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Exploring the nexus between artificial intelligence capability, multidimensional intellectual capital, and organizational agility of SMEs

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A B S T R A C T

Artificial intelligence (AI) represents a disruptive technology that is affecting the dynamics of many businesses in ways that will determine their future trajectories and potential ability to navigate uncertain environments. Recent studies have proposed the concept of AI capability (AIC) to capture the strategic ability of firms to integrate and leverage AI in their organizational structures. The emerging literature on AICs is still in its infancy, thus calling for more studies to shed light on their effects on firms and their resources or abilities. This study explores the impact of AICs on the individual dimensions of SMEs' intellectual capital (IC), considering the recent and more comprehensive multidimensional IC construct composed of six dimensions (human, relational, structural, renewal, trust, and entrepreneurial capital) and how these latter influence firms' organizational agility (OA). We adopted a quantitative approach based on PLS-SEM and tested the proposed research model on 376 SMEs in Europe. The findings highlight that AICs positively influence the dimensions of IC and that these, expect for trust capital, enhance SMEs' OA. AICs thus represent relevant opportunities for SMEs to improve their IC, which in turn makes a crucial contribution to their OA. These findings suggest that firms should develop and nurture AICs to harness the potential of AI tools and gain long-term strategic benefits for their IC assets and agility.

Introduction

Artificial intelligence (AI) is a disruptive technology that has emerged globally in recent decades, gaining considerable popularity and becoming a particularly vibrant research topic for scholars (Cimino et al., 2025; Dwivedi et al., 2021; Filippelli et al., 2026; Haenlein & Kaplan, 2019). The growth of the AI market has increased significantly over the years, and projections indicate that it will reach $300 billion by 2026 (Bloomberg, 2021; Fosso-Wamba et al., 2024a) and exceed $1 trillion by 2031 (Statista, 2025; UNCTAD, 2025). AI is therefore essential for firms to stay innovative, remain at the cutting-edge, and avoid being left behind in an ever-changing environment (Tingbani et al., 2025). Innovation in firms is currently strongly influenced by AI, which plays a crucial and positive role in innovation management and multiple aspects of innovation analysis (Kakatkar et al., 2020; Khan et al., 2025; Obreja et al., 2024). Firms are therefore frequently integrating AI into their business models and, in many cases, investing heavily in it to support their growth, performance, and competitiveness (Davenport & Ronanki, 2018).

Notably, AI adoption is changing the sources of competitive advantage of firms (Krakowski et al., 2023), and recent studies have highlighted firms' ability to sustain competitive advantages according to their AI capabilities (AICs)—that is, their ability to integrate AI with organizational structure, culture, and strategy (Zhang et al., 2025). More and more firms are currently channeling resources into AI. As a result, they need to develop a set of complementary resources (e.g., tangible, intangible, and human resources) to apply AI successfully and leverage specific AICs (Colther & Doussoulin, 2024; Drydakis, 2022; Mikalef & Gupta, 2021). The alignment of a firm's resources depends on its specific capabilities; in this view, Teece (2018) has argued that the speed and degree of alignment of a firm's resources are determined by the strength of its dynamic capabilities (DCs).

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AICs are novel capabilities that support the adoption of new approaches based on AI tools for value creation and competitive advantage (Mikalef & Gupta, 2021). AICs represent specific firm abilities organize and manage AI resources. Fosso-Wamba et al. (2024a) recently argued that AICs encompass specific components, including the infrastructure, and several studies have provided evidence of the importance of AICs in improving firm performance (Fosso-Wamba et al., 2024a; Mikalef & Gupta, 2021; Wamba-Taguimdje et al., 2020). AICs are crucial for firms to extract valuable information from large amounts of data, provide fundamental support for managers' decision-making, and enhance employee skills and knowledge in various fields (e.g., innovation and sustainable development; Sahoo et al., 2024; Zhang et al., 2025). As Zhang et al. (2025) have highlighted, this is made possible by intellectual capital (IC) and AICs have been shown to have a positive impact on green IC.

IC represents the sum of intangible assets or resources (including knowledge, skills, and relationships); it plays a key role for firms in leveraging strategic capabilities and, consequently, in gaining significant competitive advantages (Ahmed et al., 2022; Mubarik et al., 2018; Mubarik et al., 2019; Troise et al., 2023). Some studies have shown that specific technology-related capabilities—such as those related to AI, digital platforms (DP), and big data analytics (BDA)—can enhance IC and ultimately organizational agility (OA) through single dimensions of this multidimensional construct (Ahmed et al., 2022; Chu et al., 2006; Mubarik et al., 2019). These studies support the idea that when firms effectively apply these specific technology-related capabilities, they are more likely to enhance their IC resources thanks to the power and enabling role of technologies in improving various business areas, promoting forms of value creation, and enhancing knowledge transfer mechanisms, among others.

Despite recent scholarly interest in exploring AICs, this emerging literature is still in its infancy (Fosso-Wamba et al., 2024a; Mikalef et al., 2022; Sahoo et al., 2024). Most studies have examined large firms, while SMEs have received less attention, which leaves a gap and the need for empirical research to shed light on the dynamics of these smaller firms (Lu et al., 2025b). AICs represent key opportunities for firms to improve their IC and OA. Despite this potential, the effects of AICs in influencing the dimensions of IC have received limited research attention. Many firms currently benefit from the flexibility of new technologies (Lu et al., 2025a)—and AI tools in particular—to face evolving and volatile, uncertain, complex, and ambiguous (VUCA) environments (Troise et al., 2022a), and AICs help firms in their innovation activities as they address volatile industry climates (Petrescu et al., 2022). The literature has already focused on the relationship between AI and OA (Atienza-Barba et al., 2024; Shafiabady et al., 2023), as well as the related improvements for firms; however, there is a lack of empirical evidence of how firms can leverage their AICs to foster the dimensions of IC and, ultimately, OA.

IC is a multidimensional construct that includes not only the traditional three parts—human, relational, and structural capital—but recent studies have underlined the importance of also consider three more recent, and relatively novel, dimensions—entrepreneurial, trust, and renewal capital (Cabrilo et al., 2024). To our knowledge, no previous research has considered this latest and more comprehensive six-part multidimensional IC, which allows for more detailed analysis (Inkinen, 2016; Inkinen et al., 2017), and its relationships with AICs and OA. This study therefore draws on the recent emerging literature on AIC, multidimensional IC, and OA, and it is grounded in DCs theory and OL theory. A quantitative methodology based on the partial-least squares approach to structural equation modeling (PLS-SEM) was adopted in this empirical research, and data were collected from 376 SMEs in the European context.

Our results demonstrate that AICs have a positive and significant impact on the individual dimensions of IC and, at the same time, that these dimensions (except for trust capital) have a positive and significant impact on SMEs' OA. This confirms the crucial role of these AICs in improving SMEs' multidimensional IC, and that the dimensions of the latter, in turn, are crucial for these firms to improve their OA and better navigate uncertain environments.

The remainder of this paper is organized as follows. The following two sections—the theoretical background and hypothesis development—discuss the theoretical foundation of the research and develop the research hypotheses, respectively. These sections are followed by a presentation of the research design used in this study, a description of the analyses conducted, and a presentation of the research findings. The last two sections conclude the paper by first providing a discussion of the results, including their implications, and finally the conclusions, highlighting limitations and future research directions. A list of abbreviations used in this paper is provided in Appendix 1.

Theoretical background

Theoretical foundation

The theories of dynamic capabilities (DCs) and organizational learning (OL) provide the conceptual model for this research. These theories outline specific approaches firms use to leverage AI tools to improve their IC and OA. The DCs theoretical framework describes how organizations evolve by identifying opportunities in the external environment and pursuing them by recombining resources and capabilities (Teece, 2018; Teece et al., 1997). DCs are built on individual and organizational strategies, activities, skills, and knowledge (Teece, 2018). DCs theory is a widely used framework in management research and is recognized as fundamental to understanding the importance of a firm's strategic capabilities (Teece, 2007; Teece et al., 1997). It is usually defined as an extension of the resource-based view and is particularly useful in assessing firms' value creation and capture processes, which are crucial for achieving lasting competitive advantages (Teece, 2007, 2014; Teece et al., 1997, 2016). This takes on further strategic relevance in reference to dynamic environments (Teece et al., 1997), especially those characterized by the advent of disruptive innovations such as AI (Cimino et al., 2025). It is therefore vital for firms to develop and adapt their (internal and external) competencies to respond to changes in the business landscape better and more rapidly (Teece et al., 1997).

DCs theory emphasizes the development and maintenance of superior capabilities to perform operational processes (Schilke et al., 2018). DCs inevitably affect firms' current positions and resources and modify them to varying degrees (Schilke et al., 2018; Zhang et al., 2025). They can affect the internal resources of firms and their routines, thus improving their organizational effectiveness (Zollo & Winter, 2002). DCs thus represent a viable and crucial opportunity for firms to build and adapt their resources, which can explain superior performance and/or improvements in Barreto (2010), Eisenhardt and Martin (2000), Schilke (2014). Firms can therefore modify and improve their resources through their own DCs. DC theory was used in prior research to explain the connection between technology-related capabilities—such as IT, BDA, DP, and AICs—and firm resources, outcomes, and agility (Ahmed et al., 2022; Al-Omoush et al., 2020; Dubey et al., 2019; Fosso-Wamba, 2022; Fosso-Wamba et al., 2024b).

According to Chiva et al. (2014), OL represents how organizations change their models, roles, processes, and knowledge to achieve (or maintain) superior performance. OL is also important and strategic for firms as they accelerate the integration of big data and AI knowledge, which can enhance their organizational knowledge structures. The transformation of individual knowledge into organizational knowledge is enabled by OL (Basten & Haamann, 2018). OL theory emphasizes the key role of knowledge management and learning culture in organizational adaptability, as well as the importance of assimilating knowledge and information to improve organizational capabilities and foster changes in organizational behavior. Some scholars (see e.g., Zhang et al., 2025) support the idea that the accumulation of IC, and its specific variants (e.g., green IC), are significant manifestations of this adaptability.

Several studies have highlighted that OL is a beneficial outcome for firms, and AICs represent a key facilitator here, because they act as a learning mechanism and tool (Su et al., 2022). From this perspective, the recent study by Zhang et al. (2025) suggested that green IC is the result of OL regarding environmental sustainability, and that its components (i.e., human, structural, and relational capital) are necessary for firms to adapt knowledge and skills, as well as to support functions and sharing. Drawing on OL theory, firms are learning organizations that prepare specific knowledge management systems to enhance IC (Mishra et al., 2022). In this study we leveraged these theoretical approaches to develop and test our theoretical model in emerging markets.

AI capability

AI has revolutionized and changed various business functions by automating tasks and improving informed decisions, as well as allowing the development of new capabilities (Petrescu et al., 2022; Sahoo et al., 2024). It is now essential for firms to nurture a culture of AI and strategically integrate it in their businesses; this ability, namely AIC, is crucial for firms to achieve superior performance, create value, and innovate their business model (Fosso-Wamba et al., 2024a; Sjödin et al., 2021; Zhang et al., 2025).

Previous studies have already highlighted the importance of AIC to leverage firm performance. For instance, Wamba-Taguimdje et al. (2020) argued that AI approaches significantly benefit financial, marketing, and administrative performance. As a consequence, AICs positively influence the business value of firms. They also pointed out the importance of management, personnel skills, and AIC infrastructure. Mikalef and Gupta (2021) also reported the impact of AICs on a firm's performance. AICs also have the power to improve both business model innovation and the value offered by the firms (Enholm et al., 2022; Sjödin et al., 2021).

Mikalef and Gupta (2021) define an AIC as "the ability of a firm to select, orchestrate, and leverage its AI-specific resource" (p. 2). This emerging and new concept focuses on the importance for businesses of leveraging the potential of AI tools and realizing value from the implementation and fruition of AI-related projects, rather than focusing only on simple AI adoption (Conboy et al., 2020). In this view, as underlined by Mikalef et al. (2022), it is important to consider all the elements, both technical and organizational, that are necessary for deploying resources effectively toward priority objectives.

Several scholars have proposed various compositions for AICs. For example, Mikalef et al. (2022) highlighted that AIC comprises a set of three AI-related resources: tangible resources (including data and the technological infrastructure to manage them); human resources (i.e., technical and management skills); and intangible resources (e.g., the ability to carry out interdepartmental coordination, organizational changes and risky projects). Fosso-Wamba et al. (2024a) also reported that AIC comprises three key resources—namely, technical and human resources, as well as infrastructure. This classification includes not only AI tools and AI-based algorithms (including related techniques, i.e., technical resources), but also the technological resources to support their application (i.e., infrastructure) and the skills, knowledge, and abilities of personnel to manage them (i.e., human resources).

Multidimensional IC

IC consists of all the intangible and knowledge-based resources that enable firms to function, gain competitive advantages, and create value (Bontis et al., 2000; Chen et al., 2005; Roos & Roos, 1997; Sullivan, 1999). The relationships and knowledge of firms embedded in IC affect their performance (Asiaei & Jusoh, 2015; Mahmood & Mubarik, 2020). Most research has considered IC as a multidimensional construct, which includes several components (Amitrano et al., 2025; Asiaei & Jusoh, 2015; Bontis et al., 2000; Cabrilo & Dahms, 2018). The traditional classification of IC consists of three main dimensions—human capital (HC), relational capital (RC), and structural capital (SC) (Asiaei et al., 2018; Bontis et al., 2000; Hormiga et al., 2011; Matricano, 2016; Troise et al., 2022c). However, recent studies have expanded this classification to provide a clearer and more complete understanding of the components of IC (H. Inkinen et al., 2017); the new components are entrepreneurial capital (EC), renewal capital (RENC), and trust capital (TC) (Buenechea-Elberdin et al., 2017; Cabrilo & Dahms, 2020; Cabrilo et al., 2024; Hussinki et al., 2017).

Human capital

HC comprises the sum of intangible assets relating to the sphere of individuals in organizations, including their knowledge, experience, know-how, skills, capabilities, engagement, and motivation (Bontis, 1998; Edvinsson, 1997; Inkinen, 2016; Inkinen et al., 2017). These intangible components are embedded in employees, who create IC and provide a significant contribution to the organization through these competences and behaviors (Bontis et al., 2000). Bontis et al. (2000) argue that "the essence of human capital is in the sheer intelligence of the organizational members" (p. 88). Employees are a fundamental corporate asset in learning organizations and represent these organizations (Bontis et al., 2000, 2002). HC thus represents a source of renewal and innovation for organizations, one that helps to improve organizational innovation performance thanks to employee engagement, motivation, and experiences (Bontis, 1999; Castro et al., 2013). The qualities of employees, such as their creativity, new ideas, and problem-solving are essential for organizations and organizational performance.

Relational capital

RC refers to the internal and external relationships of an organization. It considers all the stakeholders and thus includes the internal relationships within the organization (e.g., the relationships between the employees) and the relationships with other stakeholders outside the organization (including suppliers, customers, etc.; Bontis, 1998, Bontis et al., 2002; Cabrilo & Dahms, 2018; Mahmood & Mubarik, 2020). These relationships are useful for creating and reinforcing networks, as well as acquiring and assimilating new knowledge and resources (Bontis, 1998). Several scholars have suggested that RC includes not only actual knowledge-based resources within the organizations, but also potential ones related to their networks and social relationships (Cabrilo et al., 2024; Inkinen, 2016). In this sense, RC represents a strategic source of new knowledge and ideas for firms to improve their performance and benefit from the collaboration, trust, and knowledge flows resulting from network ties (Cabrilo et al., 2020). In specific work units, these relationships between employees can assume high quality and strategic importance for mutual benefit in terms of learning and knowledge sharing (Carmeli & Azeroual, 2009).

Structural capital

The concept of SC derives from the stock of non-human-based knowledge possessed by organizations. It represents the internalized knowledge of the firm and incorporates different components such as infrastructural assets, R&D, intellectual property rights (IPRs), and other activities, including those in the sphere of technological innovation (Bontis et al., 2000; Hormiga et al., 2011). Numerous studies have highlighted that SC includes organizational procedures, information systems, databases, manuals, processes, culture, and data (Asiaei & Jusoh 2015; Beltramino et al., 2020; Hormiga et al., 2011; Rehman et al., 2022a). In short, SC is an expression of the processes and organizational value of the firm. SC is part of the firm that owns it and influences both HC and RC, as well as the ultimate innovation efforts of the organization (Beltramino et al., 2020; Cabrilo & Dahms, 2018). SC thus represents a crucial infrastructure for firms to improve their performance, including innovative performance.

Renewal capital

RENC is among the new dimensions recently proposed in the literature (Cabrilo et al., 2024; Hussinki et al., 2017). This dimension has historically been overlooked by scholars, although it has a strong value for businesses (Kianto, 2008; Kianto et al., 2010). RENC represents the set of intangible assets related to the growth and long-range R&D of organizations, thus influencing their performance (Rehman et al., 2022b). It is a human-based component of IC and is a relevant learning capability of organizations that enables them to gain competitive advantages (Buenechea-Elberdin et al., 2017; Rehman et al., 2022a; Ritala et al., 2023). It includes the learning capability of firms and their growth potential, considering both individual and organizational levels (Cabrilo & Dahms, 2020; Inkinen et al., 2017). As reported by Cabrilo et al. (2024), "RENC contains the firm's resources for renewing what it knows and can do through learning" (p. 3). Through RENC, firms can increase their knowledge by creating new knowledge based on existing knowledge (Buenechea-Elberdin et al., 2017).

Trust capital

Scholars have described TC as the level of trust and confidence in organizational networks (Cabrilo et al., 2020). In recent literature, TC has been defined as a key factor for firms to build and strengthen their networks—both internal and external to the organization—and, consequently, their social or relational capital (Cabrilo et al., 2024; Lyu et al., 2022). TC considers the levels of trust and confidence between employees (i.e., internal network), and stakeholders outside the organization (i.e. external network). Most studies have underlined the key role of TC in providing a significant contribution by facilitating knowledge exchange within networks and the development of collaborative behaviors (Inkinen, 2016). These are crucial for organizations, especially considering the importance of collaborative environments. Similarly, scholars have argued that TC allows firms to improve their organizational abilities and, in turn, their knowledge management (Cabrilo et al., 2020). This takes both the exploitation of the basic knowledge already existing within the firm and its ability to source new knowledge from outside and integrate it internally into account.

Entrepreneurial capital

EC is an expression of the entrepreneurial attitude of an organization and, hence, its employees' propensity and orientation toward entrepreneurship (Buenechea-Elberdin et al., 2017). Scholars have proposed that EC represents the level of entrepreneurial attitudes, behaviors, beliefs, and skills of employees, as well as the organizational support that enables them to behave proactively and take risks (Cabrilo & Dahms, 2020; Castro et al., 2013). It considers several abilities that employees have related to the sphere of entrepreneurial orientation and opportunities, including, for example, opportunity discovery (i.e., identifying business opportunities), risk taking (i.e., the propensity to take risks in exploring new and uncertain projects or ideas), and proactivity (i.e., proactively seeking new solutions and leveraging market innovations; Buenechea-Elberdin et al., 2017; Cabrilo & Dahms, 2020; Troise et al., 2022b). These, in turn, also refer to entrepreneurial self-efficacy—that is, "a person's belief that he/she is capable of successfully performing the various roles and tasks of entrepreneurship" (Chen et al., 1998, p. 295). These abilities are essential for employees to engage in entrepreneurial and innovative behaviors, which in turn foster entrepreneurial and innovative thinking and action in the organization, as well as a culture of learning.

Organizational agility

OA is a concept widely discussed in literature. It represents a key organizational asset for firms to improve their performance, competitiveness, and innovation, as well as to gain competitive advantages (Bresciani et al., 2022; Ferraris et al., 2022; Ravichandran, 2018; Troise et al., 2022a). According to Lu and Ramamurthy (2011), it is the ability of firms to "cope with rapid, relentless, and uncertain changes and thrive in a competitive environment of continually and unpredictably changing opportunities" (p. 932). OA allows firms to react promptly and effectively to external changes, as well as to be agile in VUCA environments (Troise et al., 2022a). Over the years, scholars have highlighted how this organizational ability is fundamental for identifying and taking advance of opportunities in VUCA environments by adopting the necessary precautions to deal with uncertain events (Sambamurthy et al., 2003). Though OA, firms can rely on their assets to respond quickly to market changes, new competitors, industry progress, and changing customer demands (Cegarra-Navarro et al., 2016). An organization's OA is thus also related to the development of flexibility. OA enables firms to renew their business and redesign or streamline their business operations; at the same time, it is fundamental for firms in generating information to support management decision-making processes and retrieve strategic knowledge from the business ecosystem.

Hypothesis development

AIC and the multiple dimensions of IC

AI represents a disruptive technology that can transform almost every aspect of an organization. This highly transformative capacity makes it a powerful tool that significantly affects organizational structure and management, including both intra- and interorganizational aspects, thus increasing their productivity and performance (Fosso-Wamba, 2022). While firms require a specific combination of resources to develop AICs (Fosso-Wamba et al., 2024a; Mikalef & Gupta, 2021), these new capabilities in turn affect the organization's resources and their development (Zhang et al., 2025). Several scholars have provided evidence that specific technology-related capabilities (e.g., those related to AI and DP) have significant effects on the various dimensions of a firm's IC (Ahmed et al., 2022; Zhang et al., 2025). We propose that the AIC of firms positively influences the individual components of multidimensional IC.

AIC and HC

Technological advances are changing organizational structures and resources (Yao et al., 2024). New technologies such as AI are influencing the profiles of workers, who need to develop greater skills, competences, attitudes, and flexibility or agility useful to address changes in an uncertain environment (Cimino et al., 2025; Hormiga et al., 2011). Malik et al. (2022) highlighted that AI enhances overall employee job performance and has positive effects on work-related flexibility, autonomy, creativity, and innovation. Currently, AICs represent valuable elements of the firm infrastructure, and their effective application can have significant effects on improving HC. AICs can bring concrete advantages to HC, as technology-related capabilities can effectively improve the firm workforce and the efficiency of employees in completing tasks (Malik et al., 2022).

Firms are massively focusing on AI and therefore assessing its value, as well as investing in specific tools and training, and refining their processes (Arroyabe et al., 2024). These activities enhance the HC of these firms. Recent studies have shown that an AIC facilitates collaborative learning and knowledge sharing among employees, sometimes on specific topics, through dedicated knowledge management systems or intelligent collaboration tools (Fosso-Wamba et al., 2024b; Jarrahi et al., 2023; Zhang et al., 2025). From this perspective, Zhang et al. (2025) argued that virtual learning communities and intelligent knowledge bases can have a crucial role for HC, as they recommend useful and significant resources based on individual needs and learning interests, which in turn can improve employees' understanding and acquisition of knowledge on specific topics (e.g., the environment). AICs can reasonably influence employee motivation and their acquisition of new skills and competences. Deploying these AICs may therefore play a key role for SMEs in improving their HC. Therefore, the following hypothesis is proposed:

Hypothesis 1a. AICs positively influence HC.

AIC and RC

RC includes all the sets of interactions and relationships (internal and external) of organizations with employees and external stakeholders, including customers and suppliers (Bontis, 1998). When firms can leverage technological tools, such as AI systems, to analyze data and share knowledge effectively, this improves their stakeholder communication and thus their RC (Ramadass et al., 2018). Indeed, new technologies can strengthen firms' RC and, consequently, their mechanisms for collaboration and communication with other stakeholders (Ahmed et al., 2022). AICs can thus reinforce firms' network ties and facilitate advances in RC across all their dimensions (Zhang et al., 2025).

AIC allows an organization to access and interpret data quickly and correctly, as well as to learn from data (Haenlein & Kaplan, 2019; Mikalef & Gupta, 2021). This new knowledge and learning, in turn, can be leveraged to forecast trends and adapt to market or industry changes or to achieve strategic objectives. Corporate RC management strategies are refined through this learning and adaptation loop. In sum, AICs can help organizations to improve their RC. The units within firms can better understand each other and trigger collaborative behaviors between employees for problem-solving or with external stakeholders. Therefore, we posit that:

Hypothesis 1b. AICs positively influence RC.

AIC and SC

This IC dimension expresses firms' internalized knowledge and their organizational value based on components such as infrastructures, technologies, IPRs, and R&D (Bontis et al., 2000). AICs can enhance the SC of organizations by combining technological and networking resources. Several scholars support the idea that the effective integration and assimilation of AI in knowledge management can contribute significantly to improving SC and, in particular, technological and organizational infrastructure (Fosso-Wamba, 2022; Zhang et al., 2025). The specific knowledge systems established with AI through data analytics and learning can enable organizations to extract information on specific topics (Bag et al., 2021). The knowledge of specific topics acquired through these systems is also useful for personalizing learning paths and related resources. AICs promote SC, which in turn provides the support infrastructure useful to both HC and RC (Beltramino et al., 2020). This capability can lead firms to improve their information systems to support their operations adequately and facilitate cooperation between employees. We therefore propose the following hypothesis:

Hypothesis 1c. AICs positively influence SC.

AIC and RENC

The development of AICs, and thus the strategic integration of AI, inevitably brings renewal for businesses, which can innovate or improve multiple aspects, including their business model and the value offered (Sjödin et al., 2021). RENC is a strategic learning capability (Buenechea-Elberdin et al., 2017; Ritala et al., 2023), and AICs can enable firms to improve it. Firms can thus improve their knowledge and the related resources for renewing what they know. Likewise, these technology-related capabilities can foster the development and strengthening of resources to renew what can be done through learning. AIC can thus have significant effects on learning organizations and enable them to acquire new abilities and knowledge—thus increasing their knowledge bases. This organizational capacity can also be fundamental to improving organizational innovations and creativity. In line with these arguments, we propose the following hypothesis:

Hypothesis 1d. AICs positively influence RENC.

AIC and TC

TC represents the trust and confidence within organizations and their networks (Cabrilo et al., 2024). AICs can strengthen network ties of firms (Zhang et al., 2025), which, in turn, can affect not only RC but also TC. AIC can in fact facilitate knowledge exchange within organizational networks. Likewise, it can enable firms to develop collaborative behaviors within the organization based on trust among employees, as well as trusted collaborations with partners and other external stakeholders (Inkinen, 2016). Firms can thus facilitate the search for new knowledge in the external environment through AICs, as well as the integration of that knowledge with the existing knowledge base. AICs can thus have significant effects on organizations' TC and, consequently, on their knowledge management (Cabrilo et al., 2020). Presumably, AICs could help build trust through how firms operate and consider their stakeholders' interests in decision-making, which in turn increases corporate reputation and trust in those stakeholders. Based on these arguments, we posit that:

Hypothesis 1e. AICs positively influence TC.

AIC and EC

Exploring the intersection of AI and entrepreneurship is an emerging and lively topic in current research. For example, Chalmers et al. (2021, p. 1028) argue that AI influences the organizational design of entrepreneurial ventures and replaces several tasks such as idea production, sales, and scaling. The recent literature review by Uriarte et al. (2025) underlined the crucial role of AI in the creation of new entrepreneurial opportunities and reshaping the entrepreneurial process. The enormous potential of AI is opening up many avenues for entrepreneurship, providing more and more opportunities for different people, such as employees, to develop their own ideas, creativity, solutions, and new knowledge. Stakeholders can also better identify new business opportunities in the market and exploit innovations through facilitated data analytics with AI. The increased skills and knowledge enhanced by AICs, and thus the ability to leverage AI tools, can lead employees to reveal entrepreneurial attitudes, beliefs, behaviors, and greater initiative proactively; they can in fact gain a strengthened belief in their abilities to complete entrepreneurial tasks successfully. Similarly, significant AI management and assimilation can facilitate the proactiveness and risk-taking propensity of employees. The massive diffusion of AI is indeed leading firms to increase their ability to manage and assimilate it, as well as their risk-taking orientation (Fosso-Wamba, 2022). We therefore posit that:

Hypothesis 1f. AICs positively influence EC.

The multiple dimensions of IC and OA

Numerous studies have been conducted on the interconnection between IC and OA, demonstrating that it is a key factor in enhancing OA (Ahmed et al., 2022; Alhosani & Ahmad, 2024; Soomro & Soomro, 2024; Zhang et al., 2025). These studies have provided evidence that individual dimensions of IC significantly influence firms' OA, albeit to varying degrees.

HC and OA

Several studies have highlighted the existing relationships between the HC and OA (Dyer & Shafer, 2003), finding that HC represents a successful factor for firms to achieve OA (Ahmed et al., 2022). Employees provide their skills and knowledge to address the challenges of an ever-changing environment (Lu et al., 2023); these competences then allow organizations to better navigate VUCA environments. Investments in HC and specific training or upskilling of existing employees can enable firms to be better equipped for these dynamic environments. The following hypothesis is therefore proposed, in line with existing research:

Hypothesis 2a. HC has a positive effect on the OA of SMEs.

RC and OA

Several scholars have shown that RC is a crucial antecedent of OA (Ahmed et al., 2022; Troise et al., 2022a). This specific ability to develop and maintain relationships with internal and external parties or stakeholders significantly influences firms' OA and their trajectories in the market (Nyamrunda & Freeman, 2021). Firms can strategically leverage specific networks for OA development; similarly, to improve their OA, they can focus their efforts on communication and knowledge exchange. Based on previous studies, we propose that:

Hypothesis 2b. RC has a positive effect on OA of SMEs.

SC and OA

Given rapid technological advances, firms need to improve their SC to face the dynamic environment. SC is the stock of knowledge that remains in the firm, which owns that knowledge, thus allowing it to have a fundamental factor in dealing with changes in the business environment. The assets included in SC—such as IPRs, knowledge, and R&D—constitute a vital resource endowment for businesses (Bontis et al., 2000; Hormiga et al., 2011) and represent a useful infrastructure for obtaining future competitive advantages. This infrastructure significantly helps businesses achieve OA and, in turn, improve their performance. Firms with greater availability of these assets and knowledge can leverage them to achieve greater OA with greater effectiveness and speed. We therefore posit that:

Hypothesis 2c. SC has a positive effect on OA of SMEs.

RENC and OA

RENC represents a firm's fundamental learning capability to attain competitive advantages (Buenechea-Elberdin et al., 2017; Cabrilo et al., 2024). Firms need to renew their resources to keep up with the times and maintain their competitiveness. This capacity for renewal is strategic and inevitably linked to improving firm agility. New knowledge created through learning can facilitate business navigation in uncertain environments; as learning organizations, firms can better adapt to challenges through their improved capabilities and knowledge, which allow them, for example, to modify their strategies, business models, or value propositions rapidly. Hence, we assume that:

Hypothesis 2d. RENC has a positive effect on OA of SMEs.

TC and OA

Trust is an important component of internal and external relationships between stakeholders (Lyu et al., 2022). Higher levels of trust can foster knowledge exchanges and collaborations (Inkinen, 2016). Trusted party networks can drive improvements in firm OA. TC enables firms to operate actively in collaborative environments and have a support base to cope with VUCA environments. Improved organizational abilities and knowledge management could be crucial to improving the OA of SMEs. Based on the above, we propose the following hypothesis:

Hypothesis 2e. TC has a positive effect on OA of SMEs.

EC and OA

Employees who demonstrate a strong attitude and high level of commitment to entrepreneurship can also proactively cultivate an innovation and learning culture (Cabrilo & Dahms, 2020; Castro et al., 2013). These factors, together with their ability to engage in potential risks, are relevant elements for firms to increase OA. Risk-taking propensity and the capability to tolerate risk are crucial when facing a volatile market and, in general, uncertain environments. Similarly, proactivity represents a necessary condition for operating in these scenarios and achieving a higher level of agility. Finally, employees with a greater spirit of initiative, idea development, problem-solving, and knowledge management can contribute significantly to improve SMEs' OA. Accordingly, we propose that:

Hypothesis 2f. EC has a positive effect on OA of SMEs.

The final conceptual model of this research is depicted in Fig. 1. This proposed conceptual model suggests direct relationships between AICs and the dimensions of multidimensional IC, and ultimately, the firm's OA.

Research design

Sample

European SMEs were surveyed for this research. As is well known, economic development is closely linked to these firms, which represent almost all entrepreneurial initiatives in Europe (approximately 99 % of firms; European Commission, 2024). We decided to focus on SMEs, as these ventures represent flexible and agile businesses thanks to their structure, which is useful in adapting to changes (Bresciani et al., 2024; Troise et al., 2022a).

In line with previous studies in the emerging field of AICs (e.g., Fosso-Wamba et al., 2024a), we collected data through a web-based survey among firms that disclosed AI adoption in their businesses. This process of identifying relevant firms that could fall into this category for the survey was conducted before the launch of the survey itself and through an analysis of the firms' public channels. Specifically, we focused on firms that had declared they had adopted AI in their businesses for at least 3 years. This process avoided firms that had recently implemented AI or had only been implementing it for a short time (1–2 years); the firms considered were thus likely to have seen some effects, even if only in the short term. To assess the correctness, familiarity with the topics, and understanding of the respondents, we conducted an initial pilot testing with five SMEs—which had adopted AI—included in the authors' contacts, who made themselves available to provide feedback on the questionnaire. Based on their comments, we refined and improved the readability of some parts of the questionnaire, the reliability of the constructs used to measure specific aspects of the organization, and corrected some typos. Measures were also adopted to reduce potential bias (e.g., retrieval, social desirability, and common method biases; Podsakoff et al., 2003; Saunders et al., 2009). The questionnaire included an opening message describing the academic initiative and the specific objectives of this study, as well as information on the anonymity of the questionnaire. Furthermore, we intermixed the survey items (i.e., varied their order) in the questionnaire.

We distributed 600 questionnaires between June 2025 and July 2025 leveraging several online channels (e.g., emails, LinkedIn, Facebook, and specific contact or messaging sections present on firm websites). Of these, 397 were returned, and 376 were valid and complete (while the rest had missing information). The SMEs included in the final sample were, on average, 9 years old, had between 50 and 100 employees, were mostly small businesses with a turnover of less than five million euros, and belonged primarily to the service and manufacturing sectors. Italy was the European country most represented in the sample.

At the end of the data collection, we verified both the quality of the responses and tested for potential non-response bias. Regarding the former, we assessed the presence of possible biases related to insufficient effort responses (IER; DeSimone et al., 2015; Huang et al., 2012). We assessed both the presence of systematic IER, through the presence of long strings, and the random component, through the Mahalanobis distance. In both cases, we found the absence of systematic and random IER in our dataset. Regarding non-response bias, we adopted the two-wave procedure (Armstrong & Overton, 1977) by comparing early and late respondents. We found that non-response bias was not a problem in this research.

Measures

After general and demographic information about their firms,

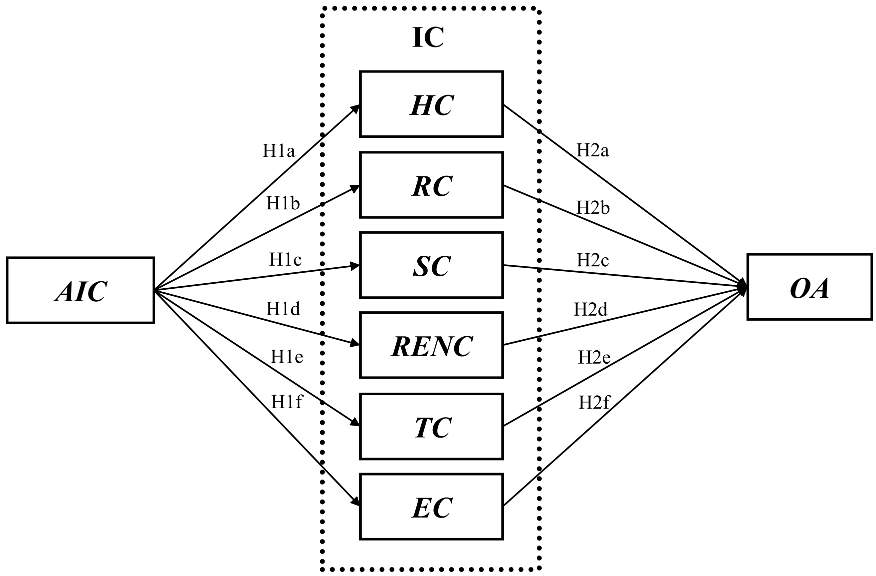

Fig. 1. Conceptual model.
Source: own elaboration

participants had to indicate on a scale from 1 (*strongly disagree*) to 7 (*strongly agree*) their level of agreement on a series of items. The measures adopted in this study were measured on 7-point Likert scales; they were retrieved from the existing literature. Table 1 reports the information on measurement items and sources for each construct. For the construct AIC, we used a second order construct—which included AI infrastructure, human, and technical resources—and adopted the scales provided by the study of Fosso-Wamba et al. (2024a) and adapted from previous studies (Chakravarty et al., 2013; Chen, 2012). To measure the multiple dimensions of IC, we adopted the latest and most comprehensive classification provided by the literature, which includes six dimensions, namely HC, RC, SC, EC, TC, and RENC (Cabrilo et al., 2024; Hussinki et al., 2017). The measurement items used for each dimension were based on established research (see Table 1). Finally, OA was measured with the scale adopted from previous research (Cegarra-Navarro et al., 2016; Troise et al., 2022a).

Analysis and results

Data analysis

We analyzed the data using PLS-SEM (Hair et al., 2017), and analyses were performed using the software SmartPLS 4.0 (version 4.1.1.3). As reported in many studies, this specific technique represents a robust and flexible approach particularly suited to exploratory research and to dealing with small sample sizes without any assumptions about the distribution of the data, thus making it possible to test models without sampling restrictions (Hair et al., 2017; Hair et al., 2019; Willaby et al., 2015).

Given the cross-sectional nature of the survey used for this research and the online survey method for data collection, a potential for common method bias (CMB) may have been created that could affect subsequent analyses. We therefore controlled for the potential problem of CMB, and the results showed that the model does not appear to suffer from it. We used Harman's single-factor test (Podsakoff et al., 2003), and the first factor extracted did not exceed the thresholds. By adopting the approach based on full collinearity variance inflation factors (VIFs), we also found that the highest value for the full VIF was 3.2 and thus below the conventional threshold (Hair et al., 2019). Following Hair et al. (2019), we used a two-stage assessment process. First, we focused on the assessment of the measurement model; this allowed us to check the validity and reliability of the constructs. Second, we focused on assessing the structural model; the latter made it possible to assess the predictive power of the model and our research hypotheses.

Measurement model

To assess the measurement model, we first examined the reliability of the indicators and constructs—that is, their convergent and discriminant validity (Hair et al., 2019). In our case, all the indicators, except two items relating to the AIC dimension, were above 0.71, thus exceeding the threshold; however, the two items below this threshold were above 0.6 and could therefore be considered acceptable for exploratory research (Hair et al., 2011). Second, we evaluated the constructs' reliability (Hair et al., 2019); following this approach, we analyzed composite reliability, Cronbach's alpha, and Dillon-Goldstein's rho (Hair et al., 2017). All the values were above 0.8, as shown in Table 2, thus exceeding the traditional threshold of 0.6. This step was followed by analysis of the average variance extracted (AVE) to assess convergent validity; all values were above 0.57 and, also in this case, exceeded the threshold. Finally, we examined the discriminant validity through the heterotrait–monotrait (HTMT) method and, as reported in Table 3, all the values were below the threshold of 0.9 (Henseler et al., 2015).

Structural model and hypotheses testing

The quality of the structural model was assessed by examining the structural path coefficients through bootstrapping with 5000 resamples, and the predictive power of the constructs through the R^2 (Chin, 1998a, 1998b; Hair et al., 2011; Hair et al., 2017). The predictive power of the model constructs in general was moderate and above the thresholds suggested in the literature (the highest R^2 was 0.657 for OA). The only two exceptions were RENC, which presented weak predictive power ($R^2 = 0.253$), and TC with a very low predictive power ($R^2 < 0.2$).

The path coefficients and results of the hypothesis testing are reported in Table 4. The results support the proposed hypotheses of the model, except for H2e. AIC has a positive and significant impact on the six dimensions of IC (all with $p = 0.001$, expect for TC with $p = 0.05$) thus supporting all the sub-hypotheses of H1 (i.e. H1a, H1b, H1c, H1d, H1e, H1f); in fact, AIC positively influences the three traditional dimensions of IC, namely HC ($\beta = 0.605$), RC ($\beta = 0.573$), and SC ($\beta =$

Table 1
Measurement items and scale.

Constructs	Measurement Items	References	Example of items
Artificial Intelligence Capability (AIC)	18	Fosso-Wamba et al. (2024a)	"The employees of AI functions have ability to lead and manage AI functions and projects"; "The employees of AI functions have ability to understand the business needs of other business functions"; "We have extensively invested in building our AI infrastructure"; "We regularly update our IT assets"
Human capital (HC)	5	Youndt and Snell (2004); Yang and Lin (2009))	"Our employees are highly skilled"; "Our employees are experts in their particular jobs and functions"
Relational capital (RC)	6	Cabrilo et al. (2020), (2024); Hussinki et al. (2017); Kianto (2008); Kianto et al. (2010)	"Our employees frequently collaborate to solve problems"; "Our company and its external stakeholders – such as customers, suppliers and partners – understand each other well"
Structural capital (SC)	4	Cabrilo et al. (2024); Kianto et al. (2010)	"Our company has tools and facilities to support cooperation between employees"; "Our company has efficient and relevant information systems to support business operations"
Entrepreneurial capital (EC)	6	Buenechea-Elberdin et al. (2017); Cabrilo et al. (2024)	"Our employees are excellent at identifying new business opportunities"; "Our employees have the courage to make bold and difficult decisions".
Trust capital (TC)	4	Hussinki et al. (2017); Kianto et al. (2010)	"The way our company operates is characterized by an atmosphere of trust"; "The expertise of our company inspires trust in stakeholders"
Renewal capital (RENC)	4	Cabrilo et al. (2024); Kianto et al. (2010)	"The operations of our company can be described as creative and inventive"; "Our company has acquired a great deal of new and important knowledge"
Organizational agility (OA)	6	Cegarra-Navarro et al., 2016; Troise et al., 2022a	"We have the ability to respond rapidly to customers' needs"; "We rapidly implement decisions to face market changes"

Source: own elaboration.

Table 2
Validity and reliability evidence.

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AIC	0.947	0.948	0.953	0.533
HC	0.861	0.866	0.900	0.643
RC	0.917	0.918	0.935	0.707
SC	0.924	0.930	0.946	0.814
RENC	0.863	0.863	0.908	0.713
TC	0.809	0.998	0.864	0.616
EC	0.921	0.923	0.939	0.718
OA	0.849	0.856	0.889	0.573

Source: own elaboration.

0.613), ($p < 0.001$), as well as the three new dimensions, namely RENC ($\beta = 0.485$), TC ($\beta = 0.175$), and EC ($\beta = 0.728$). The minor effect is visible on TC, which highlights the small effect of AIC on this IC dimension, while its effects on the other dimensions are—at various levels—more or less high. These results underline that AIC represents a relevant factor for SMEs to enhance IC.

Our analysis revealed that these dimensions of IC positively influence SMEs' OA; they all have a significant impact, expect for TC, which was not statically significant, thus not supporting our H2e. Our results did, however, support all of the other hypotheses: H2a ($\beta = 0.294$, $p < 0.001$), H2b ($\beta = 0.115$, $p < 0.05$), H2c ($\beta = 0.186$, $p < 0.05$), H2d ($\beta = 0.141$, $p < 0.05$), and H2f ($\beta = 0.279$, $p < 0.001$). These five dimensions of IC (i.e. HC, RC, SC, RENC, and EC) are therefore relevant factors in improving SMEs' OA.

Discussion and implications

Discussion

The results of our research highlight that AICs have positive and significant effects on the dimensions of IC, although to different extents. This confirms that these capabilities play a crucial role for SMEs to improve their overall IC. These findings confirm our theoretical argumentations and research hypotheses (H1a, H1b, H1c, H1d, H1e, and H1f), and they also provide evidence that SMEs leveraging AICs are more likely to enhance the different dimensions of their IC. The greater the AIC, the greater the improvements in IC. Firms that nurture and disclose an ability to integrate and leverage AI have benefits for their IC. Among the dimensions of IC, the one most influenced by AICs is EC, which is among the new recent dimensions included in the multidimensional IC construct (Cabrilo et al., 2024; Hussinki et al., 2017). This finding shows how AICs are affecting the entrepreneurship domain and

Table 3
Heterotrait-Monotrait ratio (HTMT).

	AIC	EC	TC	OA	RC	RENC	SC	HC
AIC								
EC	0.777							
TC	0.168	0.133						
OA	0.724	0.682	0.292					
RC	0.607	0.518	0.275	0.645				
RENC	0.532	0.381	0.226	0.606	0.498			
SC	0.643	0.502	0.292	0.782	0.626	0.580		
HC	0.650	0.490	0.431	0.803	0.569	0.518	0.898	

Source: own elaboration.

Table 4
Path coefficient and hypotheses testing.

HPs	Path	β	Sample mean (M)	SD	T_stat	2.50 CI	97.50 CI	Support
H1a	**AIC ➔ HC**	0.605***	0.608	0.046	13.208	0.511	0.692	YES
H1b	**AIC ➔ RC**	0.573***	0.576	0.049	11.612	0.475	0.668	YES
H1c	**AIC ➔ SC**	0.613***	0.614	0.049	12.616	0.510	0.702	YES
H1d	**AIC ➔ RENC**	0.485***	0.486	0.057	8.527	0.366	0.590	YES
H1e	**AIC ➔ TC**	0.175**	0.191	0.082	2.134	0.044	0.324	YES
H1f	**AIC ➔ EC**	0.728***	0.730	0.032	22.794	0.664	0.789	YES
H2a	**HC ➔ OA**	0.294***	0.297	0.082	3.601	0.132	0.454	YES
H2b	**RC ➔ OA**	0.115**	0.116	0.055	2.090	0.007	0.222	YES
H2c	**SC ➔ OA**	0.186**	0.181	0.087	2.146	0.015	0.353	YES
H2d	**RENC ➔ OA**	0.141**	0.144	0.056	2.533	0.035	0.253	YES
H2e	**TC ➔ OA**	0.017	0.022	0.048	0.357	−0.077	0.112	NO
H2f	**EC ➔ OA**	0.279***	0.279	0.061	4.607	0.157	0.393	YES

Note:
** $p < 0.05$.
*** $p < 0.001$. *Source*: own elaboration.

empowering employees to act proactively. These capabilities—and therefore the ability to exploit and manage AI tools—positively influence employee behavior, as employees demonstrate greater initiative, creativity, ideas, innovation, problem-solving, and confidence in their entrepreneurial abilities, particularly thanks to their new knowledge and skills. This confirms the strategic potential of AICs in contributing to the creative process and innovation (Mikalef & Gupta, 2021).

In addition to EC, the other dimensions that are most affected and benefit from AICs are the three traditional dimensions of IC—namely SC, HC, and RC. This confirms that SMEs benefit from the effects of AICs on several components, including their relationships, intangible assets related to employees (i.e., knowledge, skills, and motivation), or internalized knowledge of organizations (i.e., infrastructures, technologies, IPRs, and R&D). AICs thus enhance both the human and non-human-based knowledge possessed by organizations. Finally, it should be noted that among the various components of the IC, AICs have the least impact on TCs, although they do enable firms to develop TC in some respects. This shows that employees' trust grows through specific capabilities, but it is a weak component. Some scholars have therefore argued that specific capabilities related to AI contribute to the development of trust in organizations (Glikson & Woolley, 2020) but some limits still exist given that characteristic aspects of AI can influence employees and their behavior (e.g., concerns about information/data security or privacy, as well as other concerns; Malik et al., 2022).

Our findings also indicate that the dimensions of IC are key drivers of enhancing the OA of SMEs. Our findings are thus consistent with the existing literature, where previous studies have demonstrated the importance of IC in determining OA (Ahmed et al., 2022; Zhang et al., 2025). In our study, all IC dimensions had significant positive effects on SMEs' OA, except for TC, the effect of which was not statically significant. The latter is a new construct that has only recently been considered independently, while in the past it was included in the RC (or social capital), we therefore have no references in the literature regarding it, unlike the other components of IC (Cabrilo et al., 2020; Hussinki et al., 2017b; Inkinen et al., 2015, H. 2017). HC is the IC dimension with the greatest impact on OA, followed by EC. This confirms the importance of HC for improving OA (Ahmed et al., 2022; Dyer & Shafer, 2003). Similarly, the positive impact of EC highlights that OA is fostered by increased levels of proactivity, creativity, innovation, and risk-taking, which are crucial for SMEs to cope with uncertain environments and react quickly to unpredictable changes.

Theoretical implications

Our research provides several implications for theory. From a theoretical perspective, this study contributes extends both DCs and OL theories by investigating the effects of AICs on IC components and the effects of those components on SMEs' OA. The exploration of AICs represents a novel lens for examining the theories of OL and DCs, as well as their new connections. Our theoretical implications are thus in line with the new trends in the literature and, in particular, the progress of studies in the AI era (e.g., the recent studies by Zhang et al., 2025). Our findings highlight the direct relationship between AICs and the dimensions of IC. Our study is among the first to adopt the AIC construct composed of three subdimensions (AI infrastructure, human resources, and technical resources) proposed by recent studies, which represents a more comprehensive and nuanced configuration of this specific capability. Our research thus also contributes to the emerging literature on AIC (Fosso-Wamba et al., 2024a, 2024b; Mikalef et al., 2022; Mikalef & Gupta, 2021; Sjödin et al., 2021) by adopting this new AIC configuration and testing it on the dimensions of IC. More specifically, we have shed light on the role of AICs in fostering IC, thus broadening the scope of how IC is developed through the lens of firm capabilities. Hence, this research provides both a contribution to the research field focused on DCs theory while enriching the emerging AICs literature (Fosso-Wamba, 2022).

Concerning the dimensions of IC, our study is one of the first to expand the literature and contribute to advancing existing research by examining the new proposed multidimensional IC components, while many studies have focused on the traditional three-dimensional structure made up of HC, RC, and SC. Our study thus tried to better frame and capture the effects of all IC dimensions individually; in doing so, this study is among the first to separate the individual dimensions of IC and examine both their outcomes on OA and the effects of AIC on them. The dimensions of IC—apart from TC—are instrumental for SMEs to achieve OA, thus supporting our theoretical argumentations. However, the dimension TC seems to suffer from its novelty as an independent construct (i.e., separated from relational or social capital).

Practical implications

This research also has several practical implications. Investment in AI is currently growing exponentially, but firms should develop and cultivate specific AICs to harness the potential of AI tools. While developing AICs requires specific investments (notably in the three AI components described above), firms should recognize that these in turn will enhance firms' IC resources with long-term strategic benefits and, consequently, greater agility. Interestingly, our results show that AICs are determinant in improving EC and HC, which in turn are the main components of IC to enhance the OA of SMEs. Despite the so-called "liabilities of technological leverage" and the fact that several AI-enabled firms, with many customers, are controlled by a few employees (Chalmers et al., 2021), EC represents the IC dimension with the greatest impact. Firms need to acknowledge the importance of AICs to foster the different dimensions of IC, which, in turn, have significant repercussions on their ability to navigate uncertain environments.

Firms that aim to improve their IC assets should therefore focus on developing AICs. From this perspective, for example, firms could support EC through AICs thanks to their strategic contribution to creative processes and innovation (Mikalef & Gupta, 2021). Firms must now nurture digital transformation and embrace AI; the development of an AI orientation within the firm is now a necessary precondition for successful deployments. Based on the above discussions, this study could be relevant in providing strategic guidance to managers and other stakeholders who plan to develop or invest in AI-based business projects. Managers and stakeholders should focus their efforts on deploying dedicated strategies supporting AICs and, ultimately, agility practices. The selection of AI deployment strategies is crucial for firms, as highlighted in previous research (Uriarte et al., 2025). AICs can be a crucial factor in guiding and shaping strategic direction, while ensuring resilience in uncertain environments (Cimino et al., 2025).

Finally, the findings also have implications for policymakers, governments, authorities, universities, incubators/accelerators, and other stakeholders, who should focus their efforts on the importance of investments in AI resources and infrastructure (Fosso-Wamba, 2022). These actors, particularly policymakers, must create specific programs and formulate ad hoc incentive policies to support the widespread adoption of AICs across all sectors and create supportive environments for the development of AI-driven capabilities and strategies. These actors should also promote a strong orientation toward learning, as it is fundamental to the transformation of firms as well as broader society.

Conclusions, limitations, and future research

Conclusions

AI has recently become a "hot" topic for scholars and has emerged as one of the most discussed disruptive technologies in current literature. Its impact on businesses needs to be thoroughly explored. Despite growing academic attention, scholars know very little about the role of AICs for organizations. The concept of AICs is still underexplored in the broader literature of firm capabilities, and there is a pressing need to further examine their effects on firm dynamics. Currently, there are only a few studies that focus on AICs and provide initial evidence on their relationships with firm performance (Fosso-Wamba et al., 2024a; Zhang et al., 2025). These studies call for more research to advance the collective understanding of the importance of AICs. Our research sheds some light on the role of AICs in influencing the multidimensional IC of SMEs and, ultimately, firm OA. We thus contribute to the current literature by exploring the impacts of AICs on individual dimensions of IC based on the recent and comprehensive classification made up of six dimensions—namely, HC, RC, SC, RENC, TC, and EC (Cabrilo et al., 2024; Hussinki et al., 2017; H. Inkinen et al., 2017)—and how these dimensions of IC, in turn, influence the OA of SMEs.

Limitations and future research directions

This study has some limitations that could represent opportunities for future studies. First, the study of the European context represents a good starting point for exploring the emerging field of AI and related capabilities. However, the massive use of AI in other contexts calls for more research in other countries to compare the findings and investigate if and to what extent cultural, political, governmental, or legal aspects affect their impact. For example, studying the U.S. and Asian contexts could be valuable opportunities to further advance this research and confirm our findings (or not).

Second, our study considered direct relationships between the examined dimensions, but did not consider potential direct effects, mediations, or moderations. A subsequent study could further expand our model by testing additional effects and adding additional parameters that could act as mediators or moderators. Another limitation lies in the lack of similar research that allows for comparisons of the results—for example, with other contexts or countries; to date, there have been no similar studies in the emerging literature on AIC that have explored its relationship with IC, particularly in the most recent configuration of this multidimensional construct (including the six dimensions examined individually). For example, the literature on independent TC is still scarce and there is a paucity of studies considering this dimension as separate from RC or social capital (Cabrilo et al., 2020, 2024). Similarly, the recent configuration of AICs—with three components—has only recently been proposed and applied to the study of business performance (Fosso-Wamba et al., 2024a).

Finally, other limitations lie in the exploratory nature of our research. Although quantitative designs are a widely adopted approach for studies in the field of AI, and PLS-SEM is particularly suitable for exploratory research, a qualitative approach could further aid in a deeper understanding of the phenomenon and possibly complement the findings derived from the quantitative approach. Subsequent studies could therefore incorporate a mixed methodological approach that could also include in-depth interviews with managers. Similarly, despite the nature and limited number of target firms available, with the growing interest in this domain, the sample size could be further enlarged in the future. Based on this growth, subsequent research could also possibly leverage a longitudinal research design and avoid the use of a cross-sectional research design through a questionnaire survey of available SMEs.

CRediT authorship contribution statement

Jintao Lu: Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Lihua Fan:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Investigation, Conceptualization. **Ciro Troise:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Stefano Bresciani:** Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

No conflict of interest exits in the submission of this manuscript, and manuscript is approved by all authors for publication.

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Appendix 1. List of abbreviations.

AI	Artificial Intelligence
AIC	Artificial Intelligence Capability
SME	Small and Medium-sized Enterprise
IC	Intellectual Capital
OA	Organizational agility
DC	Dynamic Capability
OL	Organizational Learning
HC	Human Capital
RC	Relational Capital
SC	Structural Capital
EC	Entrepreneurial Capital
RENC	Renewal Capital
TC	Trust Capital
PLS	Partial Least Squares
SEM	Structural Equation Modelling
DP	Digital Platform
BDA	Big Data Analytics
AVE	Average Variance Extracted
VIF	Variance Inflation Factor
CMB	Common Method Bias
HTMT	Heterotrait–Monotrait
IER	Insufficient Effort Responses

Source: own elaboration.

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