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Minds and machines: Rethinking absorptive capacity in the age of artificial intelligence

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ABSTRACT

The absorptive capacity construct derives its functions, dimensions, and internal relationships from the implicit assumption that humans are the only learning agents underlying knowledge absorption. I posit that the emergence of artificial intelligence (AI) challenges this assumption and requires a re-examination of the construct. Through a theory-building abductive study combining conceptual mapping with qualitative interviews, this work investigates the complex relationship between AI and knowledge absorption. It theorizes new dimensions of absorptive capacity pertaining to AI-driven processes and analyzes the interactions between these new dimensions and the traditional facets of the construct. Ultimately, the paper seeks to reaffirm the importance of absorptive capacity in the age of AI and develop a nuanced understanding of AI's role in reshaping the construct's antecedents, mechanisms, and implications.

1. Introduction

Knowledge provides the foundation for sustaining and dynamically renewing firms' competitive advantage (Grant, 1996; Helfat and Raubitschek, 2000; Wang et al., 2009). The absorptive capacity construct (ACAP) explains how firms recognize the value of new knowledge, assimilate it, and apply it to commercial ends (Cohen and Levinthal, 1990). Since Cohen and Levinthal's seminal article (1990), the ACAP stream has built on cognitive and behavioral science to investigate how individuals (and, by extension, firms) value, acquire, assimilate, transform, and exploit knowledge. Key points are the path dependence of knowledge accumulation, the relevance of the extant knowledge stock for assimilating and transforming incoming knowledge, and the mechanisms underlying knowledge diffusion (Cohen and Levinthal, 1990; Lane et al., 2006; Lewin et al., 2011; Song et al., 2018; Todorova and Durisin, 2007; Volberda et al., 2010; Zahra and George, 2002).

For the past three decades, ACAP research has relied on the implicit assumption that humans are the only learning agents underlying knowledge absorption at the firm level. As a result, the functions and dimensions of ACAP derive their properties from the cognitive features of humans (e.g., associative learning) and the interactions among them in the organizational context (e.g., socialization-based knowledge transfer). The present work stems from the observation that this assumption can no longer be taken for granted, as artificial intelligence (AI) occupies an increasingly prominent role in firms' knowledge absorption process.

AI can be defined as *machines that are trained to perform tasks associated with human intelligence—that is, interpret external data, learn from that external data, and use that learning to flexibly adapt to tasks to achieve specific outcomes* (Shepherd & Majchrzak, 2022: p. 2). Deep learning-based AI algorithms fed by big data have emerged as powerful radars, processors, and transmitters of knowledge. However, they elaborate knowledge differently from humans. AI-based applications detect patterns and infer relationships on purely statistical grounds based on large quantities of data (Pakarinen and Huising, 2023; Tschang and Almirall, 2021). As a result, they are capable of automating tasks, performing complex analyses, and generating key inputs for the creative process (Amabile, 2020; Brynjolfsson and McAfee, 2014; Mateja and Heinzl, 2021; Wu et al., 2019). Conversely, humans rely on intuition, heuristics, and cross-domain expertise to achieve such outcomes (Hodgkinson and Sadler-Smith, 2018; Kahneman and Frederick, 2002). I posit that the coexistence and interaction of these alternative cognitive architectures[1] imply changes in the way firms organize to absorb knowledge.

Recent research documents the positive effects of AI on knowledge flows toward and within firms. These include helping firms widen their

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[1] Throughout the manuscript, "cognitive architecture" denotes the foundational framework that defines the mechanisms and processes underlying cognition, while "cognitive structure" refers to the mental pattern used to interpret and organize knowledge.

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search scope, detect missing knowledge, identify knowledge complementarities, pool heterogeneous knowledge, provide learning by training, and overcome cognitive limitations (Brea and Ford, 2023; Broekhuizen et al., 2023; Gaessler and Piezunka, 2023; Lee et al., 2022; Manis and Madhavaram, 2023; Pedota et al., 2025; Raisch and Fomina, 2025). Concurrently, other studies caution against overreliance on AI due to the opacity of its cognitive processes and its proclivity to error as external conditions evolve (Csaszar and Steinberger, 2022; Felin and Holweg, 2024; Fügener et al., 2021; Loru et al., 2025; O'Leary, 2022; Raisch and Krakowski, 2021; Sturm et al., 2021; Townsend et al., 2025; Van den Broek et al., 2021). While these studies confirm the relevance of AI for knowledge elaboration, the field still lacks a precise understanding of how AI affects the various dimensions of the ACAP construct and its underlying mechanisms. Developing fine-grained insights in this direction may not only refine the explanatory power of the ACAP construct, but also open a new perspective on knowledge-based competitive advantage (Helfat, 1997; Kogut and Zander, 1992; Wang et al., 2009).

Given the novelty and complexity of the topic, this paper adopts a two-phase abductive theory-building approach (Dubois and Gadde, 2002; Klag and Langley, 2013; Sætre and Van de Ven, 2021; Shepherd and Sutcliffe, 2011). As AI is a boundary-spanning technology and ACAP a multidimensional construct, I first perform a conceptual mapping of scientific papers that relate AI to knowledge elaboration in firms. This preliminary step serves to structure the scattered contributions on AI and knowledge elaboration (even those that do not explicitly mention ACAP) to diagnose conceptual gaps and anomalies (Sætre and Van de Ven, 2021; Shepherd and Sutcliffe, 2011), informing the interview protocol for the subsequent theory-building phase. I then conduct an interview-based qualitative study drawing on expert informants across eight AI-first firms to address the gaps identified previously and uncover the mechanisms through which AI reshapes ACAP.

This work contributes to ACAP scholarship by identifying new AI-relevant dimensions at the level of the absorptive effort, absorptive knowledge base, and absorptive process of the firm (Song et al., 2018), accounting for the antecedents, mechanisms, and implications of AI-driven knowledge absorption. Specifically, I show that AI reshapes absorptive effort by introducing a distinct form of data absorption effort alongside traditional knowledge search; reconfigures the absorptive knowledge base by elevating data heritage and AI-relevant knowledge to generative and path-dependent resources; and transforms the absorptive process through mechanisms such as the virtualization of tacit knowledge and cognitive duality, which enable the coordination and exploitation of human and artificial cognition. By integrating these elements, the paper moves beyond a purely human-centric view of ACAP and conceptualizes it as a dual learning architecture in which human and artificial cognition jointly shape knowledge absorption.

2. Theoretical background

2.1. Absorptive capacity: construct overview

Individuals and, by extension, firms acquire knowledge by building on extant knowledge (Cohen and Levinthal, 1990). Research on cognition and memory asserts that learning is associative: individuals internalize further ideas by linking them to extant ideas (Bower and Hilgard, 1981; Lindsay and Norman, 1977). Similarly, problem-solving capabilities build on pre-existing heuristics, often through analogy (Pirolli and Anderson, 1985). Besides promoting learning, extant knowledge helps firms recognize the value of new knowledge, a key prerequisite for knowledge acquisition (Todorova and Durisin, 2007). Thus, ACAP is path dependent: as firms accumulate domain-specific knowledge, their learning efforts gravitate toward those domains.

For acquired knowledge to be useful, it must be assimilated, which presupposes intraorganizational knowledge transfer (Szulanski, 1996). The more codified and explicit the acquired knowledge, the easier it is to understand and diffuse throughout the firm (Nelson and Winter, 1982; Zollo and Winter, 2002). By contrast, tacit knowledge requires employees to be proficient in the same knowledge domain for assimilation by association.

While Cohen and Levinthal's (1990) seminal article stressed the path dependence of associative learning, subsequent contributions also highlighted its transformative aspects (Matusik and Heeley, 2005; Song et al., 2018; Zahra and George, 2002). Assimilated knowledge can be modified and reinterpreted, leading to entrepreneurial action, organizational transformation, and strategic change (Christensen et al., 1998; McGrath and MacMillan, 2000; Todorova and Durisin, 2007; Zahra and George, 2002). Todorova and Durisin (2007) also stressed that assimilation and transformation are not necessarily sequential processes and can involve not only knowledge, but also employees' cognitive structures themselves.

Ultimately, firms need to implement routines to integrate the assimilated and/or transformed knowledge into their operations and exploit it (Lewin et al., 2011; Van den Bosch et al., 1999; Zahra and George, 2002). This requires systems and socialization capabilities, such as formalization and connectedness (Jansen et al., 2005; Volberda et al., 2010). Other examples are routines for knowledge transfer, opportunity identification, and replication of best practices (Lewin et al., 2011; Szulanski, 1996). Being the last steps toward competitive advantage, transformation and exploitation capabilities are often regarded as realized ACAP, as opposed to acquisition and assimilation capabilities, which constitute potential ACAP (Zahra and George, 2002).

Despite its success, the concept of ACAP has often been criticized for its opacity and reification (Lane et al., 2006; Song et al., 2018; Volberda et al., 2010). For this reason, Song et al. (2018) seek to enhance conceptual clarity by decomposing ACAP into three key functions and three corresponding dimensions. The radar function underlies the firm's ability to scan the external environment and recognize the value of external knowledge. The processor function encompasses the elaboration, transformation, and recombination of knowledge. The converter-transmitter function refers to the capability of translating and diffusing external knowledge. These functions are driven by three underlying dimensions: absorptive effort, the active involvement of the firm in the search for new knowledge (primarily affecting the radar function); absorptive knowledge base, the stock of knowledge enabling the assimilation of incoming knowledge (primarily affecting the processor function); and absorptive process, the set of mechanisms for intraorganizational communication, learning, and knowledge transfer (primarily affecting the converter-transmitter function).

2.2. Absorptive capacity and information technology

Within the broader ACAP literature, a significant body of scholarship has explored its intersection with information technology (IT). Given their involvement with the storage, elaboration, and dissemination of information, IT tools such as enterprise systems, data repositories, and knowledge-sharing platforms have the potential to improve ACAP by offering analytical insights and facilitating knowledge transfer (Bloom et al., 2014; Chatterjee et al., 2002; Gold et al., 2001; Heim and Peng, 2010; Masini and Van Wassenhove, 2009; Roberts et al., 2012; Setia and Patel, 2013; Trantopoulos et al., 2017). They also strengthen organizational memory by acting as repositories and templates that provide convenient entry points for assimilating and applying knowledge (Hendricks et al., 2007; Jensen and Szulanski, 2007; Tseng, 2008).

A key feature of the relationship between IT and ACAP is its bidirectionality. Complex IT tools require specialized know-how and complementary capabilities that accumulate through learning-by-using (Attewell, 1992; Elbashir et al., 2011; Liang et al., 2007). As a result, IT-savvy firms not only derive greater ACAP benefits from IT, but also develop IT-relevant ACAP, reinforcing future benefits. A central component of IT-relevant ACAP is business-IT knowledge (Roberts et al., 2012; see also Boynton et al., 1994; Nelson and Cooprider, 1996), which enhances both the assimilation of IT-related knowledge and overall firm performance by aligning business and IT objectives (Kearns and Sabherwal, 2006; Roberts et al., 2012).

2.3. The distinct role of artificial intelligence

Among recent IT advancements, AI has prominently emerged as a general-purpose cognitive technology (Bresnahan and Trajtenberg, 1995; Trajtenberg, 2019), its influence being compared to revolutions like electrification, personal computers, and the internet (Acemoglu et al., 2023; Agrawal et al., 2023). Recent studies offer reasons to believe that, like other IT tools, AI may alter the way firms assimilate, transform, and exploit knowledge, thanks to its scanning, predictive, processing, and generative features (Jacobides et al., 2021; Mikalef and Gupta, 2021; Pedota et al., 2025; Raisch and Krakowski, 2021; Raisch and Fomina, 2025; Shepherd and Majchrzak, 2022; Sturm et al., 2021). However, unlike other IT tools, AI has distinct characteristics that may also, and more importantly, reshape the underlying dimensions of absorptive effort, absorptive knowledge base, and absorptive process.

Traditional IT tools enhance ACAP by supporting human cognitive and socialization mechanisms, for instance through data access and network connectivity (Roberts et al., 2012; Trantopoulos et al., 2017). By contrast, AI autonomously extracts insights from vast datasets through its own cognitive mechanisms. Instead of merely facilitating knowledge absorption, AI provides a different knowledge absorption channel based on pattern recognition rather than associative learning. Thus, while traditional IT tools mainly act as facilitators for human cognitive and socialization mechanisms, AI provides a distinct set of cognitive mechanisms, which interact with human cognition in complex ways (Raisch and Krakowski, 2021; Raisch and Fomina, 2025; Townsend et al., 2025).

Most notably, unlike humans, AI bridges the gap between data and knowledge without relying on associative learning. Rather than forming semantic links between new and existing knowledge, it generates insights by processing large volumes of data on purely statistical grounds. This shift in both the object and the mode of absorption is likely to reshape firms' absorptive effort and knowledge base. Furthermore, AI challenges traditional, socialization-based knowledge diffusion (Song et al., 2018; Szulanski, 1996; Volberda et al., 2010), requiring new mechanisms for AI-human and human-AI knowledge transfer. Thus, the nature of the absorptive process may change as well. Further research is needed to clarify how these interdependent factors interact with the core dimensions of ACAP.

3. Conceptual mapping of artificial intelligence and knowledge elaboration

3.1. Methodology

By definition, the status of AI as a cognitive technology implies a relationship between AI and knowledge elaboration. However, this relationship is often treated as implicit, with prior contributions typically examining isolated aspects of AI-enabled knowledge processes rather than an integrated account of how AI reshapes ACAP within firms. As a result, a consolidation of these perspectives is needed to surface conceptual gaps, anomalies, and tensions, in line with abductive theorizing (Sætre and Van de Ven, 2021; Shepherd and Sutcliffe, 2011).

To map how AI has been linked to knowledge elaboration in firms, the study proceeds from a structured analysis of the relevant literature.[2] I identified an initial corpus of publications through a Scopus search combining keywords related to AI (e.g., artificial intelligence, machine learning, deep learning, big data analytics) and knowledge elaboration (e.g., absorptive capacity, knowledge acquisition, assimilation, transformation, and diffusion). I then applied iterative screening criteria to retain papers with clear relevance to the relationship between AI and knowledge elaboration, excluding purely technical or operational contributions (e.g., on robotics or computer vision). From the resulting sample of papers, I extracted relevant excerpts and conducted open coding, prioritizing process and causation coding to capture how AI relates to different dimensions of knowledge absorption. First-order codes were then grouped into second-order themes and aggregate dimensions based on conceptual similarity. Fig. 1 presents the resulting data structure, while Table 1 links the identified themes to the corresponding body of literature.

3.2. Overview of main themes

This conceptual mapping exercise highlights three main themes (see Fig. 1 and Table 1). Two of these (AI-relevant knowledge and ACAP functions) underscore the notion that, like other IT tools, AI maintains a bidirectional relationship with knowledge: while it has the potential to enhance all ACAP functions, it requires AI-relevant knowledge to be deployed effectively. As an instance of tool-relevant knowledge, AI-relevant knowledge appears to have a complex characterization, encompassing technical and organizational dimensions.

Firms need to equip themselves with the technical knowledge of how to devise, modify, interpret, and adjust AI algorithms (Gama and Magistretti, 2023; Jacobides et al., 2021; Jee and Sohn, 2023; Lee et al., 2022; Mikalef and Gupta, 2021). They also need knowledge of how to effectively implement AI within the firm, for instance by developing cross-unit collaboration, intra- and interdepartmental coordination, and routines for the identification of AI-driven opportunities (Gama and Magistretti, 2023; Jacobides et al., 2021; Korayim et al., 2024; Mikalef and Gupta, 2021; Oesterreich et al., 2022; Zhang et al., 2024). Furthermore, they need awareness of the relevance of data for AI's functioning and knowledge of how to gather, systematize, and preprocess it (Caputo et al., 2019; Hartmann and Henkel, 2020; Jacobides et al., 2021; Jordan and Mitchell, 2015; Lee et al., 2022; Lundvall and Rikap, 2022). AI and big data are so tightly intertwined that they are often conflated in practice, with many studies referring to big data as both the data itself and the AI-based techniques to analyze it (Boyd and Crawford, 2012; Pedota, 2023; Wamba et al., 2015).

Provided AI-relevant knowledge is in place, AI has the potential to contribute to all ACAP functions. Big data analysis may improve firms' dynamic capabilities (Eisenhardt and Martin, 2000; Teece et al., 1997; Teece, 2007) by enhancing firms' sensing of opportunities and heightening their responsiveness to change (Conboy et al., 2020; Côrte-Real et al., 2017; Mikalef et al., 2020; Mikalef et al., 2021; Pedota, 2023). Through both supervised and unsupervised learning algorithms, AI may expand the breadth and the frequency of search for new information, facilitate the retrieval and interpretation of heterogeneous data, and combine it with information generated internally (Brea and Ford, 2023; Manis and Madhavaram, 2023; Presti et al., 2023; Van Rijmenam et al., 2019; Wamba et al., 2023). Furthermore, unsupervised learning algorithms can spot patterns of anomalies in data without any prior instruction, thereby remaining free of those human biases, heuristics, and preconceptions that limit the search scope. Such patterns may then act as attention drivers that facilitate the identification of opportunities for knowledge gathering (Jordan and Mitchell, 2015; Raisch and Krakowski, 2021; Shepherd and Majchrzak, 2022).

AI is also acknowledged to enhance information processing, improve creativity by discovering hidden patterns, and facilitate the recombination of existing knowledge (Grashof and Kopka, 2023; Haefner et al., 2021; Just, 2024; Lanzolla et al., 2021; Liu et al., 2020; Mikalef and Gupta, 2021; Pedota et al., 2025; Raisch and Fomina, 2025; Shepherd

[2] Please note that, despite using systematic methods, this step is intended as a structured conceptual mapping of prior research, rather than a formal systematic review. Its aim is to surface conceptual anomalies and tensions, rather than to provide an exhaustive summary of prior research.

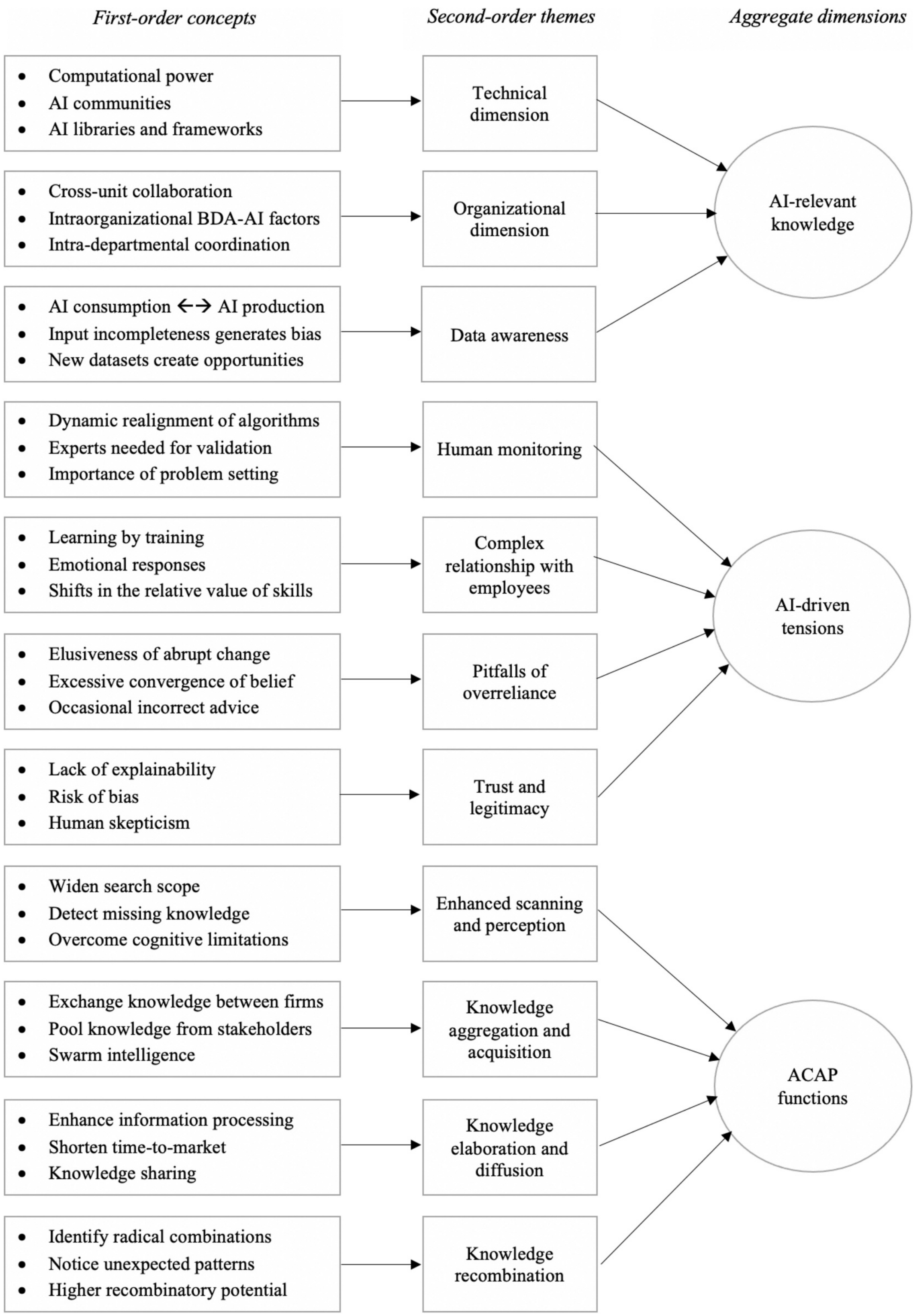

Fig. 1. Data structure of the conceptual mapping exercise.

and Majchrzak, 2022). Similarly, there is a general understanding that AI may facilitate knowledge diffusion (Gama and Magistretti, 2023; Liu et al., 2020). Some studies suggest that AI may facilitate information sharing (Wamba et al., 2023), help cross-functional teams exchange data and insights in real time (Yu et al., 2021), and smooth the process of knowledge integration by providing visualization and categorization (Brea and Ford, 2023; Khan and Vorley, 2017).

However, these advantages come with important tensions. A number of studies warn that AI outputs are only as good as the underlying data, and biased datasets risk systematically leading to incorrect conclusions (Ahsen et al., 2019; Choudhury et al., 2020; Lee et al., 2022; Shrestha et al., 2021). As organizational and environmental conditions evolve, knowledge embedded in algorithms may become obsolete, requiring firms to strike a balance between the biases inherent in the algorithms and the human biases potentially introduced through their reconfiguration (Diakopoulos, 2016; Schuetz and Venkatesh, 2020; Sturm et al.,

Table 1
Relevant literature by second-order theme and aggregate dimension.

Aggregate dimension	Second-order theme	Relevant literature
AI-relevant knowledge	Technical dimension	Gama and Magistretti, 2023; Jacobides et al., 2021; Jee and Sohn, 2023; Lee et al., 2022; Mikalef and Gupta, 2021.
	Organizational dimension	Bag et al., 2023; Cadden et al., 2023; Gama and Magistretti, 2023; Jacobides et al., 2021; Korayim et al., 2024; Mikalef and Gupta, 2021; Oesterreich et al., 2022; Patrucco et al., 2023; Zhang et al., 2024
	Data awareness	Caputo et al., 2019; Choudhury et al., 2020; Conboy et al., 2020; Côrte-Real et al., 2017; Hartmann and Henkel, 2020; Jacobides et al., 2021; Jordan and Mitchell, 2015; Lee et al., 2022; Lundvall and Rikap, 2022; Pedota, 2023; Shepherd and Majchrzak, 2022.
AI-driven tensions	Human monitoring	Choudhury et al., 2020; Fügener et al., 2021; Hadjimichael and Tsoukas, 2019; Iaia et al., 2024; Shrestha et al., 2021; Sturm et al., 2021; Van den Broek et al., 2021.
	Complex relationship with employees	Agrawal et al., 2017; Ahsen et al., 2019; Arias-Pérez and Vélez-Jaramillo, 2022; Choudhary et al., 2023; Fügener et al., 2021; Jacobides et al., 2021; Jia et al., 2024; Raisch and Krakowski, 2021; Schuetz and Venkatesh, 2020; Song et al., 2022; Sturm et al., 2021; Van den Broek et al., 2021.
	Pitfalls of overreliance	Ahsen et al., 2019; Choudhury et al., 2020; Fügener et al., 2021; Hadjimichael and Tsoukas, 2019; Schuetz and Venkatesh, 2020; Sturm et al., 2021; Van Rijmenam et al., 2019.
	Trust and legitimacy	Csaszar and Steinberger, 2022; Diakopoulos, 2016; Gama and Magistretti, 2023; O'Leary, 2022; Shrestha et al., 2021.
ACAP functions	Enhanced scanning and perception	Abou-Foul et al., 2023; Al-Omoush et al., 2024; Brea and Ford, 2023; Broekhuizen et al., 2023; Christensen et al., 2018; Conboy et al., 2020; Côrte-Real et al., 2017; Jordan and Mitchell, 2015; Manis and Madhavaram, 2023; Mikalef et al., 2020; Mikalef et al., 2021; Pedota, 2023; Presti et al., 2023; Rialti et al., 2019; Shepherd and Majchrzak, 2022; Van den Broek et al., 2021; Van Rijmenam et al., 2019; Warner and Wäger, 2019.
	Knowledge aggregation and acquisition	Brea and Ford, 2023; Elia et al., 2022; Jee and Sohn, 2023; Korayim et al., 2024; Liu et al., 2020; Manis and Madhavaram, 2023; Plantec et al., 2023; Presti et al., 2023; Shepherd and Majchrzak, 2022.
	Knowledge elaboration and diffusion	Bahoo et al., 2023; Brea and Ford, 2023; Gaessler and Piezunka, 2023; Gama and Magistretti, 2023; Haefner et al., 2021; Khan and Vorley, 2017; Kopka and Fornahl, 2023; Lanzolla et al., 2021; Liu et al., 2020; Raisch and Krakowski, 2021; Shepherd and Majchrzak, 2022; Van Rijmenam et al., 2019; Wamba et al., 2023; Wu and Kane, 2021; Yu et al., 2021.
	Knowledge recombination	Grashof and Kopka, 2023; Haefner et al., 2021; Just, 2024; Lanzolla et al., 2021; Liu et al., 2020; Mikalef and Gupta, 2021; Shepherd and Majchrzak, 2022; Van Rijmenam et al., 2019.

2021; Van den Broek et al., 2021). These problems are exacerbated by opacity: most AI algorithms are only partially explainable, which may reduce learning opportunities, weaken the legitimacy of the decisions taken, and make it difficult to understand when the logic of the algorithm ceases to fit the context (Anthony et al., 2023; Csaszar and Steinberger, 2022; Diakopoulos, 2016; O'Leary, 2022; Shrestha et al., 2021).

Taken together, these insights reveal a fragmented and incomplete understanding of the relationship between AI and ACAP. While the literature points to AI's potential to enhance all ACAP functions, it also reveals ambiguities regarding the conditions under which such potential is realized, particularly in relation to the interplay between technical, organizational, and data-related knowledge, as well as the tensions stemming from bias and opacity. Abductive theorizing traditions prescribe addressing these gaps and anomalies through targeted, theory-building empirical inquiry (Sætre and Van de Ven, 2021; Shepherd and Sutcliffe, 2011). Accordingly, the second phase consists of a qualitative study based on interviews with knowledgeable informants, aimed at abductively deepening, refining, and potentially challenging the preliminary insights emerging from the conceptual mapping exercise (Dubois and Gadde, 2002; Klag and Langley, 2013; Sætre and Van de Ven, 2021; Shepherd and Sutcliffe, 2011). This approach enables emerging hunches to be assessed against experiential knowledge, thereby advancing a more nuanced and integrative understanding of how AI reshapes ACAP within firms.

4. Qualitative interview study

4.1. Methodology

In line with abductive theorizing, I complement this top-down account of AI and ACAP with a qualitative interview study based on expert informants across eight AI-first firms. Interviews with domain experts are an established method to refine theoretical constructs in a variety of real-world contexts (Bell et al., 2017; Fischer et al., 2020; Myers and Newman, 2007; Rüffin, 2020; Snell and Wong, 2007; Venable et al., 2016). This method suits the present work because it generates rich, first-hand insights into how AI is concretely deployed within firms. Given the novelty, opacity, and socio-technical complexity of AI, its relationship with ACAP is difficult to infer from extant literature alone and requires direct engagement with knowledgeable practitioners. By grounding emerging constructs in the lived experience of such practitioners, this approach supports the abductive refinement of theory and ensures that the resulting extensions of ACAP are both empirically informed and analytically robust.

I interviewed informants in leading technical and managerial roles in eight AI-first firms from various industries. AI-first firms are defined as firms treating AI as a core asset and a strategic priority (Fontana, 2019). Furthermore, they all act as both users and providers of AI solutions. On the one hand, these characteristics make informants theoretically relevant, as they are knowledgeable and up-to-date about the potential of AI and have accumulated substantial learning over time. On the other hand, informants embedded in these firms have a twofold perspective incorporating both an internal and an external viewpoint on the role of AI in affecting knowledge absorption. As the perspectives of an active user and an external provider of AI may differ in terms of focus, orientation, and even potential biases, carrying both perspectives at the same time allows informants to provide a richer and more reliable picture.

Consistent with the objective of capturing a wide range of expert perspectives on a complex phenomenon, I prioritized breadth across informants over in-depth analysis of individual organizational contexts (e.g., through single or comparative case studies). This enabled the collection of information not only about AI implementations at the level of the firm where informants are primarily embedded, but also about the other firms they worked with, which they were often able to follow throughout and after AI-relevant projects. This kind of flexibility and informational variety is important because AI is a complex general-purpose technology, leading to substantial variation in usage. Thus, the identification of commonalities across a large number of cases is useful to abstract from contextual specificities in theory building. As a further benefit, the identification of the same patterns across informants embedded in different firms increases reliability alongside generalizability (Eisenhardt, 1991; Eisenhardt and Graebner, 2007; Yin, 2009).

I recruited informants through eight AI-first firms characterized by different degrees of industrial specialization, in order to access a wide range of AI usage contexts. This approach aims to maximize variation in informants' exposure to AI-driven knowledge elaboration, thereby enabling the identification of theoretically relevant commonalities across heterogeneous applications.[3] In particular, informants draw on experiences spanning AI usage for describing, predicting, or creating. Such heterogeneity enhances the analytical leverage of the study by ensuring that emerging patterns are not confined to a single type of application, but reflect underlying mechanisms that cut across diverse contexts. This rationale resulted in recruiting informants from both generalist AI providers and firms operating in industries such as healthcare, finance, and creative content generation. These industries were chosen for the significance of AI within them and for their differing balance among knowledge used for description, prediction, and creation.

For each firm, I conducted in-depth interviews with both technical and business experts. This twofold view on technical and business dimensions served to highlight the links between the technical properties of AI and their organizational implications. As the study progressed, I often went back to the literature to sharpen the emerging conceptualization and fine-tune the protocol for subsequent interviews, drawing on abductive logic. The data structure emerging from the conceptual mapping exercise facilitated the iteration between theory and data by allowing me to check for commonalities, complementary insights, and persistent conceptual gaps with increased precision. Coupled with the centrality of the informants' roles, this facilitated the attainment of theoretical saturation, achieved at 40 interviews (lasting between 60 and 90 min) transcribed verbatim and coded. For contextual transparency, Table 2 indicates, for each firm, its focal industry, size,[4] total number of interviews, and roles interviewed.

For the analysis, I adopted a mix of in-vivo, process, and causation coding (Saldaña, 2021), aiming for balance between fidelity to the text and elucidation of causal mechanisms. Subsequently, I abstracted from first-cycle codes by identifying second-order themes and then aggregate dimensions. As a last step, in line with abductive theorizing, I analyzed the dimensions and themes emerging from the conceptual mapping exercise and the qualitative interview study to harmonize the respective insights. Fig. 2 provides the data structure emerging from the qualitative interview study.

Table 2
Contextual information on interviews.

Firm	Size	Focal industry	Brief description	Roles interviewed	Total number of interviews
Mercury	Small	Healthcare	Specialized in ultrasound solutions for diagnostics.	CEO; Head of AI.	4
Venus	Medium	None	Data management, automation, and decision support service provider.	CEO; Head of Innovation; Head of Analytics.	7
Earth	Small	None	Predictive risk analysis service provider.	Chief Risk Officer; R&D Director; R&D Team Member.	5
Mars	Medium	Creative content	AI-driven content generation provider leveraging advanced NLP.	CEO; CTO; Data Scientist.	6
Jupiter	Small	None	Quality control and forecasting service provider.	CEO; CTO.	5
Saturn	Small	Finance	Specialized in financial assessment and credit scoring.	Head of Product; Head of Technology.	4
Uranus	Medium	Finance	Specialized in credit risk assessment and management.	CEO; Head of Fintech; Sales Account Specialist.	5
Neptune	Medium	Healthcare	Specialized in biomarkers and predictive medicine.	CEO; Machine Learning Engineer.	4

4.2. Findings

4.2.1. The data absorption channel

While AI is widely recognized to require voluminous data, findings clarify how data shapes ACAP's conceptual core: path-dependent knowledge absorption. First, data alters the knowledge generation function of AI. Traditionally, data has always been a key input to knowledge elaboration, such as in customer relationship management or enterprise resource planning systems. However, non-AI tools operate through pre-programmed rules: their ability to extract insights depends on human-defined schemas ex ante and human interpretation ex post. As a result, they cannot generate insights beyond their predefined logic. Given the same data, they produce the same output unless manually modified.

By contrast, AI autonomously updates its knowledge generation function based on ingested data. Through the reweighting of neural connections, it learns from data and alters not only its outputs but also the very way it generates knowledge. Therefore, data shifts from a passive input to an active resource that shapes learning and, ultimately, the firm's knowledge absorption trajectory.

> "*I'd say that the key difference is that before AI, data just sat there until someone decided what to do with it. Now with AI the data actively drives the learning. The more we feed it, the smarter the system gets, and that in turn changes how we approach problems. It's not just about storing data anymore but rather evolving with it.*"
>
> (Head of Innovation, Venus)

Second, AI generates knowledge not only through vertical but also through horizontal accumulation. ACAP scholarship conceptualizes knowledge accumulation as vertical, with associative learning enabling the progressive development of knowledge within related domains. While breadth can also enhance innovation by fostering novel connections, it eventually leads to cognitive overload and attention dilution,

[3] To preserve relevant contextual differences while limiting exposure to cultural, institutional, and macroeconomic variation, informants were selected from firms in different industries but based in the same country (Italy).

[4] "Small" denotes firms with 49 employees or fewer, while "medium" denotes firms with a number of employees higher than 49 and lower than 250. None of the interviewed firms had 250 employees or more at the time of the interviews.

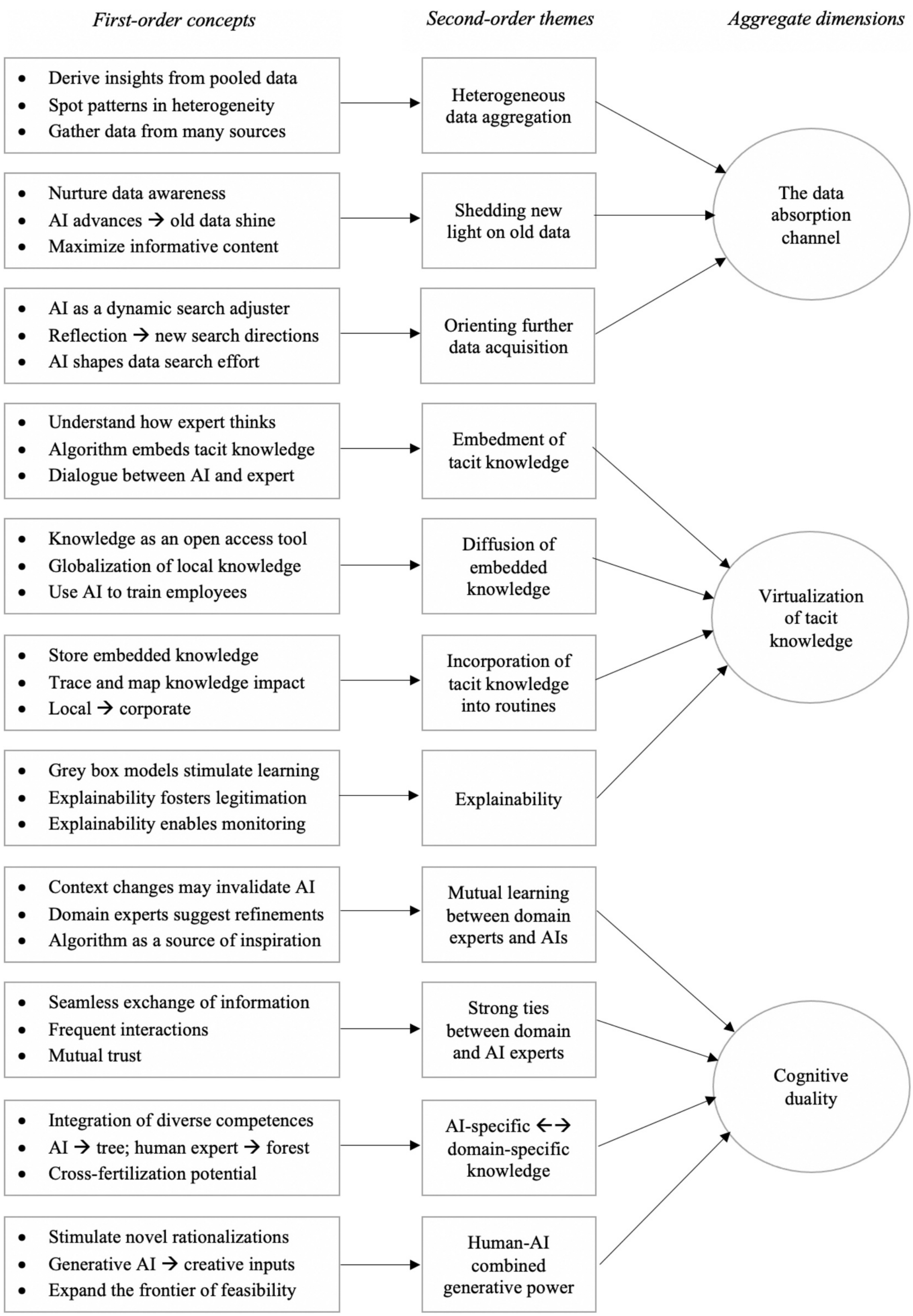

Fig. 2. Data structure of the qualitative interview study.

due to bounded rationality (Laursen and Salter, 2006). Conversely, unconstrained by such cognitive limits, AI benefits from increasing data in both scale and scope (Gregory et al., 2021). Therefore, while traditional IT tools merely help users manage bounded rationality, AI introduces a qualitatively different cognitive architecture that leverages data heterogeneity to enhance itself through neural reweighting and identify distant connections autonomously.

"*Thanks to AI we can foresee scenarios that we could not have imagined before, because we could not even dream of bringing together such heterogeneous data.*"

(CEO, Uranus)

For example, non-AI-based tools such as product lifecycle management platforms can support heterogeneous knowledge recombination by allowing engineers to manually search across domains, drawing on both biomedical coatings and aerospace materials to inspire a new surface treatment. However, while such recombinations may be facilitated by the system (e.g., through intelligent data retrieval and pre-programmed analyses), they ultimately depend on the engineer's cognition, which is subject to bounded rationality (Simon, 1955). By contrast, an AI-based R&D support system trained on internal lab reports, external publications (potentially in multiple fields), failure logs, and even design sketches can actively generate cross-domain insights that may be cognitively inaccessible to human engineers.

Taken together, these two characteristics imply a shift in the conceptualization of the firm's data heritage. The ACAP literature (particularly its IT stream) conceptualizes data in a given domain as part of the specialized knowledge base related to that domain. For example, data on software bugs would be considered part of an IT firm's specialized knowledge base in the software domain. While this remains true, findings suggest that, in the age of AI, the overall data heritage of the firm also plays a role as a self-standing component of the absorptive knowledge base. This is because, independently of the domain, accumulated data expands the range of neural connections AI systems can build during (re)training and the number of patterns they can identify (including cross-domain ones). In this way, extant data changes the way AI absorbs further data, potentially affecting knowledge absorption in multiple domains.

> "*With traditional data analysis systems, we'd always hit a ceiling. You could only get answers to the questions you already knew to ask. But with AI models, the system brings patterns we hadn't even thought to look for. It doesn't just help us answer questions; it helps us ask better ones. The data we gather shapes how we learn.*"
>
> (Head of Analytics, Venus)

Findings bring to light another aspect of data accumulation. Traditionally, firms acquire knowledge through R&D and knowledge search routines. These might also include forms of data gathering, especially in response to the emergence of new tools (e.g., a DNA sequencer incentivizing the gathering of DNA samples). However, AI is trained on big data, whose volume and variety require distinctive, resource-intensive routines, including data collection, web scraping, database management, and data integration. When coordinated effectively, such routines constitute higher-level capabilities in data orchestration.

These routines and capabilities differ fundamentally from those underlying standard knowledge acquisition, as they require specialized expertise and distinct human capital (i.e., data scientists). They also introduce new forms of path dependence: AI evaluates potential new data in light of existing data and steers absorptive effort accordingly. Because firms must balance the absorption of big data with that of traditional knowledge, which implies a trade-off in resource allocation, I introduce a distinction within the absorptive effort dimension between knowledge absorption effort and *data absorption effort*. Data absorption effort can be defined as the tangible and intangible resources (including time) devoted to the purposeful acquisition and management of big data for AI-driven knowledge absorption.

> "*We're exploring a new trend. It involves using techniques to beef up databases when you only have a handful of available data points. The idea is to craft databases with a strategy that squeezes out the maximum informational potential from the given data. This, in turn, supercharges the whole creative process, especially in product development scenarios. We recently took on a project in the world of Formula One, and we're rolling out the same playbook with a major company focused on CO_2 capture from depleted natural gas reservoirs. I can't spill all the details on that. However, our game plan involves helping them pick new samples for analysis using techniques that stretch the informational boundaries. We're maximizing the information that a handful of new data points bring to the table, as opposed to randomly chosen ones.*"
>
> (Head of Analytics, Venus)

> "*Even when we measure new, somewhat unconventional data, we put it into the algorithm to assess its true relevance. You basically hand it over to the algorithm and it tells you how that parameter impacts the situation on its own and whether it's relevant, and it can also build more intricate structures by combining that parameter with other indicators already embedded in its decision-making models.*"
>
> (Head of Fintech, Uranus)

> "*You put the GPS on to find the least traffic, to take the fastest route without any traffic. AI is like a GPS that tells you which is the best way as you go along. We gather, process, and know the route to take.*"
>
> (R&D Director, Earth)

These factors combined have significant implications for ACAP. Firms' knowledge acquisition now depends not only on the current stock of similar knowledge but also on the overall data heritage, subject to accumulation through data absorption effort. This introduces a new layer of recursion. As AI is trained on progressively larger and more diverse datasets, it becomes more capable of detecting, evaluating, and integrating future knowledge inputs (including data). The result is a self-reinforcing feedback loop in which future ACAP increasingly depends on cumulative data absorption effort, reflected in the quality, volume, and diversity of the firm's data heritage. As data accumulates, it enhances both the value of existing data and the effectiveness of AI deployment, making firms progressively more capable of gathering further data and knowledge (of any kind), squeezing more informative content from extant data, predicting which data to gather next, and continuously reconsidering old data.

Such path-dependent, self-reinforcing dynamics echo the cumulative properties of knowledge building and the "learning to learn" concept in ACAP research (Cohen and Levinthal, 1990; Ellis, 1965; Estes, 1970), but with important differences. Knowledge accumulation facilitates further knowledge acquisition due to the properties of associative learning, thereby constraining the scope of knowledge acquisition to similar knowledge. Conversely, the accumulation of data enables a more effective use of AI for acquiring further data and knowledge of any kind. This is because AI's ability to derive knowledge from data does not depend on previous knowledge held in the same domain, but only on the volume, variety, and quality of data coupled with the effectiveness of AI algorithms. Hence, I advance the following two extensions:

Extension 1: Data heritage is introduced as a new component of the absorptive knowledge base.

Extension 2: A distinction between data absorption effort and knowledge absorption effort is introduced within the absorptive effort dimension.

4.2.2. Virtualization of tacit knowledge

Tacit knowledge can be defined as knowledge that is subjective, tied to action, and mostly elusive to consciousness (Nonaka, 1994; Nonaka and Takeuchi, 1995; Nonaka and von Krogh, 2009). Bread-making, childcare, and managerial decision-making are examples of activities requiring tacit knowledge, as they involve automatic physical routines, intuition, and/or implicit heuristics and rules of thumb coming from experience. Tacit and explicit knowledge lie along a continuum, and the extent to which the former can be converted into the latter remains a recurrent topic of academic debate (see Hadjimichael and Tsoukas, 2019 for an extensive review). Tacit knowledge is widely acknowledged as a source of competitive advantage, as its elusiveness shields it from imitation (Berman et al., 2002; Grant and Phene, 2022; Hadjimichael and Tsoukas, 2019; Helfat, 1997; Lecuona and Reitzig, 2014). However, within organizational boundaries, conversion of tacit into explicit knowledge is essential to knowledge creation and diffusion, as it makes knowledge less costly to share and turns it into a basis for reflection and conscious action (Nonaka and von Krogh, 2009). Thus, the absorptive process dimension includes mechanisms for conversion of tacit into explicit knowledge, as codification is conducive to both understanding and sharing.

AI is now capable of performing activities requiring significant tacit knowledge. For example, it may learn to diagnose diseases, adjudicate legal cases, operate complex equipment, or evaluate investment opportunities. This property can be understood and generalized through a logic of knowledge virtualization. Extensions 1 and 2 stem from the notion that AI can turn data into knowledge; however, it can also turn knowledge into data (more specifically, vector embeddings). Knowledge virtualization can be defined as the encapsulation of tacit knowledge in vector embeddings for subsequent use. Findings suggest that knowledge virtualization has two implications for ACAP.

First, it provides an additional channel to elevate individual tacit knowledge to the firm level. Normally, this would require mechanisms like the combination of individual cognitive schemata through shared mutual experience (Berman et al., 2002). Individual and team-level tacit knowledge can also be encapsulated in routines' procedural memory (Nelson and Winter, 1982). As routines solidify and become widespread, the knowledge they embed diffuses and may even survive the departure of employees who originally possessed it.

By encapsulating tacit knowledge in vector embeddings, AI introduces a qualitatively different mechanism for knowledge retention and diffusion. While traditional IT tools like knowledge storage platforms can preserve codified knowledge, their effect on the perpetuation of tacit knowledge is only indirect (e.g., by facilitating communication). By contrast, AI provides a direct means to store tacit knowledge in vector embeddings, complementing existing mechanisms for stabilizing a firm's knowledge base.

> "*These algorithms can really revolutionize the way knowledge is shared within companies. They learn and translate even stuff that's hard to put into words unless you spend a ton of time and resources, which is often impossible.*"
>
> (Chief Risk Officer, Earth)

> "*Imagine this experienced production director who knows the company and its market really well. Now, you combine that expertise with a tool that supports decision-making by analyzing massive amounts of data, not just the strong signals the production director is used to. It achieves two things: often, it improves the performance of the production director, and it also transforms that knowledge into a company asset rather than an individual asset. This is becoming more and more important because companies integrate a strong wealth of experience that, especially in small firms, is often tied to an individual, and, in larger companies, to a team.*"
>
> (Head of Innovation, Venus)

> "*Thanks to AI knowledge becomes a shared asset rather than something latent and exclusively owned by the business analyst, data scientist, or manager in charge. It turns into an open-access tool that unlocks incredible opportunities.*"
>
> (CEO, Mars)

> "*We never create algorithms that take over decision-making, except for super-rare cases. So, it'll still be a tool that supports us, but one that's picked up a ton of knowledge, not from some textbook, but from the way our company has put that textbook know-how into action with our processes, customers, and products.*"
>
> (CEO, Jupiter)

Second, the virtualization of tacit knowledge may enable a new form of learning. Once AI encapsulates tacit knowledge in vector embeddings, the cost of redeployment often becomes negligible, allowing employees across units to benefit from expertise they have not directly encountered. Although this primarily reflects knowledge use rather than transfer, repeated interaction with AI models can still enable partial learning. The extent of learning depends on factors such as users' receptivity, the duration of interaction, and the model's explainability.

Efforts can be directed toward the creation of partially explainable ("grey box") models that balance interpretability and performance. Such models facilitate mutual learning between humans and AI by enabling users to understand the drivers of algorithmic decisions and thereby internalize part of the tacit knowledge they embed. For example, attention mechanisms in natural language processing models or feature importance scores in ensemble methods (e.g., random forests) serve as cognitive bridges between algorithmic behavior and human understanding. These tools highlight which variables influenced a decision, in which direction, and to what extent, allowing users to reconstruct a symbolic reasoning process.

Furthermore, explainability contributes to trust and engagement. Employees are more likely to rely on, learn from, and integrate recommendations from AI models that they understand, even if only partially. This not only facilitates a better use of the embedded knowledge but also fosters its internalization over time. The more insights employees have into how a model reaches its conclusions, the more likely they are to spot limitations, contextualize recommendations, and reconstruct a partial symbolic logic to support learning.

> "*So, when you delve into the explanation of the AI model and how AI is making decisions, you start to see patterns that a human wouldn't have considered. That's valuable information, because when you give it to an expert in corporate governance, risk management, or any related field, the expert can then craft a narrative around that explanation and capture conditions that simply didn't occur to humans initially.*"
>
> (Chief Risk Officer, Earth)

> "*The goal is to make algorithms super easy to understand. We're putting in a ton of work on algorithm development, especially focusing on explainability. We want to make it clear to users interacting with AI what kind of decisions the AI is nudging them toward, so that they can reflect on them.*"
>
> (CTO, Jupiter)

> "*Even if I don't fully get the math behind it, just seeing why it suggests something helps me trust it more. It's like, okay, I see what it's picking up on, then I can decide if it fits our context. That back-and-forth helps me actually learn from it, not just follow it blindly.*"
>
> (CEO, Jupiter)

> "*Another benefit of grey box models is they bring out elements that a human might not have noticed or thought about.*"
>
> (R&D Director, Earth)

These findings highlight new dynamics in the absorptive process dimension of ACAP. This dimension has traditionally encompassed routines, processes, and socialization-based mechanisms for human-to-human knowledge transfer. IT tools are acknowledged to facilitate these mechanisms and enable the preservation of codified knowledge by acting as repositories or knowledge-sharing platforms (Chatterjee et al., 2002; Gold et al., 2001; Roberts et al., 2012; Setia and Patel, 2013). However, firms have traditionally relied on organizational mechanisms (e.g., the procedural memory of routines) to store tacit knowledge. By virtualizing knowledge through encapsulation in vector embeddings, AI provides a technological means to store tacit knowledge, which also enables new forms of learning. The effectiveness of these mechanisms for storage and learning is no longer determined solely by traditional drivers of knowledge transfer (e.g., socialization), but also by entirely new factors, like AI models' explainability and employees' receptivity to it. Therefore, I introduce the following extension:

Extension 3: Virtualization of tacit knowledge is introduced as a new component of the absorptive process of a firm.

4.2.3. *Cognitive duality*

In line with the conceptual mapping exercise (Section 3), empirical findings also underscore the more problematic side of AI. Common issues include hallucinations, brittleness, and various forms of bias (e.g., dataset imbalance and overfitting). These problems are exacerbated when AI is deployed in contexts that differ from its training conditions. As real-world environments evolve, continuous monitoring and periodic retraining are required to prevent performance degradation. Furthermore, AI and human biases may compound (e.g., through overconfidence driven by prior success with a given algorithm), making these issues particularly insidious.

> "*When the company begins to trust that algorithm, that's when you've got to be cautious about the boundaries. Because, you see, major shifts in the context, and unfortunately they happen quite often, or significant changes in the company's processes, well, the algorithm might interpret them in ways quite different from what we wanted to integrate and spread.*"
>
> (CTO, Jupiter)

Findings suggest that addressing these challenges requires *cognitive duality*, defined as the capability to combine domain-specific and AI-relevant knowledge in coordinating the strengths of human and artificial cognition. Deep domain-specific knowledge leads to a clear identification of the function and expected performance of AI algorithms within the domain of interest. This helps domain experts articulate their needs, promptly recognize anomalies in analyses or predictions, identify areas for improvement (especially as environmental conditions change), and spot opportunities for innovation. Conversely, AI-relevant knowledge, whether held by the same individual or (more often) by closely collaborating experts, supports the effective design and fine-tuning of algorithms, as well as the understanding of computational feasibility. Thus, coupling AI-relevant knowledge with domain-specific knowledge enables continual reconfiguration of algorithms as environmental conditions and internal processes evolve, thereby mitigating AI-driven biases stemming from context mismatch.

More subtly, bias mitigation may also flow from AI to humans. Cognitive duality may mitigate cognitive inertia by accelerating the recognition of the inadequacy of extant cognitive structures (Todorova and Durisin, 2007). The tendency to assimilate knowledge with inadequate cognitive structures is a well-known source of failure, as evidenced across industries such as photography, newspapers, and typewriter manufacturing (Danneels, 2011; Gilbert, 2005; Tripsas and Gavetti, 2000). Precisely because of their prior effectiveness, cognitive frames that made firms successful in the past may hinder adaptation (Tripsas, 2009). Given that AI models are characterized by different cognitive frames, they do not suffer from the same biases (Gregory et al., 2021). Biases in AI mostly emerge due to errors and imbalances in training datasets, as well as context mismatch (Anthony et al., 2023; Sturm et al., 2021; Tambe et al., 2019). Through a continual and informed reconfiguration of algorithms, cognitive duality not only mitigates AI-related biases but also leverages AI-driven insights to challenge and update existing human cognitive structures, improving their alignment with new knowledge.

Beyond mutual bias mitigation, the cross-fertilization of domain-specific and AI-relevant knowledge inherent in cognitive duality enhances all ACAP functions. By creating a virtual synaptic bridge between human and artificial cognition, it generates synergies in both the content and the elaboration of knowledge. While AI contributes computational power, pattern recognition capabilities, and proficiency in narrow tasks, humans provide intuition, experience, and contextual understanding to guide AI, interpret its outputs, and more effectively transform knowledge.

> "*There always has to be a dialogue between humans and machines. They each bring unique perspectives that give additional insights. For example, we can find that a specific financial profile of a certain type of customer is more willing to invest in cryptocurrencies. Then, we can move in that direction and offer services related to that industry.*"
>
> (Head of Technology, Saturn)

Like other socio-psychological constructs, cognitive duality may be evaluated at the level of the individual, the team, and the whole firm. At the level of teams and whole firms, findings suggest that cognitive duality is enhanced by the strength of the ties between AI experts and domain experts. Irrespective of the way AI experts and domain experts are brought together (e.g., mixed teams, interdepartmental coordination, or dedicated cross-functional tasks), cognitive duality requires not only organizational proximity, but also proactive interactions and a constant cross-fertilization between the two perspectives, with frequent and bidirectional information flows.

Effective algorithm reconfiguration requires AI experts to be kept informed about the state of the domain (especially if fast-paced). Symmetrically, it requires domain experts to know the logic of AI algorithms to assess their suitability for the evolving conditions. The mitigation of cognitive inertia requires AI experts to have a sense of the cognitive structures used by domain experts to assimilate incoming knowledge. Symmetrically, it requires domain experts to have enough faith in AI predictions (at least when informed by expert judgment) to doubt their own cognitive structures. Leveraging AI for knowledge transformation requires AI experts to know what qualifies as a breakthrough in the domain of interest, what sub-domain areas are promising candidates for AI-driven search and recombination, and what parameters to optimize at each iteration. Symmetrically, it requires domain experts to know the potential and limitations of AI in the focal domain, the available approaches (e.g., generative, predictive, or mixed), the data requirements, and the interpretation of results at each iteration.

All these instances require mutual trust and seamless exchange of information. Thus, organizations characterized by close, frequent, and proactive interactions between AI experts and domain experts (i.e., organizations with cognitive duality) are more likely to assimilate data and knowledge through the appropriate cognitive structures, achieving mutual bias mitigation. Furthermore, they are more likely to leverage their accumulated stock of data and knowledge in a creative way, continually complementing the distinct lines of reasoning of humans and AI to achieve the level of variation that leads to serendipitous breakthroughs.

> "*I believe the ability to overperform in any context depends on how small the gap is between the super expert in data science and the super expert in the specific vertical domain.*"
>
> (Head of Analytics, Venus)

> "*So, there's this kind of transfer, like a general template where the deep learning expert has a ton of expertise. Then, domain experts use their domain knowledge to tailor it for that specific domain. In the past 10 years, I've never seen anyone with deep learning skills having the insight into a specific business problem to generate disruptive innovation. Or on the flip side, people who know their domain perfectly often can't even explain what they need or what an artificial intelligence would require to generate innovation. It's when domain experts and deep learning experts work together closely that you can really take a step forward, rather than just marginally improve performance.*"
>
> (Head of Innovation, Venus)

This leads to my last extension.

Extension 4: Cognitive duality is introduced as a new component of the absorptive process.

4.3. An extended model of absorptive capacity

Taken together, my findings lead to a revised model of ACAP where Extensions 1, 2, 3, and 4 form a system of relationships that jointly reshape the absorptive effort, absorptive knowledge base, and absorptive process of firms. At the core of the model is the interaction between two co-evolving components of ACAP: a human-centric component and an AI-centric component (see Fig. 3). The human-centric component remains grounded in domain-specific knowledge and knowledge absorption effort, following the path-dependent logic of associative

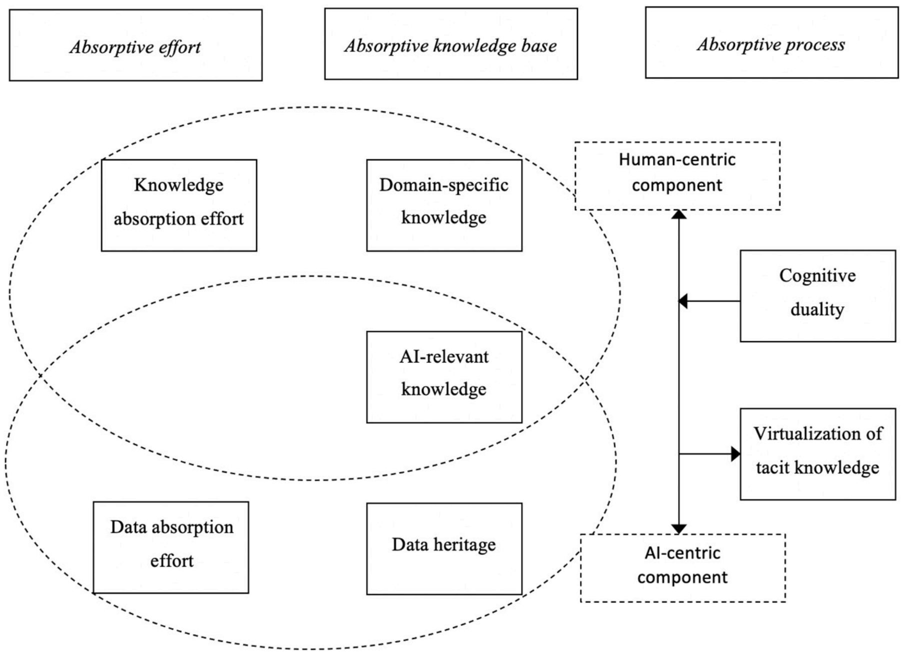

Fig. 3. An extended model of ACAP.

learning in line with the ACAP tradition. By contrast, the AI-centric component is grounded in data heritage, data absorption effort, and AI-relevant knowledge, and evolves through data-driven learning, whereby AI models update their knowledge generation function based on the volume, variety, and quality of data.

The first set of relationships concerns the internal dynamics of the AI-centric component. Data absorption effort and data heritage are linked through a recursive, self-reinforcing mechanism. Data absorption effort directly contributes to the accumulation of data heritage. In turn, data heritage enhances the firm's ability to extract information from both existing and new data, improving the effectiveness of AI deployment and guiding subsequent data absorption effort. This feedback loop introduces a form of path dependence that differs from that of domain-specific knowledge: rather than constraining future absorption to related domains, accumulated data expands the firm's ability to absorb data and knowledge across domains. As a result, the AI-centric component evolves through increasing returns to data accumulation in both scale and scope, which progressively enhance the firm's overall ACAP.

These dynamics extend beyond the AI-centric component and affect the absorptive knowledge base as a whole. Data heritage operates as a generative layer that interacts with domain-specific knowledge, influencing not only the output of knowledge elaboration but also the direction of future absorptive effort. In this sense, data heritage not only complements domain-specific knowledge but also alters the conditions under which knowledge is acquired and evaluated.

At the level of the absorptive process, virtualization of tacit knowledge and cognitive duality are also interdependent and closely linked to the composition of the absorptive knowledge base. Virtualization of tacit knowledge presupposes the existence of domain-specific knowledge to be virtualized. However, it also depends on the existence of a sufficiently rich data heritage and effective AI-relevant knowledge to train AI models capable of encapsulating that knowledge in vector embeddings. The resulting virtualized knowledge, in turn, becomes part of the firm's absorptive knowledge base, as it stabilizes and diffuses rather than remaining tied to individuals or routines. This induces an additional feedback loop: as virtualized knowledge accumulates, it enhances the firm's ability to generate further knowledge through both the human-centric and the AI-centric components of ACAP.

Cognitive duality acts as the central integrative mechanism connecting these components. By combining domain-specific knowledge with AI-relevant knowledge, cognitive duality enables the effective coordination of human and AI cognition. This coordination operates along multiple dimensions. First, it conditions the effectiveness of data absorption effort, as domain-specific knowledge guides the identification of relevant data, while AI-relevant knowledge supports its integration and use. Second, it enhances the value of the data heritage by enabling its interpretation and contextualization within domain-specific knowledge structures. Third, it governs the use and learning potential of virtualized tacit knowledge, as employees need both domain-specific knowledge and AI-relevant knowledge to interpret and internalize AI outputs.

Importantly, cognitive duality also introduces reciprocal feedback effects between the human-centric and AI-centric components. On the one hand, it enables the continual reconfiguration of AI models based on domain-specific knowledge, mitigating biases stemming from context mismatch. On the other hand, it allows AI-generated insights to challenge and update existing cognitive structures, reducing cognitive inertia and improving the alignment between prior and new knowledge. Through these mechanisms, cognitive duality ensures that the outputs of associative and data-driven learning are not isolated from but actively integrated with one another. As a result, ACAP encompasses not only how firms acquire, assimilate, transform, and exploit knowledge, but also how they manage the recursive interactions between data accumulation, knowledge virtualization, and the coordination of human and artificial cognition.

5. Discussion

5.1. Theoretical contributions

This paper contributes to ACAP scholarship by challenging its implicit human-centric foundation and reconceptualizing it as a dual learning architecture in which knowledge absorption emerges from the interaction between human and artificial cognition. While prior research has extensively examined how firms acquire, assimilate, transform, and exploit knowledge through human cognition and socialization mechanisms (Cohen and Levinthal, 1990; Lane et al., 2006; Lewin et al., 2011; Song et al., 2018; Todorova and Durisin, 2007;

Volberda et al., 2010; Zahra and George, 2002), it has largely overlooked the implications of non-human learning agents. By incorporating AI as a distinct, data-driven learning architecture, I advance ACAP theory in three main ways.

First, I reframe the foundational logic of ACAP. Traditional conceptualizations of ACAP are grounded in associative learning, whereby prior domain-specific knowledge shapes the recognition and assimilation of new knowledge (Bower and Hilgard, 1981; Cohen and Levinthal, 1990; Lindsay and Norman, 1977; Song et al., 2018; Todorova and Durisin, 2007). My findings show that, in the presence of AI, this logic coexists with a fundamentally different mechanism: data-driven learning, through which knowledge is generated from patterns in large-scale datasets rather than semantic associations. As a result, ACAP can no longer be understood as a purely human-centric capability. Instead, it becomes a dual learning architecture consisting of a human-centric component and an AI-centric component, each characterized by distinct forms of path dependence and learning dynamics. This reconceptualization extends the explanatory scope of ACAP by accounting for heterogeneous epistemologies within the firm.

Second, I extend the dimensional structure of ACAP by introducing four novel elements that capture AI-driven knowledge absorption. At the level of the absorptive effort, I distinguish between knowledge absorption effort and data absorption effort, highlighting the growing importance of purposeful data acquisition and orchestration. At the level of the absorptive knowledge base, I introduce data heritage as a distinct and generative resource that shapes the firm's ability to extract insights and guide future learning. At the level of the absorptive process, I identify two new mechanisms: virtualization of tacit knowledge, through which AI encapsulates experiential knowledge in vector embeddings, and cognitive duality, defined as the capability to integrate domain-specific and AI-relevant knowledge in coordinating human and artificial cognition. These extensions refine the internal structure of ACAP by incorporating elements that are specific to data-driven, AI-augmented contexts.

Third, I redefine the nature of the absorptive process. In traditional ACAP theory, knowledge absorption heavily relies on socialization-based mechanisms, such as communication, shared experience, and routines that enable the transfer and recombination of knowledge within the firm (Jansen et al., 2005; Lewin et al., 2011; Szulanski, 1996; Volberda et al., 2010). My findings suggest that, with AI, the absorptive process expands to include the orchestration of heterogeneous learning mechanisms across human and artificial cognition. Virtualization of tacit knowledge provides a technological channel for storing and redeploying knowledge, while cognitive duality enables the continual alignment and mutual adjustment of human and artificial cognition. This shift transforms the absorptive process from a predominantly social and cognitive phenomenon into a socio-technical one in which learning is distributed, recursive, and mediated by data and AI.

Taken together, these contributions make it possible to explain and predict phenomena that would remain theoretically opaque under the traditional ACAP model. Specifically, they help account for how firms generate valuable insights beyond the boundaries of their prior knowledge domains through data-driven learning; why firms with similar knowledge bases may exhibit different learning trajectories depending on their data heritage and AI capabilities; how tacit knowledge can be stabilized, scaled, and redeployed without relying solely on socialization mechanisms; and under what conditions the interaction between human and artificial cognition leads to superior learning outcomes versus bias amplification or misalignment. Table 3 contrasts the traditional ACAP construct with the extended model and outlines the corresponding theoretical implications.

5.2. Managerial and policy implications

Resource-based and knowledge-based traditions in management have established the role of knowledge as a key source of sustainable competitive advantage (Barney, 1991; Grant, 1996; Grant and Phene, 2022; Helfat, 1997; Helfat and Raubitschek, 2000; Kogut and Zander, 1992; Volberda et al., 2010; Wang et al., 2009). In addition to being valuable, rare, costly to imitate, and non-substitutable, firm-specific knowledge also enables firms to adjust to the environment and dynamically reconfigure their other resources and capabilities (Eisenhardt and Martin, 2000; Teece et al., 1997; Teece, 2007).

The present work underscores new resources and capabilities underlying the attainment of knowledge-based competitive advantage. Findings suggest that being able to absorb knowledge better than competitors now requires firms to accumulate AI-relevant knowledge, orchestrate the acquisition and management of data from multiple sources, develop rich and varied proprietary databases, virtualize their tacit knowledge, and achieve cognitive duality. The complexity, cost, and path dependence inherent in this bundle of resources and capabilities make imitation difficult, likely resulting in sustainable competitive

Table 3
The extended ACAP model: theoretical implications.

Dimension	Traditional ACAP	Extended ACAP	Theoretical implications
Absorptive effort	Focus on knowledge absorption effort (e.g., R&D, knowledge search initiatives). Effort is directed toward acquiring and assimilating knowledge.	Differentiates between: – Knowledge absorption effort (human-centric). – Data absorption effort (AI-centric: data sourcing, curation, integration).	– Reframes absorptive effort as driven not only by knowledge search but also by data gathering and orchestration capabilities. – Introduces a new source of path dependence based on data accumulation, with increasing returns in both scale and scope.
Absorptive knowledge base	Built on domain-specific knowledge stock. Learning is path-dependent and constrained by prior knowledge (associative learning).	Expands to include: – Data heritage. – AI-relevant knowledge (technical + organizational).	– Introduces data-driven learning as a new learning mechanism based on the overall data heritage of the firm. – Characterizes data-driven learning as a potential enabler of cross-domain knowledge absorption. – Conceptualizes AI-relevant knowledge as a meta-absorptive layer that conditions the firm's ability to configure, interpret, and update AI models, thereby shaping the quality and direction of both data-driven and associative learning.
Absorptive process	Based on socialization-based mechanisms and routines (e.g., communication, shared experience). Tacit knowledge transfer is indirect and costly.	Introduces: – Virtualization of tacit knowledge (AI encapsulating knowledge in vector embeddings). – Cognitive duality (coordination of human and AI cognition through domain-specific and AI-relevant knowledge).	– Alters the ontological status of tacit knowledge by making it partially storable and redeployable through AI. – Couples socialization mechanisms of knowledge transfer with technology-mediated knowledge virtualization. – Introduces coordination between different cognitive architectures as a core condition for effective knowledge absorption.

advantage. Furthermore, firms possessing cognitive duality are more likely to achieve resilience, as the coordination of AI-relevant and domain-specific knowledge supports not only the continual alignment of AI algorithms with changing conditions but also the updating of human cognitive structures, mitigating cognitive inertia (Danneels, 2011; Gilbert, 2005; Tripsas and Gavetti, 2000; Tripsas, 2009).

To these ends, managers should build internal capabilities for data collection, curation, and integration, as well as establish mechanisms to extract actionable knowledge from both structured and unstructured data sources. Firms that develop robust data infrastructures and routines for ongoing data enrichment will enjoy a cumulative advantage, as data and AI-relevant knowledge reinforce each other in a path-dependent and self-reinforcing manner.

Managers should also embrace the virtualization of tacit knowledge to transform individual expertise into scalable organizational assets by embedding tacit knowledge in AI systems. This not only safeguards against knowledge loss due to personnel turnover but also facilitates internal learning, as employees interact with AI and uncover previously inaccessible insights.

Furthermore, managers should foster strong, bidirectional ties between technical and domain experts to achieve cognitive duality. To this end, they could promote the formation of cross-functional teams, joint problem-solving workshops, rotational programs between departments, and shared performance metrics that reward collective outcomes. Crucially, managers should also nurture a culture of mutual respect and learning, where domain experts are encouraged to understand AI principles and technical experts are incentivized to immerse themselves in domain-specific problems. Such reciprocal upskilling not only enhances communication but also empowers both groups to jointly refine models, spot contextual anomalies, and co-create more relevant and robust solutions. Over time, these practices are likely to institutionalize cognitive duality as an organizational capability, enabling a more fluid and adaptive engagement with knowledge absorption.

At the policy level, my findings suggest that fostering AI-enabled absorptive capacity requires going beyond traditional support for R&D and knowledge diffusion toward a broader focus on data and socio-technical capabilities. Policymakers should recognize data heritage and data absorption capabilities as strategic assets, encouraging investments in data infrastructure, interoperability standards, and secure data-sharing ecosystems that enable firms to access and combine heterogeneous data sources. Public initiatives aimed at developing AI-relevant skills should not be limited to technical training but also promote hybrid profiles that bridge domain expertise and data science, thereby facilitating the emergence of cognitive duality at scale. Concurrently, regulatory frameworks should strike a balance between data accessibility and protection, ensuring that firms can maintain trust and accountability while also leveraging data for learning.

Finally, given that AI-driven knowledge absorption is path-dependent and cumulative, early access to data and AI capabilities may generate widening gaps between firms and regions. This calls for targeted policies (e.g., shared data platforms, public-private partnerships, and support for experimentation) that reduce entry barriers and prevent the concentration of learning advantages among a few dominant actors. By enabling the development of dual human-AI learning architectures across a broader set of firms, such policies can enhance not only firm-level competitiveness but also the overall dynamism and resilience of innovation systems.

5.3. Future research directions

The conceptual extensions proposed in this study open various promising avenues for future research. First, scholars can empirically test the extended model using quantitative methods. Like traditional ACAP dimensions, the new dimensions can be proxied through measures such as the number of big data sources, the proportion of data scientists employed, the stock of AI patents, and survey-based indicators. I encourage future research to develop dedicated questionnaires to capture the newly introduced dimensions and measure their impact on innovation performance and organizational learning. In this way, empirical studies could explore the moderating role of cognitive duality in the relationship between AI deployment and absorptive outcomes or assess the extent to which the firm's data heritage enhances innovation performance, contingent on the strength of the absorptive process dimension.

Second, future work could explore boundary conditions and contingencies. What organizational structures, cultures, or leadership styles are most conducive to fostering cognitive duality? Under what conditions does the virtualization of tacit knowledge generate meaningful learning, rather than mere automation? Through configurational approaches, future research could identify the combinations of capabilities and contextual factors that lead to high-performance outcomes in AI-enabled knowledge absorption.

Third, this framework could be applied across diverse organizational and industrial contexts. The present study draws on knowledgeable informants from small and medium AI-first firms across relevant industries in a homogeneous geographical context, to isolate AI-driven changes in the focal construct. While these choices have advantages, they also constitute limitations (e.g., findings may not be directly generalizable to all contexts). Future studies could investigate how the extended ACAP model applies to very large firms, low-tech industries, or developing economies. Such inquiries could illuminate whether and how the newly introduced extensions emerge under resource constraints, resource abundance, differing institutional conditions, or varied levels of AI maturity. Comparative case studies and longitudinal designs could be especially insightful in capturing the evolution of these capabilities over time and in different contexts.

The revised ACAP model could also be integrated with related theoretical perspectives. Scholars could investigate the interaction between the AI-centric and human-centric components of ACAP through the lens of organizational ambidexterity or sociomateriality. For example, how does the presence of dual cognitive architectures reshape the balance between exploration and exploitation? What new tensions or complementarities arise when machine learning systems become co-constitutive elements of organizational routines?

Finally, future research could delve deeper into the micro-foundations of the concepts introduced here. Ethnographic studies, cognitive task analyses, or experimental designs could shed light on how individuals interact with AI models to co-construct knowledge, navigate the ambiguities of algorithmic interpretation and reconfiguration, or adapt their own cognitive frames in response to AI-driven insights. Such a granular understanding could recast cognitive duality from a firm-level capability to an emergent property of everyday interactions between humans and AI.

6. Conclusion

Leveraging AI to absorb knowledge requires more than merely adopting the technology and gathering big data. It entails the interaction between two different cognitive architectures, leading to increased organizational complexity. The present work helps explain this complexity by theorizing new AI-relevant dimensions at the level of the absorptive effort, absorptive knowledge base, and absorptive process. These extensions call for further investigation into how traditional and AI-driven absorptive processes coexist, interact, and evolve across different organizational contexts. In this way, I hope to stimulate a new wave of research on ACAP embracing both the established and the emerging dimensions of the construct.

CRediT authorship contribution statement

Mattia Pedota: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The author declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Non-confidential data may be shared upon reasonable request.

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