the Triple Helix Twin perspective, we examine how AI capabilities are associated with different innovation trajectories and performance dynamics across firms.

This study makes several contributions. First, we move beyond binary adoption indicators and equal-weighting approaches by constructing a latent AI Capability Index that integrates tangible, human, and intangible knowledge through factor analysis. This measure reflects the multidimensional nature of AI capabilities emphasized in the management literature and responds directly to concerns about construct validity and measurement overlap in prior empirical work on AI and innovation.

Second, we extend the Triple Helix perspective by empirically examining its "twin" dimension. Rather than treating government support as uniformly beneficial, our findings suggest that the association between public support and innovation outcomes depends on firms' underlying AI capabilities. Among firms with stronger capabilities, government support is associated with a higher likelihood of sustainability-oriented (green) innovation,

whereas among firms with weaker capabilities, government support is more closely associated with efficiency-oriented (brown) innovation. This evidence clarifies how institutional interventions are associated with different outcomes depending on firm-level capabilities and helps reconcile mixed findings in the literature on industrial policy and innovation direction. Conceptually, this positions the Triple Helix Twin as a portable mechanism for understanding capability-contingent policy outcomes, particularly in contexts where broad institutional support interacts with heterogeneous organizational capabilities and where innovation may follow multiple strategic directions.

Third, we separate the performance implications of different innovation paths. Brown innovation is associated with sizable, short- and medium-term improvements in productivity and revenue, underscoring its economic relevance. However, only green innovation is consistently associated with sustained productivity and revenue growth over a four-year horizon. This pattern is consistent with arguments in the Porter Hypothesis literature, but the results also suggest that differences in firm-level AI capabilities help account for why sustainability-oriented innovation is associated with more persistent growth outcomes even after accounting for industry and regional heterogeneity.

Finally, by linking survey data to a large LinkedIn dataset, we show that baseline AI capabilities are strongly associated with subsequent AI adoption. This pattern is consistent with path-dependent dynamics in AI-driven transformation, whereby firms with stronger initial capability foundations appear more likely to deepen their engagement with AI technologies over time. Taken together, the findings suggest that AI adoption, innovation direction, and performance are not independent phenomena, but part of an interrelated capability-building process.

From a managerial perspective, the findings suggest that firms are more likely to realize sustained value from AI when they develop balanced tangible, human, and organizational capabilities rather than focusing narrowly on technology acquisition alone. For policymakers, the results highlight the importance of capability-sensitive support mechanisms, as similar policy interventions may be associated with different innovation trajectories depending on firms' underlying absorptive capacities.

8. Future research

This study opens several avenues for future research on AI capabilities and innovation. One promising direction would be to unpack the internal configuration of AI capabilities more explicitly. While the present study models AI capabilities through a composite index to capture broad system-level capability intensity, alternative approaches could examine complementarities, sequencing effects, and bottlenecks across tangible, human, and intangible knowledge resources. Longitudinal designs would be particularly valuable for tracking how AI capabilities evolve over time and how feedback loops between adoption, innovation, and performance unfold across different stages of organizational transformation. Such designs would allow researchers to examine capability accumulation, persistence, and potential lock-in effects more directly. Second, future work could move beyond aggregate measures of AI adoption to examine specific AI technologies, such as natural language processing, computer vision, or generative AI. Technology-specific analyses would provide more fine-grained insights into how different AI applications are associated with innovation strategies and performance outcomes across industries. Third, the interaction between AI capabilities and other digital technologies, including the Internet of Things, blockchain, and green digital technologies, warrants further attention. Studying these complementarities would contribute to a more integrated understanding of digital transformation and its sustainability implications. Finally, comparative cross-country studies would help assess how institutional, regulatory, and cultural contexts associate the relationships between AI capabilities, innovation direction, and performance. Extending the analysis beyond Italy

9. Limitations

Several limitations should be acknowledged. First, the empirical analysis focuses on Italian firms operating in an institutional environment characterized by a large share of small and medium-sized enterprises. While this context is well suited to studying capability constraints and policy interactions, caution is warranted in generalizing the findings to other national settings. Second, the survey-based measures of AI capabilities are cross-sectional, which limits our ability to observe dynamic capability development directly. Although we complement the survey with longitudinal LinkedIn data on AI adoption and examine multi-period performance outcomes, future research using panel data would allow stronger identification of temporal dynamics. Third, while the LinkedIn-based measure of AI adoption mitigates self-reporting bias and enables longitudinal tracking, it may undercount adoption among micro firms and firms that are less active on professional online platforms. As a result, our adoption analysis is more informative about patterns of path dependence among observable adopters than about the full population-wide diffusion of AI. We therefore interpret the adoption results as evidence of cumulative capability dynamics rather than as a comprehensive census of AI uptake across all firms. Future studies could strengthen measurement validity by triangulating survey responses with administrative data, transaction-level information, or additional digital traces. Despite these limitations, this study provides a comprehensive and empirically grounded account of how AI capabilities, policy support, and innovation orientation are jointly associated with firm performance, and providing a foundation for future research on the strategic and sustainability implications of AI-driven transformation. Accordingly, the relationships documented in this study should be interpreted as theoretically informed associations observed within a specific institutional and empirical setting rather than as definitive causal effects.

About the authors

Syed Muhammad Ali Shah is a post-doctoral researcher in Economics at Università Politecnica delle Marche (Italy). His main areas of interest are artificial intelligence and industrial organization, innovation and new technologies. He is currently working on the adoption of AI in companies, AI investment and metrics, AI-related business model design and firms' co-creation in industrial ecosystems. He has published in topics related to AI identification, AI skill analysis and text-based methods for data analysis.

Michele Cincera is Professor of Industrial Economics at the Solvay Brussels School of Economics and Management – Université Libre de Bruxelles. Since 2012, he has been director of the International Center for Innovation, Technology and Education Studies (iCite). In 2009–2010, he visited EC-JRC-IPTS as a senior scientist. His research interests include quantitative evaluation at the micro level of innovative and entrepreneurial activities, their determinants and socio-economic impacts, as well as the analysis of national innovation systems and policies supporting science, research and innovation.

Marco Cucculelli (PhD Rome) is Professor of Applied Economics at Università Politecnica delle Marche (Italy) and director of the PhD in Economics. He is the Secretary General of the Italian Economic Association and Fulbright Distinguished Chair at the University of Pittsburgh (USA). He held visiting positions at Indiana University, St. Andrews University and Cracow U. of Economics.

He has published on innovation, corporate finance, entrepreneurship and industry studies in several international journals. Marco is an associate editor of *JSBE* and the *Italian Economic Journal*. He is a founding member of the Industry Studies Association. In 2012 he was elected as Director at-large to the Board of the International Council for Small Business, Washington, D.C.

Table A1. Factor structure and reliability of the AI Capability Index

Pillar	Items	Eigenvalue (factor 1)	Variance explained (%)	Cronbach's alpha
Tangible Source of knowledge	21	3.63	17.3	0.743
Human Source of knowledge	11	2.62	23.9	0.640
Intangible Source of knowledge	10	2.54	25.4	0.613

Note(s): Exploratory factor analyses were conducted separately for tangible, human, and intangible knowledge using principal-component factor extraction with one retained factor per pillar. In all cases, a dominant factor emerged with satisfactory loadings (all main loadings ≥ 0.30). Cronbach's alpha is reported for reference, recognizing that the indicators capture heterogeneous organizational practices rather than reflective psychometric scales. Bartlett factor scores were rescaled to the [0,1] interval and aggregated to construct the AI Capability Index (Section 4.2)

Table A2. Second-stage results: overall Innovation and firm performance (log revenue per employee $t \dots t+4$)

Variables	(1) Log revenue per employee (t)	(2) Log revenue per employee (t+1)	(3) (t+2)	(4) (t+3)	(5) (t+4)
Overall Innovation (t)	0.179*** (0.0247)	0.182*** (0.0253)	0.189*** (0.0244)	0.179*** (0.0245)	0.159*** (0.0283)
Log capital (t)	0.176*** (0.00913)	0.156*** (0.00978)	0.160*** (0.00980)	0.160*** (0.0101)	0.143*** (0.0110)
Log employment (t)	-0.167*** (0.0130)	-0.120*** (0.0134)	-0.128*** (0.0136)	-0.122*** (0.0140)	-0.0997*** (0.0163)
Constant	4.063*** (0.214)	3.940*** (0.215)	4.058*** (0.208)	3.958*** (0.209)	4.366*** (0.243)
Industry FE	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES
Observations	5,085	4,972	4,879	4,726	3,469
R-squared	0.350	0.341	0.348	0.342	0.330

Note(s): Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

All columns include industry and region FEs; robust SEs; controls include log capital, and log employment

Table A3. Second-stage results: Brown Innovation and firm performance (log revenue per employee $t \dots t+4$)

Variables	(1) Log revenue per employee (t)	(2) Log revenue per employee (t+1)	(3) (t+2)	(4) (t+3)	(5) (t+4)
Brown Innovation (t)	0.922*** (0.132)	0.858*** (0.138)	0.955*** (0.136)	0.934*** (0.138)	0.965*** (0.159)
Log capital (t)	0.179*** (0.00909)	0.160*** (0.00976)	0.163*** (0.00978)	0.163*** (0.0100)	0.145*** (0.0109)
Log employment (t)	-0.119*** (0.0138)	-0.0742*** (0.0141)	-0.0774*** (0.0142)	-0.0727*** (0.0148)	-0.0498*** (0.0173)

(continued)

Table A3. Continued

Variables	(1) Log revenue per employee (t)	(2) Log revenue per employee (t+1)	(3) (t+2)	(4) (t+3)	(5) (t+4)
Constant	4.669*** (0.229)	4.513*** (0.230)	4.682*** (0.221)	4.559*** (0.222)	4.979*** (0.264)
Industry FE	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES
Observations	5,087	4,974	4,881	4,728	3,473
R-squared	0.349	0.339	0.348	0.342	0.332
Note(s): Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ All columns include industry and region FEs; robust SEs; controls include log capital, and log employment					

Table A4. Second-Stage results: Green Innovation and firm performance (log revenue per employee t . . . t+4)

Variables	(1) Log revenue per employee (t)	(2) Log revenue per employee (t+1)	(3) (t+2)	(4) (t+3)	(5) (t+4)
Green Innovation (t)	0.179*** (0.0265)	0.186*** (0.0272)	0.192*** (0.0261)	0.182*** (0.0263)	0.153*** (0.0300)
Log capital (t)	0.177*** (0.00915)	0.157*** (0.00979)	0.160*** (0.00981)	0.160*** (0.0101)	0.144*** (0.0110)
Log employment (t)	-0.177*** (0.0133)	-0.129*** (0.0137)	-0.137*** (0.0139)	-0.131*** (0.0142)	-0.106*** (0.0166)
Constant	4.185*** (0.214)	4.061*** (0.215)	4.179*** (0.208)	4.071*** (0.209)	4.460*** (0.243)
Industry FE	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES
Observations	5,103	4,989	4,896	4,743	3,482
R-squared	0.348	0.339	0.347	0.341	0.329
Note(s): Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ All columns include industry and region FEs; robust SEs; controls include log capital, and log employment					

Table A5. Second-stage results: innovation type and firm growth (4-year revenue growth)

Variables	(1) Four-year growth rate (firm revenue)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Overall Innovation (<i>t</i>)	0.0304*** (0.0117)	0.110*** (0.0194)	0.0436*** (0.0153)	–	–	–	–	–	–
Brown Innovation (<i>t</i>)	–	–	–	–0.0196 (0.0203)	0.418*** (0.0947)	0.0477 (0.0771)	–	–	–
Green Innovation (<i>t</i>)	–	–	–	–	–	–	0.0763*** (0.0141)	0.115*** (0.0201)	0.0541*** (0.0158)
Change in log capital ($t_4 - t$)	–	–	0.0675*** (0.0179)	–	–	0.0702*** (0.0178)	–	–	0.0665*** (0.0178)
Change in log employment ($t_4 - t$)	–	–	0.548*** (0.0342)	–	–	0.550*** (0.0344)	–	–	0.549*** (0.0340)
Constant	0.171*** (0.00876)	0.126* (0.0748)	0.0321 (0.0807)	0.155*** (0.0169)	0.462*** (0.0986)	0.0814 (0.0955)	0.196*** (0.00938)	0.177** (0.0735)	0.0460 (0.0802)
Industry FE	NO	YES	YES	NO	YES	YES	NO	YES	YES
Region FE	NO	YES	YES	NO	YES	YES	NO	YES	YES
Observations	4,888	4,888	4,715	4,890	4,890	4,717	4,905	4,905	4,732
R-squared	0.001	0.049	0.261	0.001	0.047	0.260	0.005	0.049	0.263

Note(s): Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Dependent variable: Δ 4-year log revenue per employee; industry and region FEs; robust SEs; “ Δ capital” and “ Δ employment” are ($t+4-t$). Specifications reported separately for overall, brown, and green innovation

Table A6. Summary of data sources, variables, and measurement

Construct	Variable(s)	Data source	Measurement/operationalization
AI capabilities	Tangible, human, and intangible knowledge	Firm survey (2019)	Latent factors via principal-component factor extraction; rescaled to [0,1]; aggregated into AI Capability Index
Innovation outcomes	Overall, green, brown innovation	Firm survey (2019)	Binary indicators based on reported innovation activities
Government support	Public support	Firm survey (2019)	Dummy = 1 if firm received subsidies, tax incentives, or grants
Firm performance	Productivity, revenue per employee	AIDA/Orbis	Log value added per employee; growth over t to $t+4$
AI adoption	AI-skilled employees	LinkedIn (2020–2023)	Dummy = 1 if firm employs ≥ 1 AI-skilled worker

Note(s): Detailed factor loadings, reliability statistics, and robustness checks are reported in [Appendix 1](#)

Table A7. Estimates of AI capabilities and government support on brown and green innovation

Variables	(1) Model 1 Brown innovation	(2) Model 2	(3) Model 3 Green innovation	(4) Model 4
AI Capability Index	0.214*** (0.0499)	0.244*** (0.0539)	1.007*** (0.0501)	0.978*** (0.0552)
Government support	0.108*** (0.0305)	0.123*** (0.0313)	0.0881*** (0.0339)	0.0645* (0.0353)
<i>Interaction term</i>				
(AI Capability Index $\times$ Government support)	−0.361*** (0.0878)	−0.379*** (0.0901)	−0.125 (0.0985)	−0.0611 (0.102)
<i>Controls</i>				
Log export turnover	—	0.0104** (0.00436)	—	0.0199*** (0.00470)
Log employment	—	−0.0156** (0.00626)	—	−0.0114* (0.00674)
Log firm age	—	−0.0102 (0.00935)	—	0.0166* (0.0100)
Industry FE	YES	YES	YES	YES
Region FE	YES	YES	YES	YES
Observations	4,780	4,347	4,795	4,352
Pseudo R^2	0.0608	0.0721	0.1225	0.1265

Note(s): Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Dependent variables are indicators for brown innovation (Models 1–2) and green innovation (Models 3–4). AI Capability Index is measured on a 0–1 scale. Government support is a binary indicator equal to one if the firm receives public incentives or grants. Models progressively include firm-level controls. All specifications include industry (2-digit NACE ATECO) and regional fixed effects. Robust standard errors are reported in parentheses. Interaction effects between AI capabilities and government support are assessed using predicted probabilities and illustrated in [Figures 2 and 3](#), as interaction coefficients in nonlinear models are not directly interpretable

Notes

1. Brown innovation refers to technological or process improvements primarily oriented toward efficiency or cost reduction without explicit environmental objectives. This contrasts with environmental (green) innovation, which explicitly targets reductions in environmental impact (see [De Marchi, 2012](#)).
2. The empirical analysis is based on Italian firms; external validity may vary across institutional contexts (see [Section 9](#)).
3. Although the term “brown innovation” is less established in the literature, it is employed here analytically to denote non-environmental and efficiency-oriented innovation paths for conceptual symmetry with “green innovation”.
4. The “Triple Helix Twin” is used here as a capability-contingent analytical extension of the classical Triple Helix framework ([Etzkowitz and Leydesdorff, 1995, 2000](#)), emphasizing how similar policy interventions may coincide with different innovation trajectories depending on firms’ underlying capabilities.
5. For more information on the survey design and data collection procedure, see [Cucculelli et al. \(2024\)](#).
6. These survey items were included to capture knowledge-related dimensions associated with the university–industry component of the Triple Helix framework.
7. The classification dataset consisted of the top 200 skill terms from each category (AI, technical, and soft skills), resulting in a manually labeled dataset comprising 600 skill terms. Skill selection was based on Burning Glass Technologies classifications and aligned with the ESCO framework. The dataset was divided into 80% training data and 20% testing data. Validation results indicate strong classification performance (F1-score = 0.92, precision = 0.90, recall = 0.94), supporting the reliability of the skill-classification procedure. BERT refers to Bidirectional Encoder Representations from Transformers; see [Devlin et al. \(2019\)](#) for methodological details.
8. Our model conceptually consists of three linked stages: (1) capability formation, (2) innovation generation, and (3) performance outcomes. The formation of firms’ AI capabilities is represented by a latent AI Capability Index constructed via factor analysis of tangible, human, and intangible knowledge sources. This factor-analytic step captures the underlying relationships among these knowledge pillars and functions as a measurement stage broadly analogous to the first component of the traditional three-equation CDM framework. The empirical estimation, however, follows a reduced two-stage structural approach.
9. In nonlinear models such as probit, interaction coefficients do not directly correspond to marginal interaction effects. We therefore follow standard practice and interpret moderation effects using predicted probabilities. Full interaction estimates are reported in [Appendix Table A7](#).

References

- Abatecola, G., Allard-Poesi, F., Ataci, T., Cristofaro, M., Kosch, O., Lee, B., Schlaile, M.P., Secchi, D., Szarucki, M. and Xian, H. (2025), “Interactive reflexivity: a means to addressing methodological challenges in international research in management”, *Management Decision*, Vol. 63 No. 13, pp. 272-281, doi: [10.1108/md-11-2023-2107](#).
- Acemoglu, D., Akcigit, U., Hanley, D. and Kerr, W. (2016), “Transition to clean technology”, *The American Economic Review*, Vol. 106 No. 1, pp. 52-104, doi: [10.1086/684511](#).
- Al Halbusi, H., Pérez-González, D. and Abdullah Alsuwaiket, M. (2025), “Exploring the nexus of knowledge management, absorptive capacity and corporate sustainable development: the moderating role of information technology (IT)”, *Business Process Management Journal*, Vol. 31 No. 5, pp. 1684-1702, doi: [10.1108/BPMJ-08-2024-0679](#).
- Almheiri, H., Ahmad, S., Khalid, K. and Ngah, A. (2024), “Examining the impact of artificial intelligence capability on dynamic capabilities, organizational creativity and performance in public organizations”, *Journal of Systems and Information Technology*, Vol. 27 No. 1, pp. 1-20, doi: [10.1108/jsit-10-2022-0239](#).

- Babashahi, L., Barbosa, C.E., Lima, Y., Lyra, A., Salazar, H., Argôlo, M. and Souza, J.M. (2024), "AI in the workplace: a systematic review of skill transformation in industry", *Administrative Sciences*, Vol. 14 No. 6, p. 127, doi: [10.3390/admsci14060127](https://doi.org/10.3390/admsci14060127).
- Block, J., Lambrecht, D., Willeke, T., Cucculelli, M. and Meloni, D. (2025), "Green patents and green trademarks as indicators of green innovation", *Research Policy*, Vol. 54 No. 1, 105138, doi: [10.1016/j.respol.2024.105138](https://doi.org/10.1016/j.respol.2024.105138).
- Bobitan, N., Dumitrescu, D., Popa, A.F., Sahljan, D.N. and Turlea, I.C. (2024), "Shaping tomorrow: anticipating skills requirements based on the integration of artificial intelligence in business organizations—a foresight analysis using the scenario method", *Electronics*, Vol. 13 No. 11, p. 2198, doi: [10.3390/electronics13112198](https://doi.org/10.3390/electronics13112198).
- Brenner, M., Browne, C., Gallen, A., Byrne, S., White, C. and Nolan, M. (2019), "Development of a suite of metrics and indicators for children's nursing using consensus methodology", *Journal of Clinical Nursing*, Vol. 28 Nos 13-14, pp. 2589-2598, doi: [10.1111/jocn.14845](https://doi.org/10.1111/jocn.14845).
- Brown, D., Foroudi, P. and Hafeez, K. (2019), "Marketing management capability: the construct and its dimensions", *Qualitative Market Research*, Vol. 22 No. 5, pp. 609-637, doi: [10.1108/qmr-10-2017-0131](https://doi.org/10.1108/qmr-10-2017-0131).
- Brynjolfsson, E., Rock, D. and Syverson, C. (2021), "The productivity J-curve: how intangibles complement general purpose technologies", *American Economic Journal: Macroeconomics*, Vol. 13 No. 1, pp. 333-372, doi: [10.1257/mac.20180386](https://doi.org/10.1257/mac.20180386).
- Bughin, J. (2023), "Does artificial intelligence kill employment growth: the missing link of corporate AI posture", *Frontiers in Artificial Intelligence*, Vol. 6, 1239466, doi: [10.3389/frai.2023.1239466](https://doi.org/10.3389/frai.2023.1239466).
- Canhoto, A.I. and Clear, F. (2020), "Artificial intelligence and machine learning as business tools: a framework for diagnosing value destruction potential", *Business Horizons*, Vol. 63 No. 2, pp. 183-193, doi: [10.1016/j.bushor.2019.11.003](https://doi.org/10.1016/j.bushor.2019.11.003).
- Castellacci, F. and Lie, C.M. (2017), "A taxonomy of green innovators: evidence from South Korea", *Journal of Cleaner Production*, Vol. 143, pp. 1036-1047, doi: [10.1016/j.jclepro.2016.12.016](https://doi.org/10.1016/j.jclepro.2016.12.016).
- Chowdhury, S., Dey, P., Joel-Edgar, S., Bhattacharya, S., Rodriguez-Espindola, O., Abadie, A. and Truong, L. (2023), "Unlocking the value of AI in HRM through an AI capability framework", *Human Resource Management Review*, Vol. 33 No. 1, 100899.
- Crépon, B., Duguet, E. and Mairesse, J. (1998), "Research, innovation and productivity: an econometric analysis at the firm level", *Economics of Innovation and New Technology*, Vol. 7 No. 2, pp. 115-158.
- Cristofaro, M. and Bañón-Gomis, A.J. (2025), "Dancing with the algorithm: a framework to navigate knowledge and autonomy in AI-assisted managerial decisions", *Journal of Knowledge Management*, Vol. 30 No. 11, pp. 1-31, doi: [10.1108/jkm-06-2025-0870](https://doi.org/10.1108/jkm-06-2025-0870).
- Cristofaro, M., Giardino, P.L. and Muldoon, J. (2025), "Entrepreneurial decision-making in the age of AI: sector knowledge at the balance of intuition and analysis", *Technology in Society*, Vol. 85, 103200, doi: [10.1016/j.techsoc.2025.103200](https://doi.org/10.1016/j.techsoc.2025.103200).
- Cucculelli, M., Cappelli, R. and Mondolo, J. (2024), "Does market power drive business model innovation? Evidence from Italian family manufacturing firms", *Small Business Economics*, Vol. 63 No. 1, pp. 447-475, doi: [10.1007/s11187-023-00834-7](https://doi.org/10.1007/s11187-023-00834-7).
- Dai, J. (2024), "Enhancing corporate innovation through AI adoption: chinese telecommunications", *International Journal of Science and Business*, Vol. 38 No. 1, pp. 18-34.
- De Marchi, V. (2012), "Environmental innovation and R&D cooperation: evidence from Spanish manufacturing firms", *Research Policy*, Vol. 41 No. 3, pp. 614-623.
- Deepa, R., Sekar, S., Malik, A., Kumar, J. and Attri, R. (2024), "Impact of AI-focused technologies on competencies for HR managers", *Technological Forecasting and Social Change*, Vol. 202, 123301.
- Devlin, J., Chang, M.-W., Lee, K. and Toutanova, K. (2019), "BERT: pre-training of deep bidirectional transformers", in *NAACL-HLT 2019*, pp. 4171-4186.

- Du, J. (2024), "AI and your job what's changing and what's next", *Frontiers in Science and Engineering*, Vol. 4 No. 7, pp. 116-124, doi: [10.54691/0dbksd82](https://doi.org/10.54691/0dbksd82).
- Edgeman, R., Bøllingtoft, A., Eskildsen, J., Kallehave, P. and Kjærgaard, T. (2013), "Sustainable enterprise excellence", *International Journal of Social Ecology and Sustainable Development*, Vol. 4 No. 4, pp. 65-76.
- El Ouadghiri, I., Peilleux, J., Platania, F. and Hernandez, C.T. (2026), "Advancing corporate green innovation through science: the role of freedom of expression and NGOs", *Technological Forecasting and Social Change*, Vol. 226, 124577, doi: [10.1016/j.techfore.2026.124577](https://doi.org/10.1016/j.techfore.2026.124577).
- Etzkowitz, H. and Leydesdorff, L. (1995), "The Triple Helix–University-industry-government relations: a laboratory for knowledge based economic development", *EASST review*, Vol. 14 No. 1, pp. 14-19.
- Etzkowitz, H. and Leydesdorff, L. (2000), "The dynamics of innovation: from national systems and 'Mode 2' to a triple helix of university–industry–government relations", *Research Policy*, Vol. 29 No. 2, pp. 109-123, doi: [10.1016/s0048-7333\(99\)00055-4](https://doi.org/10.1016/s0048-7333(99)00055-4).
- Fedyunina, A. and Radosevic, S. (2022), "The R&D–innovation–productivity link in emerging economies: CDM and alternatives", *Economic Systems*, Vol. 46 No. 3, 100998.
- Ferrigno, G., Barabuffi, S., Marcazzan, E. and Piccaluga, A. (2025), "What 'V' of the big data support firms' radical and incremental innovation?", *Technovation*, Vol. 146, 103295, doi: [10.1016/j.technovation.2025.103295](https://doi.org/10.1016/j.technovation.2025.103295).
- Festa, G., D'Amato, A., Palladino, R., Papa, A. and Cuomo, M.T. (2026), "Digital transformation in wine business—from marketing 5.0 to industry 5.0 in the world of wine adopting artificial intelligence", *European Journal of Innovation Management*, Vol. 29 No. 3, pp. 728-744, doi: [10.1108/ejim-04-2024-0465](https://doi.org/10.1108/ejim-04-2024-0465).
- Giachino, C., Cepel, M., Truant, E. and Bargoni, A. (2025), "Artificial intelligence-driven decision making and firm performance: a quantitative approach", *Management Decision*, Vol. 63 No. 10, pp. 3454-3476, doi: [10.1108/md-10-2023-1966](https://doi.org/10.1108/md-10-2023-1966).
- Girma, L., Oduro, S., Cucari, N. and Cristofaro, M. (2025), "Venturing green: the impact of sustainable business model innovation on corporate environmental performance in social enterprises", *Management Research Review*, Vol. 48 No. 13, pp. 20-44, doi: [10.1108/mrr-07-2024-0534](https://doi.org/10.1108/mrr-07-2024-0534).
- Horvat, D., Baumgartner, M., Kinkel, S. and Mikalef, P. (2023), "Examining heterogeneous patterns of AI capabilities", in Alfnes, E., Romsdal, A., Strandhagen, J.O., von Cieminski, G. and Romero, D. (Eds), *Advances in Production Management Systems. Production Management Systems for Responsible Manufacturing, Service, and Logistics Futures. APMS 2023*, Springer, Cham, Vol. 690, doi: [10.1007/978-3-031-43666-6_42](https://doi.org/10.1007/978-3-031-43666-6_42).
- Iansiti, M. and Lakhani, K.R. (2020), "Competing in the age of AI: how machine intelligence changes the rules of business", *Harvard Business Review*, Vol. 98 No. 1, pp. 60-67.
- Kafouros, M. and Aliyev, M. (2016), "Institutions and foreign subsidiary growth in transition economies: the role of intangible assets and capabilities", *Journal of Management Studies*, Vol. 53 No. 4, pp. 580-607, doi: [10.1111/joms.12169](https://doi.org/10.1111/joms.12169).
- Khanfar, A.A., Kiani Mavi, R., Iranmanesh, M. and Gengatharen, D. (2025), "Factors influencing the adoption of artificial intelligence systems: a systematic literature review", *Management Decision*, Vol. 63 No. 10, pp. 3727-3755, doi: [10.1108/md-05-2023-0838](https://doi.org/10.1108/md-05-2023-0838).
- Leemann, N. and Kanbach, D.K. (2022), "Toward a taxonomy of dynamic capabilities—a systematic literature review", *Management Research Review*, Vol. 45 No. 4, pp. 486-501, doi: [10.1108/mrr-01-2021-0066](https://doi.org/10.1108/mrr-01-2021-0066).
- Li, S., Li, X., Zhao, Q., Zhang, J. and Xue, H. (2022), "Dimensional constructs of green innovation: scale development", *Sustainability*, Vol. 14 No. 24, 16919.
- Lisi, W., Zhu, R. and Yuan, C. (2020), "Embracing green innovation via green supply chain learning", *Sustainable Development*, Vol. 28 No. 1, pp. 155-168.
- Liu, L., Zhou, L., Sharma, P., Alzeiby, E.A. and Dash, S. (2026), "Triple helix trust and spillovers for sustainable innovation: the role of governance, openness, and digital infrastructure",

- Technological Forecasting and Social Change*, Vol. 225, 124548, doi: [10.1016/j.techfore.2026.124548](https://doi.org/10.1016/j.techfore.2026.124548).
- Luengo-Valderrey, M.J., Pando-Garcia, J., Perianez-Canadillas, I. and Cervera-Taulet, A. (2020), "Analysis of the impact of the triple helix on sustainable innovation targets in Spanish technology companies", *Sustainability*, Vol. 12 No. 8, p. 3274, doi: [10.3390/su12083274](https://doi.org/10.3390/su12083274).
- Ma, L. and Chang, R. (2025), "How big data analytics and artificial intelligence facilitate digital supply chain transformation: the role of integration and agility", *Management Decision*, Vol. 63 No. 10, pp. 3557-3598, doi: [10.1108/md-10-2023-1822](https://doi.org/10.1108/md-10-2023-1822).
- Mancuso, I., Petruzzelli, A.M., Panniello, U. and Vaia, G. (2025), "The bright and dark sides of AI innovation for sustainable development: understanding the paradoxical tension between value creation and value destruction", *Technovation*, Vol. 143, 103232, doi: [10.1016/j.technovation.2025.103232](https://doi.org/10.1016/j.technovation.2025.103232).
- Mikalef, P. and Gupta, M. (2021), "Artificial intelligence capability: conceptualization, measurement, and effects", *Information and Management*, Vol. 58 No. 3, 103434.
- Mikalef, P., Fjørtoft, S.O. and Torvatn, H.Y. (2019), "Developing an AI capability: a framework for business value", *BIS 2019 Workshops*, Springer, pp. 409-416.
- Nonnis, A., Bounfour, A. and Kim, K. (2023), "Knowledge spillovers and intangible complementarities", *Research Policy*, Vol. 52 No. 1, 104611.
- Noya, S., Taneo, S.Y. and Melany, M. (2023), "Triple helix innovation ecosystem and SME performance", *Quality Innovation Prosperity*, Vol. 27 No. 1, pp. 46-61.
- Porter, M.E. and van der Linde, C. (1995), "Toward a new conception of the environment–competitiveness relationship", *The Journal of Economic Perspectives*, Vol. 9 No. 4, pp. 97-118, doi: [10.1257/jep.9.4.97](https://doi.org/10.1257/jep.9.4.97).
- Randolph-Seng, B., Atinc, Y., Bui, S. and Malik, Z. (2024), "Big data and the disillusioned employee: inside the ethical internet of things", *Technological Forecasting and Social Change*, Vol. 201, 123271, doi: [10.1016/j.techfore.2024.123271](https://doi.org/10.1016/j.techfore.2024.123271).
- Ransbotham, S., Khodabandeh, S., Fehling, R., LaFountain, B. and Kiron, D. (2019), "Winning with AI", *MIT Sloan Management Review*, available at: <https://sloanreview.mit.edu/projects/winning-with-ai/>
- Sallah, C.A. and Caesar, L.D. (2020), "Intangible resources and the growth of women's businesses", *Journal of Entrepreneurship in Emerging Economies*, Vol. 12 No. 3, pp. 329-355, doi: [10.1108/jee-05-2019-0070](https://doi.org/10.1108/jee-05-2019-0070).
- Secundo, G., Spilotro, C., Gast, J. and Corvello, V. (2025), "The transformative power of artificial intelligence within innovation ecosystems: a review and a conceptual framework", *Review of Managerial Science*, Vol. 19, pp. 2697-2728, doi: [10.1007/s11846-024-00828-z](https://doi.org/10.1007/s11846-024-00828-z).
- Sha, X. (2024), "Application of management accounting tools and enterprise value creation based on the value chain", *Sage Open*, Vol. 14 No. 4, 21582440241303219, doi: [10.1177/21582440241303219](https://doi.org/10.1177/21582440241303219).
- Sjödin, D., Parida, V., Palmié, M. and Wincent, J. (2021), "How AI capabilities enable business model innovation", *Journal of Business Research*, Vol. 134, pp. 574-587.
- Stackpole, B. (2026), "What leaders still get wrong about AI", *MIT Sloan Management Review*, 18 May, available at: <https://mitsloan.mit.edu/ideas-made-to-matter/what-leaders-still-get-wrong-about-ai>
- Verma, A., Lamsal, K. and Verma, P. (2022), "Skill requirements in AI/ML job advertisements", *Industry and Higher Education*, Vol. 36 No. 1, pp. 63-73.
- Wang, M., Zhou, J., Xia, X. and Wang, Z. (2022), "Environmental regulation and financing constraints: green technological innovation", *International Journal of Environmental Research and Public Health*, Vol. 19 No. 19, 11972.
- Wang, S., Zhang, Y., Xiao, Y. and Liang, Z. (2025), "AI policy frameworks in China, the EU and the US: a structural topic model", *Technological Forecasting and Social Change*, Vol. 212, 123971.

World Economic Forum (2025), “Impact report January 2025: centre for the fourth industrial revolution network 2023-2024”.

Wu, W., Xu, J., Li, Y., Fan, Y. and Tang, S. (2026), “How AI innovation shapes supplier concentration under the triple helix framework: evidence from emerging markets”, *Technological Forecasting and Social Change*, Vol. 226, 124579, doi: [10.1016/j.techfore.2026.124579](https://doi.org/10.1016/j.techfore.2026.124579).

Zhou, C. and Etzkowitz, H. (2021), “Triple helix twins: a framework for achieving innovation and UN sustainable development goals”, *Sustainability*, Vol. 13 No. 12, p. 6535, doi: [10.3390/su13126535](https://doi.org/10.3390/su13126535).

Corresponding author

Syed Muhammad Ali Shah can be contacted at: s.shah@pm.univpm.it