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Integrating AI in organizations for value creation through Human-AI teaming: A dynamic-capabilities approach

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ABSTRACT

Although the potentialities of artificial intelligence (AI) are motivating its fast integration in organizations, our knowledge on how to capture organizational value out of these investments is still scarce. Relying on an approach to dynamic capabilities that focuses on the team level, we examine how humans and AI create interactions that engage both agents in productive dialogue for value co-creation. Our analysis is based on a longitudinal case of the development of a recruitment algorithm at a national subsidiary of Santander bank. Our results allow to identify three main sets of human-AI teaming interactions: achieving interoperability, building trust, and producing mutual knowledge gains. We elaborate a set of propositions on how the value of AI is increased when such interactions are created through productive dialogue, opening the scope for further research on the teaming dynamics that turn the collaboration between both agents into a source of value creation for companie

1. Introduction

The growing availability of artificial intelligence (AI) is stimulating its rapid drive for integration into organizations (Kinkel et al., 2022). AI is fundamentally related to autonomous decision-making (Berente et al., 2021), and it has therefore attracted companies' interest because of its potential to extend their scope to domains that have been exclusively human (Dwivedi et al., 2021), revolutionizing how business creates value for organizations (Mikalef & Gupta, 2021). Thus, the implementation of these technologies is gaining momentum (Ångström et al., 2023), and senior executives seem to agree on the criticality of AI as a game changer in the current business scenarios (Ångström et al., 2023; van de Wetering et al., 2022). However, organizations are still struggling with the issue of how to capture value from AI (Berg et al., 2023), with only 20 percent of companies declaring an impactful exploitation of AI applications (Akter et al., 2021) and studies showing that investments in this technology may even negatively impact market value (Lui et al., 2022). In this context, scholars are shifting the focus from the benefits of AI from a technological perspective toward a more holistic approach to how to leverage AI and what its real sources of value are (Enholm et al., 2022).

From a theoretical perspective, scholars have relied on the dynamic-capabilities (DCs) framework to explain how firms can transform their resources to persistently maintain value creation (Ambrosini & Bowman, 2009; Teece, 2014). DCs have traditionally been studied both at the macro-level of organizational routines (Felin & Powell, 2016; Fainshmidt et al, 2016; Bingham et al., 2015) and micro-level of executive decisions (Day & Schoemaker, 2016; Kor & Mesko, 2013). However, scholars have proposed an emergent, *meso*-level of DC development that considers team learning as the source of their dynamism and acts as a link between the macro and micro ones (Harvey et al., 2022; Salvato & Vassolo, 2018). DCs are enabled at this *meso*-level when teams establish high-quality interactions through productive dialogue (Tsoukas, 2009). Thus, teammates are motivated to change how they work and produce joint learning that is translated into adaptive organizational routines (Enholm et al., 2022; Harvey et al., 2020).

In the present paper we contend that this *meso*-level of analysis becomes particularly consequential when examining how to capture value out of the integration of AI in organizations. In this scenario, AI is an agent in full who should collaborate closely with humans to improve performance through the augmentation of their capabilities (Raisch & Krakowski, 2021). Considering AI's peculiarities regarding volatility, opaqueness, or elusiveness of human control (Hassija et al., 2023; Mikalef & Gupta, 2021) we face unique inquiries in terms of how to team

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up with the technology to leverage its value (Ångström et al., 2023). While the scholar literature is examining how to develop DCs through human-AI teaming both from a micro perspective (Weber et al, 2022; Brau et al, 2023) and also at a macro level (Mikalef & Gupta, 2021), to the best of our knowledge there are no studies of human-AI teaming which place the focus on the *meso*-level of DCs. Following the call for research on the mechanisms that reveal the interplay that underlies human-AI teaming (Ångström et al., 2023; O'Neill et al., 2022), we contend that this *meso*-level is key to explain how companies can leverage the value of AI, and rely on the literature on productive dialogue as a source of value creation (Keeling et al., 2021; Tjosvold et al., 2014; Tsoukas, 2009) to discuss how to achieve quality teaming interactions between humans and AI. Given these considerations, the following research question is posed: *How should human-AI teams develop through productive dialogue to create value for an organization?* Based on the productive dialogue literature, we explore how humans and AI create interactions that engage both agents at the team-based, *meso*-level of DC development in gaining leverage on the technology. Specifically, we identify three categories of interactions, aiming at (i) negotiating the terms of interoperability among the agents, (ii) nurturing trust to enrich the outcomes of the teaming relationship and (iii) creating mutual learning along the way.

In attempting to deal with these issues, we rely on a longitudinal case study on how a human-AI team develops over a period of four years. Given the relevance of the evolving nature of these capabilities, we draw on a process ontology (Tsoukas & Chia, 2002) to develop our case study, which emphasizes the temporal evolution of phenomena (Sharma & Bansal, 2020). We focus on a particular type of AI application, a machine-learning (ML), supervised-classification algorithm for screening candidates in a large bank's recruitment processes. The hiring function offers a particularly rich context for delving into human-AI teaming (Chowdhury, Dey, et al., 2023) because experiences thus far manifest how AI may destroy value through unintended consequences, thus demanding intensive interactions with humans for monitoring and correction purposes (Soleimani et al., 2022; Teodorescu et al., 2021). In addition, only a small proportion of companies report being able to integrate these applications into their processes (Laurano, 2022), mainly due to a lack of knowledge of what it represents for the human-resource (HR) department in terms of assumed risks and work to be done (Hocken & King, 2023). We could systematically monitor the implementation of AI in a talent-acquisition department from its inception, focusing on the quality of the interaction within the human-AI team that enabled a valuable integration of the technology into the organization.

This study extends our current knowledge on the organizational integration of AI-based applications in several ways. First, we contribute to the development of the *meso*-level approach to DCs integrating AI as a unique, new team member, therefore adding to the scarce literature in this field (Harvey et al., 2022; Salvato & Vassolo, 2018). Our findings illustrate how, while engaged in cycles of interactions, the team facilitated the dynamic sensing-seizing-reconfiguring pathway characteristic of DCs (Chirumalla, 2021; Krakowski et al., 2023). Second, our research points to the relevance of productive dialogue between humans and AI to allow for the creation of organizational value (Keeling et al, 2021; Tjosvold et al, 2014). Thus, our study shows that it is not only the quantity but also the quality of interactions between humans and AI that captures value out of the technology. We contribute to the human-AI teaming literature by elaborating a set of propositions on how the value of AI is increased when such interactions are developed through productive dialogue. This way, our study suggests novel extensions on the teaming strategies that engage both agents in value creation.

Finally, our study contributes to the practical approach to human-AI teaming at the *meso*-level of analysis by providing managerial insights into how to design team interactions that facilitate the integration of AI, augmenting the capacity of humans and leveraging the value that the technology can create for the organization.

2. Theoretical background

2.1. Dcs

Recent studies propose that, when properly integrated into an organization's socio-technical system, AI creates value for the firm by enacting DCs (Drydakis, 2022; Mikalef & Gupta, 2021; Schoemaker et al., 2018). By contrast with ordinary capabilities, DCs are defined as "the firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments." (Teece, 2007, p.316). Importantly, DCs cannot be acquired but can only be developed internally (Easterby-Smith et al., 2009), and they do not directly impact organizational performance but through a change of already-existing, ordinary enterprise capabilities (Chatterji & Patro, 2014). In addition, DCs are path-dependent, going through iterative cycles of sensing-seizing-reconfiguration through which opportunities are grasped and developed, thus leading to organizational learning and resource transformation (Easterby-Smith et al., 2009; Helfat & Peteraf, 2009). Therefore, the passage of time is critical for these capabilities to reach their maturity stage and become embedded in organizational processes, learnings, and routines (Pan et al., 2022).

Along the lines of the previous arguments, among the premises derived from the DC framework is that value creation does not depend on a company's investment of resources but on how such resources are combined and deployed to create organizational learning and dynamic adaptation (Lockett, 2005). Until recently, DC scholars have examined this phenomenon at two distinct levels. On the one hand, there is ample literature concentrated on the macro-level of operational routines and decision-making systems, given their relevance in providing reliability to companies (Teece, 2007, 2014). For example, Helfat and Peteraf (2003) examined the high-level origins of organizational capabilities and the specific sources of heterogeneity that support competitive advantage. Also from a macro perspective, DCs have been approached from the view point of organizational learning (Denford, 2013; Kaur, 2019) or of their role in adapting to disruptions at the company and market levels (Karimi & Walter, 2015). Researchers have also adopted a distinct approach to DCs focusing on the micro-level of managerial (Adner & Helfat, 2003) or top executive decisions (Day & Schoemaker, 2016). By contrast to the macro-level, this approach opens the scope for change as decisions are flexible and subject to change; however, it limits the view of the DC-creation process to individual decisions and therefore conceals our understanding of how routines are created (Helfat & Peteraf, 2015; Salvato, 2021).

Although both approaches to DC have led to relevant insights, neither explains how individual decisions may be aggregated in a manner that reconfigures resources and transforms routines at the organizational level. To address this issue, further conceptual developments propose a *meso*-level in which interpersonal connections among employees act as connectors between the micro- and macro-levels (Salvato & Vassolo, 2018). In this approach, companies leverage the joint effect of the adaptation to change triggered by top-level decisions and the stability created by organizational routines when employees are interconnected through teamwork, engaged to envision opportunities for improvement and willing to act, thus constituting the source of the dynamization of organizational capabilities (Peteraf et al., 2013).

This *meso*-level perspective emphasizes productive dialogue as a critical aspect of the teaming-development process: "We see productive dialogue as the means through which individual employees' proposals for change become aggregated into a firm-level dynamic capability" (Salvato & Vassolo, 2018, p. 1730). Productive dialogue assumes that agents recognize the "otherness" of their mates, act candidly, engage in mutual interaction, and stimulate action out of collective learnings (Berkovich, 2014; Tsoukas, 2009). As a result of productive dialogue, employees genuinely engage in improving current routines by devising new reconfigurations of resources and prompting action, their joint efforts resulting in changes in how a unit operates (Salvato & Vassolo, 2018) and creating value (Keeling et al., 2021). Therefore, the sensing-seizing of opportunities and final reconfiguration of resources that characterize DCs and create business value (Teece, 2014) emerge from these inner teaming flows that evolve in collective learning cycles over time (Harvey et al., 2022). Such a myriad of interactions brings about process and resource reconfigurations that are unique and difficult to imitate, thus reinforcing competitive advantage (Molloy & Barney, 2015).

This complex system of interactions through productive dialogue that characterizes the *meso*-level reveals as particularly relevant when exploring the integration of AI in organizations. The research literature has growingly recognized that, to realize its benefits, AI cannot work in isolation but only woven into human's daily practices, which demands a close collaboration on the part of both agents (Moser et al, 2022; Johnson & Vera, 2019). Additionally, the teaming between humans and AI poses specific challenges involving the adaptation to the specificities of this new sociotechnological scenario (Musick et al, 2021; Ängstrom et al, 2023). Scholars have approached these aspects of human-AI teaming in different ways as well. At the macro level, Mikalef et al (2021) identify the routines that companies should develop to best support B2B via AI, and others follow similar approaches at a more general level of application of AI (e.g., Kemp, 2023). More recently, Akter et al. (2023) develop a framework for the application of AI to service innovation focusing on the most relevant organizational capabilities that turn AI into a competitive advantage in the area. Conversely, working at the micro level, Weber et al (2023) interview a group of experts in the field of AI with distinct background and degrees of experience regarding their perspectives on the design of processes for developing organizational capabilities that allow for an effective implementation of the technology. Similarly, Brau et al. (2023) analyze the effectiveness of different executive profiles to examine how their AI-based decisions determine the performance of digitized retail supply chains. A recent survey (Ångström et al., 2023) also collects the opinions of a wide sample of executives with AI expertise on the challenges they face when integrating this technology and the decisions that delineate a successful, value-creating implementation. Finally, scanty studies deal partially with human-AI teaming at the *meso*-level of analysis, e.g., examining the patterns of interdependency that connect the different actors involved in AI performance (Jacobides et al., 2021) or exploring specific aspects of human-AI collaboration such as the effects of interactions being voluntary or hierarchically imposed (Bezrukova et al., 2023).

Our study focuses on how human-AI teaming develops at this *meso*-level perspective of DC creation. We argue that quality interactions based on productive dialogue motivate effective teaming development. Through productive dialogue, teammates prepare to change how they perform their work and based on such interactions, organizations enact DCs. We contend that researching at this *meso*-level requires to first examine the unique features that AI may provide to organizations and then review the current body of knowledge on how such distinct but complementary agents engage in human-AI teaming for value creation.

2.2. AI as a potential source of organizational value

Although scholars agree that there is not a single, univocal definition of AI, most concur on referencing it to human intelligence. Therefore, AI has recently been defined as "the ability of a system to identify, interpret, make inferences and learn from data to achieve predetermined organizational and societal goals" (Mikalef & Gupta, 2021, p. 3). Operating in this way, AI speed and information-processing capacities have proven to outperform those of humans in different scenarios, such as in the management of routine and codifiable work (O'Neill et al., 2022), prediction tasks (Choudhury et al, 2020), and situations that demand the fitting of models to large sets of alternatives (Weber et al., 2023). Yet, the most distinct feature of AI is its ability to "learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan & Haenlein, 2019a, p. 17). It is this capacity of AI to optimize itself through learning that shows the greatest potential to dynamically transform organizations' operating architecture and redefine how they capture and share value (Ångström et al., 2023).

While these benefits are already apparent for companies, it is also accepted that the performance of AI applications to realize value is limited by several factors (Ångström et al., 2023; Revilla et al., 2023). One key factor concerns the quantity and quality of the data used for training it (Kaplan & Haenlein, 2019; Sarker, 2021; Vial et al., 2021). Although data collection is rapidly growing in organizational contexts, available databases may not be appropriate for AI's learning process (Berente et al., 2021), and there are also data-privacy and related legal issues that may limit its use (Van Den Broek et al., 2022). Furthermore, unlike humans, AI lacks the ability to interpret contextual cues and anticipate the consequences of its decisions (Krakowski et al., 2023; Lindebaum & Ashraf, 2023), and this introduces relevant margins of error when facing ill-structured problems under conditions of complexity, ambiguity, and scarce information (Madni & Madni, 2018). AI may also produce senseless outcomes in problems involving social issues because it lacks the ability for moral deliberation (Hasija & Esper, 2022; Moser et al., 2022). Finally, a severe limitation of AI is its lack of transparency and explainability regarding how data are integrated and the knowledge that is gained by processing them (Chowdhury et al., 2023). This "black boxing" prevents humans from understanding its intentions, reasoning, and performance (Hasija & Esper, 2022; Vössing et al., 2022), and it consequently creates mistrust and reluctancy to collaborate with the technology (Dorton & Harper, 2022).

These unique characteristics of AI demand an intense, high-quality collaboration with humans to identify and correct flaws to make the most of its potentialities (Balasubramanian et al., 2022; Weber et al., 2023). However, scholars have claimed that, when this teaming is effective, AI can in turn augment human capabilities and improve decision making through a mutual learning process (Weiss & Spiel, 2022).

2.3. Human-AI teaming, sources of dynamism, and value creation

The application of a *meso*-level approach to the creation of DCs in the context of AI calls for the above type of human-AI teaming, which involves the interaction of "at least one human and one autonomous agent where the autonomous agent has a significant role and is treated as a full teammate instead of a simple tool" (Schelble et al., 2022). Such a definition recognizes that human-AI teaming means not simply adding a new resource but also undergoing an internal redesign of the human team operations in light of the new capacity (Mikalef & Gupta, 2021; Saenz et al., 2020), and accumulating evidence shows that the consideration of AI as one more group member significantly impacts the team's performance (Hauptman et al., 2023).

Scholars have mostly tried to understand the terms of the interaction between humans and AI relying on the extensively studied field of human teams (Endsley et al., 2022; Johnson & Vera, 2019). These analyses reveal three main factors that have proven fully applicable to the type of quality interaction that the *meso*-level model of DCs discusses when it proposes productive dialogue as a core mechanism for enacting the dynamism of organizational capabilities (Salvato & Vassolo, 2018). The first one is the recognition of interdependency between the teammates (Kozlowski, 2015) to determine the workflow structure and terms of the exchanges (Kozlowski & Ilgen, 2006). To engage in productive dialogue, AI should integrate in a team's activities while simultaneously demonstrating a level of agency in its outcomes that convinces humans of the unique value that this technology can provide beyond a traditional information and telecommunications (IT) application (Musick et al., 2021; O'Neill et al., 2022). From this starting point, humans and AI should share a profound understanding of each other's capacities and complementarities (Hauptman et al., 2023) and for this purpose, the issues of explainability and transparency are critical for humans to intervene in a timely manner (Endsley, 2023; Endsley et al., 2022). Humans should be able to understand why a system makes specific decisions, which represents a challenge because AI procedures and outcomes are typically opaque (Ångström et al., 2023; Kellogg et al., 2020) and AI can change its capacities in unpredictable, non-obvious ways (Endsley, 2023). A recent review of empirical research on human-AI teaming (O'Neill et al., 2022) revealed that interdependence and training in each other's awareness were positive for the team (Johnson et al., 2021; Li et al., 2022; Xiong et al., 2023), and that low levels of reliability in AI could be balanced by increasing transparency (Chowdhury, Joel-Edgar, et al., 2023; Vössing et al., 2022).

Another exportable aspect of human teams for achieving the productive dialogue that creates efficient teaming with AI is trust, regarded as an important antecedent of mutual understanding and team cohesion (Feitosa et al., 2020). Trust, defined as "the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability" (Dorton & Harper, 2022; Lee & See, 2004), is fundamental for humans to become willing to accept AI as an equal partner (McNeese et al., 2021). Trust has also proven to be key to reinforcing interactions and extracting value from them (Hoff & Bashir, 2015). However, trust is not a binary phenomenon but rather operates as a continuum where there is a continuous calibration over interactions between the agents (Yang et al., 2023), and how this works for AI is yet to be fully explored (Dorton & Harper, 2022a). For example, trust grows with increased connection among humans; in human-AI teaming, however, it may decline if interactions reveal flaws or malfunctions of the technology (Glikson & Woolley, 2020); it may also rise if humans are seen to identify and correct the failure to utilize an opportunity to learn more about the boundary conditions of the technology (Dorton & Harper, 2022).

Finally, in the course of this continuous interdependency-based interaction reinforced by trust, learning emerges as a third decisive attribute at the *meso*-level (Harvey et al., 2020). As a result of gaining collective experience in decision-making and problem-solving through productive dialogue, team members engage in a process of mutual learning, in which two agents adapt their behavior and/or mental states during continuous interaction (Peeters et al., 2020), and they in turn reinforce the acknowledgement of their respective agencies in the decision-making processes (Weiss & Spiel, 2022). In the context of human–human interaction, mutual learning is a natural phenomenon because teammates recognize the need to co-adapt and become predictable and explainable to facilitate collaboration (Harvey et al., 2022). In the case of human-AI interactions, it should be noted that learning extends well beyond the training of the algorithm, and that every interaction is an opportunity to extract knowledge about how to best perform the task at hand by learning from each other's mental models and consequences of their chosen course of action (van Zoelen et al., 2021).

Research design

Case-selection strategy

We adopted an interpretive case-study approach, which focuses on revealing how a theory applies to a particular context (Eisenhardt & Graebner, 2007). Our setting for the case study is the Talent Acquisition (TA) department of Santander bank in Spain, which provides recruitment and selection services to source a national region of 20,000 employees. We followed several criteria for selecting this case. First, it is "particularly suitable for illuminating and extending relationships and logic among constructs" (Eisenhardt & Graebner, 2007, p.27). The case is theoretically representative of the organizational context of a large company that plans for the implementation of an AI-based application; therefore, it faces the challenges and opportunities of developing human-AI teaming to create value for the organization. Additionally, the AI application is an algorithm that supports hiring processes, for which the collaboration between humans and developers has been regarded as critical (Soleimani et al., 2022; Teodorescu et al., 2021). Furthermore, the accessibility to multiple data sources allowed a synergistic collection of evidence to warrant the validity of our findings (Eisenhardt, 1989). From project inception, we could systematically and regularly observe the interactions leading to human-AI teaming. We combined these observations with interviews and archival data, mainly internal communications and project presentations in public fora. This strengthened the grounding of the theory, which is an important point because the theoretical development in the field is limited (Musick et al., 2021). The longitudinal data allowed us to follow a process-based approach, which is considered important for our objectives given the consideration of DCs as evolving change-management phenomena and the need to focus on the "know-how knowledge" of their development (Langley et al., 2013).

2.4. *Case setting*

In 2016, motivated by the fast-growing introduction of big data and analytics in business organizations, the TA manager of Santander Spain bank started to explore the application of these technologies in hiring processes within the bank's national market. As a result of the department's long experience in the practice, they were clear that the final "hire" decision should be in the hands of a human. However, a whole set of opportunities emerged as some tasks could greatly benefit from the use of AI. First of all, the volume of applications for junior positions was very high due to the prestigious-employer branding of Santander bank and its widespread commercial network. When the project started, the department received an average of 4,000 applications per sales vacancy; under time pressure to fill the positions, they could review and reach out to only approximately 900, thus rendering a significant amount of potential talent unexplored. Another relevant opportunity for the TA team came up from the fact that candidates' profiles were highly heterogeneous, given the applicants' lack of experience. This made the CV-screening process time-consuming; for every candidate considered valid for a telephone interview, they had to go through more than 30 applications. Finally, the screening was conducted on a "first-come-first-served" basis, which might have left out talented late applicants. Due to its unrelenting information-processing capability, the algorithm could process the information on the candidates and update the ranking regardless of the exact time the application came in; the TA team would thus obtain the best matches at the top of the list in real-time throughout the entire selection process, which constituted a huge opportunity to improve the efficiency of the department's operations.

After exploring the market, a decision was made to start collaboration with IIC, a research-and-development (R&D) institute specializing in big data. The objective was to develop an algorithm to support the screening of the massive selection processes in the bank, focusing on the sales force, who constituted the bulk of the positions in the more than 12,000 branches in the country. From the different types of AI-based learning models, a decision was made to choose an ML supervised-learning application, mostly used by companies because its mode of operation is relatively understandable and the final objective of the process is more controllable by humans (Balasubramanian et al., 2022; Kaplan & Haenlein, 2019). In the most extended uses of supervised ML, humans feed the algorithm with a set of predetermined categories and a large set of data, and the machine learns to estimate the correspondence of cases to one of the categories. The development of these algorithms comprises a training stage in which the AI builds the learning model, and a further testing phase involving the AI making decisions autonomously with a human monitoring the quality of the outcomes (Campesato, 2020).

2.5. *Data collection*

The data collection included the entire process of AI-teaming development over a period of four years. The most differential aspect of the case study was the monitoring of the development and implementation of the algorithm from its inception by the first author, who met with the TA manager by-monthly for a systematic follow-up. This allowed us to meet one of the prior conditions in case study research, which is “the development of testable, relevant and valid theory requires intimate connection with the real world” (Verleye, 2019). Our monitoring focused on the *meso*-level of analysis of DC development, that is, the set of collective interactions based on productive dialogue that might eventually translate into transformation of the department’s routines.

The project team was composed of five persons: two on the side of the developers (a project manager, psychologist with postgraduate training in AI-based applications, and a data scientist with experience in machine learning), and two domain experts (selection technicians with a long experience in hiring processes) and the TA manager on the side on the bank. Our monitoring of the case permitted us to gain insights on the interactions maintained over the teaming-development process, as the algorithm was trained and then integrated into the bank’s systems. We complemented the systematic monitoring and informal interactions with the team with four semi-structured interviews (one per year) with the manager to check his perception of the evolution of the project and discuss the decisions made by the team throughout the process. We also performed six semi-structured individual interviews, one with each of the developers and domain experts and two with the TA as the project was considered finalized to assess their perceptions in retrospect. We relied on the principles of responsive interviews (Rubin & Rubin, 2012; Yin, 2018) to produce the interview guides. At least two of the three authors were present in the final interviews, which were led by the first author to guarantee a consistent and rigorous coverage of the interview guides and make sure that the priority was placed on *meso*-level interactions vs. individual team members’ communication processes with the AI.

The project’s regular monitoring and interviews were complemented with a review of thirty-two relevant documents, mainly email forms, memoranda, notifications and correspondence with candidates, templates, progress reports, and presentations to external audiences about the project. We also gained access to the Applicant Tracking System (ATS) platform, through which we could observe how the algorithm had been integrated as well as the evolution of its interface according to the users’ feedback. Finally, attendance at conference presentations constituted a relevant source of observations of team members in a scenario in which they formally reflected upon the dynamics of the project and summarized what they jointly considered to be the key takeaways from the project in terms of interactions, performance, and mutual learning.

2.6. Data analysis

We followed a theory-elaboration model of analysis (Verleye, 2019) because we rely on theoretical insights of the *meso*-level DC framework to identify the teaming mechanisms that create value but challenge them by including AI as a unique member of the team. The data analysis was conducted in three main stages using thematic analysis (Miles et al., 2013), with several rounds of triangulation and checking with key informants. During the first stage, following the prescriptions of process studies (Langley et al., 2013), the first author contrasted the monitoring observations with the interview notes, collected company records, and depicted the process model based on a chronological tabulation of the data (Fig. 1).

In the second stage, the three researchers examined the contents, categorized the quotes and ideas, identified common patterns, and produced a first-order coding that was then discussed and integrated into themes. The authors’ different academic backgrounds (HR, operations, and technology) allowed us to adopt a strategy of multiple triangulations of data, investigator, and theory (Patton, 2015). This reinforced construct validity, which is an important aspect due to the current limited theoretical development in this field (Yin, 2018). Multidisciplinary triangulation was also performed, which contributed to a better understanding of how to interpret the key findings in the case (Verleye, 2019). The first-order coding expressed the rendering of the team’s perceptions of the interactions as the project progressed and the actions they adopted to adapt their operations as the need arose. We then compared and contrasted these views with our own observations and extracted second-order themes that represented forms of creating value through productive dialogue. Table 1 presents the results of the coding process derived from the analysis.

During the last stage, relying on the *meso*-level DC tenets, we

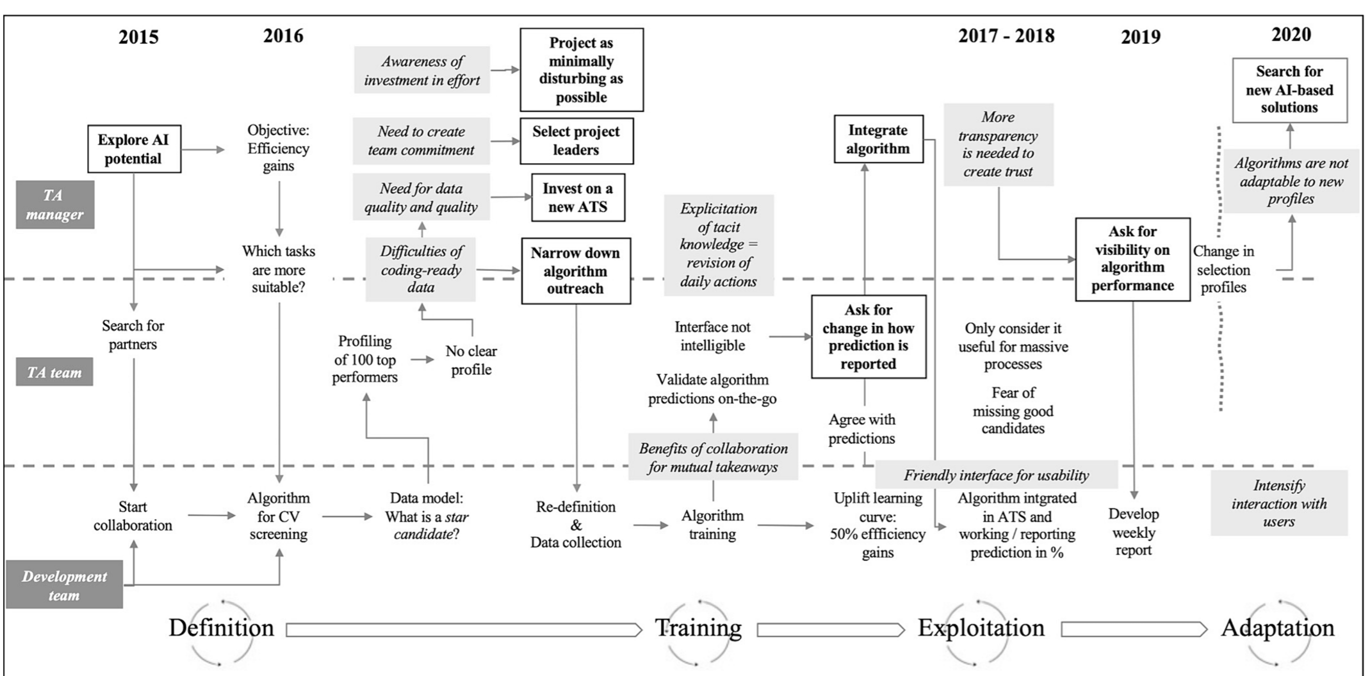

Fig. 1. Process of human-AI teaming development at Santander bank.

Table 1
Coding of empirical data.

First-order quotes (examples)	Second-order themes
“It was clear from the beginning where the role of the human was critical, especially in validating ambiguous data and checking the reliability and relevance of the algorithm’s performance” *(developer)*	**Realization of complementarities**
“ There are not plug-in solutions as we expected” *(TA manager)*	
“For us this is not a matter of ’having an algorithm’ but of fine-tuning the processes for which data management is critical” *(TA manager)*	
“Beyond the algorithm, AI showed us parallel ways of automating sub-processes with other technologies (e.g., chatbots)” *(TA manager)*	
“Mathematical models sometimes render flawed results, and only a human expert can validate the model and make sense of it” *(developer)*	**Management of data requirements**
“There are critical moments in which humans and technology have to interact to clarify cases. Without this it is not possible to train the system” *(developer)*	
“Machine learning requires time and lots of data for working better. If anything changes along the way, it does not work” *(developer)*	
“Developing a full-functional AI application demands volumes of high-quality data about the candidates that we cannot easily get” *(TA team)*.	
“A key condition from the beginning was that the algorithm had to be fully integrated with our processes and as transparent as possible. In other areas of the bank similar applications have not worked because they are not integrated” *(TA manager)*	**Anticipation of organizational constraints**
“We proposed to do more experimental things but Santander did not want to interfere their processes” *(developer)*	
“The objective of the algorithm cannot move, while priorities in Santander changed several times over the development process” *(developer)*	
“The requirements of integration and automation minimized the person-machine interaction, and as a result we miss both learning and potential performance. For example, we could not introduce tests for checking confirmation biases as it would demand extra time from the staff” *(developer)*	
“The project team had to be extended to the legal and IT areas in order for the user to understand the global picture” *(developer)*	
“In this bank selection is handicraft production. The human is the ultimate decision-maker and will always be” *(TA team)*	**Dispositional trust**
“I don’t want to miss real good talent for leaving decision capabilities to a machine – we are talking about people here” *(TA team)*	
“We are always challenging the performance of the algorithm, and we do not want to lose our critical spirit about the technology” *(TA manager)*	
“In spite of what the machine says, the team always has the last word” *(TA manager)*	
“Candidates hide information, may lie as well – how that can be managed by a technology?” *(TA team)*	
“The effort required to develop the AI application made us unsure about the trade-off in terms of benefits” *(TA manager)*	**Maximizing perceived value**
“The uplift curve that showed an efficiency gain of 50 % was determinant for our go-decision” *(TA team)*	
“We send them weekly reports so that they can check regularly how the algorithm performs” *(developer)*	
“Trust development has been a long process, because when we realize its value is only for massive processes” *(TA manager)*	
“The algorithm is like the intern that saves you the tedious tasks” *(TA team)*	
“We needed something automatic, that prevented errors and was as transparent as possible for the team” *(TA manager)*	**Boosting transparency**
“Currently users do not have visibility over how the algorithm works. The EU is currently regulating this increase in transparency for AI” *(developer)*	
“At the beginning we got a number that could not understand, which undermined our trust in the predictive capability of the algorithm” *(TA team)*	
“We needed to make some domain experts proficient in how to run these projects. Otherwise we would be losing capacity for the future ” *(TA manager)*	**Role specialization**
“As I see the team, diversity of knowledge about AI is good to push us to challenge our role vs. AI’s in every project we face ” *(TA team)*	
“We needed to make some domain experts proficient in how to run these projects. Otherwise we would be losing capacity for the future ” *(TA manager)*	**Role specialization**
“As I see the team, diversity of knowledge about AI is good to push us to challenge our role vs. AI’s in every project we face ” *(TA team)*	
“Now I see we had been trying to respond the wrong answer. It is not a matter of getting an algorithm that anticipates ’the best new hires’. The real value of this teaming is turning the AI into a partner that continuously enriches our information about the candidates, a technology that helps us augment our decision capabilities in any stage of the selection process… and use data to challenge –or reinforce- our intuitions.” *(TA manager)*	**Data-driven culture**
“We realized that we were very far from what was needed in terms of data quantity and quality to develop an AI-based application” *(TA manager)*	
“We are much more data-driven now, and aware of what data quality means” *(TA manager + TA team)*	
“As we learned to codify data we realized unconscious biases in the process that turned our processes much improved” *(TA team)*	
“We had put numbers to our intuitions; the transition from hunches to certainties has been a huge learning for the team” *(TA manager)*	
“AI changes our perception of the process, provides insights and pushes us to re-think our daily work” *(TA team)*	**Socialization of knowledge explicitation**
“A key takeaway is that resources are not direct costs but team effort for the training phase, no matter the AI-based technology you use” *(TA manager)*	
“As we learned to codify data ew realized unconscious biases in the process that turned our processes much improved” *(TA team)*	
“An important lesson was to gain awareness of how much algorithms are tailor-made and to what extent investments pay off” *(TA team)*	
“Now we understand what the role of the AI and the human are for the type of work that we do” *(TA team)*	
“The interaction with data scientists and the experience of joint development has got the team ready for new AI project developments” *(TA manager)*	
“Now we invest a lot of effort in explaining what AI development means, the investments it requires on the part of the team. This still looks like magic and both mistrust and overconfidence are bad” *(developer)*	
“The legacy of this algorithm is that the team is now excited to explore and test other tools that may be coming up in the market” *(TA manager)*	
“The project has helped us differentiate the value from the noise in the market of AI for our function. Technology becomes obsolete soon – the capacities are what matter” *(TA manager)*	
“Facing new selection challenges, we are now ready to assess upcoming applications as they appear in the market. We are no longer dazzled by the technology. Now we know what we want, and what the trade-off is in terms of investment and benefits.; we have developed criteria for assessing the validity of AI in our practice and reorganized to get ready to integrate the emerging technologies in our daily owrk” *(TA manager)*	

performed a theoretically grounded classification of the categories of interactions deployed by the team according to their respective objectives as they facilitated the sensing, seizing, and reconfiguring of resources throughout the project. The results of this analysis are presented in Table 2.

Table 2
Classification of problem-solving actions according to their contribution to the creation of human-AI teaming as a dynamic capability.

Objective	Productive dialogue issues	Sensing	Seizing	Reconfiguring
Negotiating Interoperability	– Realizing complementarities – Managing data requirements- Anticipating organizational constraints	– Visualize the opportunity to learn from interdisciplinar alliances for the purposes of innovation. – Adopt an exploration attitude for the project. – Comprehend the value AI may provide for the department..- Grasp the benefits of data quantity and quality.	– Negotiate reciprocalities – Sign condition based on time limitations of TA team- Change data collection strategy to enrich decision-making of the TA team through quality machine learning.	– Narrow down the scope of the algorithm. – Enrich data collection process with psychometric tests. – Implement new ATS.- Involve IT and legal departments for algorithm integration in the bank's systems.
Building Trust	– Maximizing perceived value- Boosting transparency	– Benefits of minimizing biases – Leverage on project to keep updated on new TA-related technologies.- Make the team aware of the transformation potential of AI-based technology.	– Visualize the project as a long-term strategy to augment the TA team's capabilities. – Explicitising knowledge to challenge experts' intuition.- Decision-making refinement through data-based reasoning.	– TA team transforms into data-driven decision-makers.- Two TA members permanently committed to exploring new technologies, and all team committed to assess them.
Producing mutual knowledge	– Specializing resources – Socializing knowledge explicitation- Fostering data-driven reasoning	– Opennes of mind to AI might eventually increase efficiency in selection.	– Job enrichment for TA members motivated by technology. – Challenge TA team's intuition by making biases explicit. – Build on obvious drawbacks of current process (e.g., talented late applicants).- Use database of TA team's 6,000 already selected candidates to train	– Assign team based on intrinsic interest in AI-based projects – Ask the developers to increase transparency when reporting results.- Regularly show efficiency of the AI to increase confidence and usability.

3. Findings

Following the recommendations for reporting case-study evidence (Eisenhardt & Graebner, 2007), in this section, we summarize the identified teaming interactions and engagement in forms of productive dialogue by humans and AI with implications for the *meso*-level of DC creation during the development of the project.

3.1. Setting the grounds for interoperability

The first set of interactions that the agents faced in their human-AI teaming endeavor was related to the definition of the operational terms (roles, responsibilities, and coordination mechanisms) for effective collaboration. Both domain experts and AI developers agreed during the interviews that the *realization of their partners' complementarities* became key to articulating the collaboration. Our monitoring of the process reinforced the relevance of this form of interaction. Thus, regarding objectives for the collaboration, the team initially agreed on the creation of an ML, binary classification algorithm to predict the matching of incoming candidates to a "star new hire" profile. As initially visualized by the TA manager, the team members recognized from the outset the value of one another's contribution and the need to engage in collective interactions in producing a successful outcome. Developers would focus on optimizing AI's data-processing and matching capabilities to rank applications as they arrived, thus augmenting the TA team's capabilities; meanwhile, only human domain experts could provide the contextual clues for producing a complete and accurate corpus of knowledge for the ML process. We also observed this awareness of mutual complementarities regarding biases. Although domain experts had already implemented controls for biases germane to selection processes, the AI raised new sources of partiality (e.g., they realized that extraversion was systematically taking precedence over IQ in their decisions). These discoveries forged the conviction that they needed one another to compensate for their own weaknesses, set a basis for mutual respect, and reinforced both agents' willingness to collaborate. While both the TA manager and the team members realized the challenges involved in getting acquainted to communicate with AI developers –so different conversational partners- the benefits involved in augmenting the capabilities of the department and grasp the opportunities stated above motivated the team to embark enthusiastically in the project.

As collective interaction evolved, the most relevant form of interaction to achieve interoperability was to *manage data requirements* for ML. When instructed by the developers, the domain experts soon realized that their available data fell short of the requirements for successful ML to meet their objectives. Furthermore, the AI required the translation of much of their expertise into formal knowledge to produce a valid outcome (e.g., how to operationalize what they considered a *star new hiring* for ML purposes). Facing these challenging requirements, the TA manager negotiated a revised objective for the project with the developers. This implied sacrificing the original outreach of the algorithm, forcing a narrowing down of the scope of the application from "predict the probability of a candidate being a star hire" to "predict the probability of a candidate being considered valid" (thus leaving aside the definition and nuances of what a "star" candidate meant). With this revised manager's objective, the algorithm could utilize a more complete database comprising all *valid* applicants. This would also permit adjusting the domain experts' interaction time for specific check points and questions. Additionally, with future developments in view, the manager decided to seize the right moment for improving the data systems for the department and, on the occasion of the project and with a view to the future, acquire a new ATS that could collect more and richer variables about applications for the purposes of a richer ML process.

Our analysis also revealed that *anticipating organizational constraints* on the integration of AI into the organization was indispensable for successfully constructing interoperability, since it would minimize the challenges imposed by the nature of the project. The first adaptation involved the above-mentioned data requirements. Developers demanded more domain experts' engagement to enrich the ML process. However, that option exposed the department's daily operations to risk, and the TA team knew that delays in the pace of new hires' sourcing would severely affect bank branches' sales. The TA manager's revision of the project objectives allowed the intensity of the domain experts' participation to be minimized.

Given business pressures, another priority for the TA manager was to fully incorporate the algorithm in the department's day-to-day work as one more member in charge of transparently providing agility to the screening process, which was one of the golden opportunities he had visualized from the beginning of the project. This implied involving other stakeholders in the bank. In particular, the role of IT was going to be critical, as it had to plug the algorithm into the corporate platforms and manage the implementation of the new ATS. Meanwhile, legal services had to join the project because guaranteeing compliance with the current data-protection regulations was particularly important when managing information from external applicants. The TA manager was then forced to divert resources to accommodate these corporate actors' requirements, which created coordination tensions and re-negotiations throughout the project's duration.

3.2. Building trust

As the project unfolded, the TA manager became aware of more opportunities that could arise if his team engaged in a confiding relationship with AI and focused on the objective of building trust among the entire TA team, so that they would accept AI as a new *de facto* member. This implication of all the department, beyond the persons directly involved in the development team, meant that AI would participate as one more member, augmenting each and every of the selection processes they were managing, thus streamlining operations and optimizing performance for the whole team.

Over the course of our data collection, we tested how departmental members showed different dispositions—depending on their backgrounds, knowledge, and experience with technology—toward the role that AI should play in their daily work. We could observe how the team resisted delegating decisions to AI and tended to double-check the predictions of the algorithm in every process to ensure the quality of the outcomes, which represented a very relevant challenge to the full integration of the AI in the department. Our conversations with the TA team revealed two main sources of reluctancy that had to be fought off. One involved the nature of the hiring activity. For the team, it was a matter of professional responsibility; as one of them stated, "We're talking about people here; we cannot leave good profiles by the wayside." Relatedly, the view that AI could never perform at the level of a human was deeply rooted in the culture of the department. AI could not deal with contextual cues that were crucial when making hiring decisions. These beliefs left AI at the level of "an intern that saves us of the tedious tasks," which was far from the consideration of the technology as an equal that was required for successful teaming.

Confronted with this situation, the TA manager realized that to consolidate the view of AI as a trustworthy partner, it would first be critical for them to visualize the "what's in it for me" of the technology, that is, *maximize the perceived value* that the algorithm could contribute to their work. Thus, he organized sessions for the team to be informed by the developers about the predictive capacity of the algorithm, until it resulted in a 50 percent gain in efficiency (Fig. 2); they discussed how, by using it, they would have to process 15 applications per valid candidate, compared to the average of 30 they used to have to go through, thus creating immediate salience of the personal benefits for team members in their daily work. Moreover, he negotiated with the developers the sending of a regular communication via mail to show the growing levels of accuracy of the algorithm in the context of each selection process (Fig. 3), so that they could check the actual benefits in terms of time and effort savings in real-time.

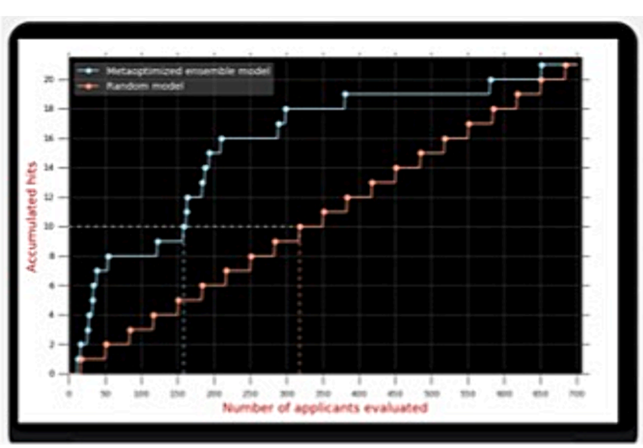

Fig. 2. Learning uplift curve for the Santander bank algorithm.

Interactions aiming at *boosting transparency* also proved critical at the relational level to create trust. In light of the success of the above actions, the TA manager demanded maximum visibility of the prediction power of the AI in real-time, so that the team could maintain control whenever they considered it necessary. This meant adding a column to the ATS screen view showing the algorithm's estimated probability of each candidate being considered valid. This upgrade in transparency allowed the TA team to better understand the AI's decisions and to make the most of the chance to tweak them to improve decisions or processes, for example reorganizing the order of the interviews when candidates received the same or very similar matching scores. With this augmented interaction, the reliability of the AI was made salient, fostering its integration into the ongoing selection processes. Consequently, the team progressively felt the added value of the algorithm as a "friendly sparring" that allowed them to question their decisions and bring to light biases that, once corrected, offered a set of opportunities to improve their professional practice.

3.3. Collaborating as production of mutual knowledge

Among the recurring issues raised during our interviews with the TA manager was how to optimize learnings from the experience for the team, which for him was the only way to consolidate a human-AI teaming routine in the department. Despite the organizational limitations in terms of time and effort and the team's high workload, who dealt with several massive selection processes in parallel, the TA manager knew that collective learning was critical to make the most of the investments in the technology and, thinking about his initial goals, seize the opportunity to augment the capacities of the department through AI. The initial exploration of AI solutions in the market had revealed that the algorithm belonged to the so-called "narrow-AI" type, that is, an ML application specialized in one very specific task. This meant that its active life was limited to the bank's need for a particular type of salesperson profile, and that consolidating human-AI teaming in the department would imply managing cycles of algorithm developments according to the bank's hiring needs. Thus, the TA manager decided to *specialize two of the team's domain experts*, setting learning objectives for

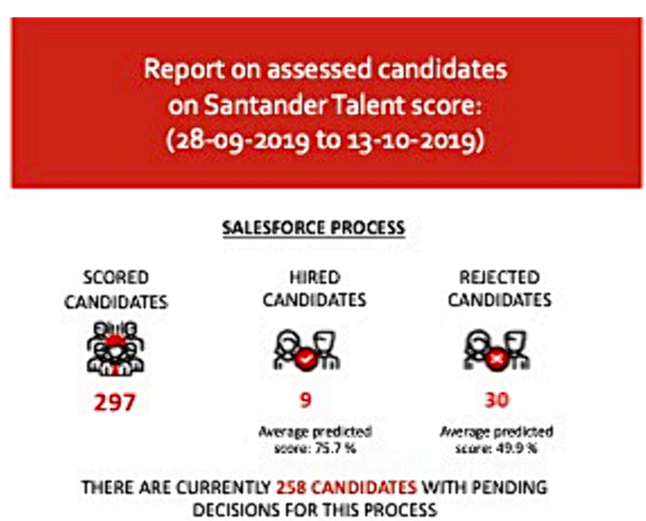

Fig. 3. Biweekly report produced by the developer for the final users of the algorithm.

them to become proficient in managing this type of projects. Although not assigned on a full-time basis, these persons would lead AI-based projects to meet the department's needs, thus leveraging the learnings acquired in the project by turning them into reinforcing arguments for the benefits of AI for the team and using them as a source of new projects for further integrating the technology into the department.

While specialization of resources was important, capitalizing on learning also required an expansion of the entire team's capabilities. Therefore, the team established follow-up meetings in which they *socialized their experiences* of training and using the algorithm with the rest of the unit, showing its benefits in challenging their beliefs and bringing their tacit expertise to the level of explicit information. For instance, during one of the meetings, we could observe a discussion about what a *valid* candidate was (e.g., what about candidates that rejected the position but who manifested interest in non-sales positions, or what about those who completely turned down the offer? Should they still be regarded as *valid*?). These issues had not previously been considered because they were irrelevant for their practice; however, raising them translated into an expansion of the team's collective savvy. Some of these meaningful conversations even ended up in changes in their routines (e.g., add a motivational test as a first step to double-check candidates' interest in the position and optimize the ratio of acceptance for their hiring offers) to mitigate biases discovered through the socialization of the team's tacit expertise.

Another way to optimize the learnings emanating from teaming with AI was fostering a culture of *data-driven reasoning*. Among the first takeaways of the project was the relevance of data quantity and quality, fundamental to approaching ML. Envisioning the value of this learning for the team, the TA manager asked the developers to report regularly on the most important variables the algorithm used for assessing the matching of candidates, as well as any other finding emanating from their data analysis. This supported the team's training in appreciating the value of introducing data-based evidence in their decisions and becoming aware of the relevance of collecting quality data not only for AI development but also for augmenting their own daily work.

4. A framework for exploring the role of human-AI teaming

Building on these findings, we propose a framework explaining how the interactions between humans and AI should take place at the *meso*-level of DC development to create value by allowing cycles of sensing, seizing, and transforming. The framework is shown in Fig. 4. It revolves around three categories of interactions between humans and AI, with distinct objectives: achieving interoperability, nurturing trust, and building mutual learning. In each of these interactions, the team engaged in productive dialogue, thus making possible the sensing, seizing, and reconfiguration cycles that enabled integrating AI in a manner that created organizational value. We also discuss managerial decisions which, although considered micro- rather than *meso*-level, constituted a drive towards team productive dialogue, and were regularly integrated in collective dynamics. This aspect is consistent with the multi-level DC literature, which contends that the *meso*-level emerges when "individual employees involved in change events interact through social interactions conducive to productive dialogue, thereby manifesting a higher-level, collective phenomenon" (Salvato & Vassolo, 2018, p.1733).

4.1. Productive dialogue for achieving interoperability

Our findings show that one of the categories of interaction at the *meso*-level of DC development aims at agreeing on the terms of interoperability between the agents. This means setting objectives, clarifying roles, negotiating responsibilities, and defining coordination mechanisms for effective collaboration (Kozlowski, 2015). Research in the field of AI implementation has argued that the lack of clarity in these terms may impact performance and even threaten the viability of the teaming efforts (Johnson & Vera, 2019). We contend that productive dialogue to achieve interoperability should focus on three issues: realizing both agents' complementarities, focusing on data requirements, and anticipating and managing organizational constraints.

The literature on AI has repeatedly stated that the potential to augment human knowledge-based activities through AI resides in compensating their mutual strengths and weaknesses, which results in increased productivity (Saenz et al., 2020; Zhang et al., 2022). Along this line, productive dialogue among team members at the *meso*-level should start from mutual recognition and respect for one another's uniqueness and the value of jointly creating and enacting proposals for change. In this sense, gaining awareness of each agent's characteristics facilitated the sensing and seizing of opportunities for the value that AI might contribute to the hiring process. Productive dialogue within the team also led to setting the bases on which the agents' capabilities, willingness, and availability defined the scope of the AI application, occasionally departing from the objectives that had originally been stated. Additionally, as discussed by the productive-dialogue literature (Keeling et al., 2021; Tsoukas, 2017), this quality interaction iterates over time, and partners progressively discovered unique characteristics in the others that opened new opportunities for interaction, seized through the agents' engagement and leading, in some cases, to unique reconfigurations of resources in the unit.

A second focus of productive dialogue concerns the complexities

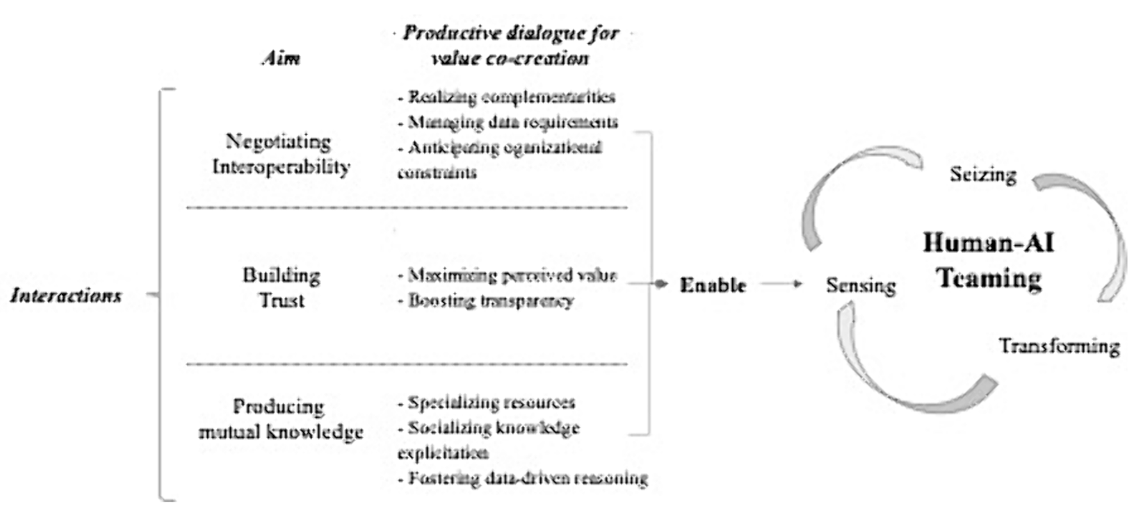

Fig. 4. Proposed framework for the development of human-AI teaming as a dynamic capability.

posed by data, a fundamental requirement for the training and successful integration of AI (Vial et al., 2021; Werder et al., 2020). The availability of high-quality data is instrumental for effective AI (Aaltonen et al., 2021), and it has been stated that practitioners generally lack both quality data and sufficient time to render accurate AI-based outcomes (Wang et al., 2020). Recent studies have moved past the belief that data are independent and objective, and they have emphasized the conditions that foster AI-domain expert interactions and the challenges involved therein (Van Den Broek et al., 2022). Through productive dialogue with AI developers, domain experts and managers may sense and seize the opportunities to reinforce the department's data strategy through the transformation of their data-collection platforms.

Finally, to consolidate interoperability, managers should anticipate and negotiate to adapt to the limitations imposed by the organization (Zhang et al., 2021). Even when decision regarding this matter may be considered managerial ones and therefore created at the micro-level, they trigger a whole set of *meso*-level interactions within team members. Productive dialogue facilitates this process, as it "amplifies employees' ability to anticipate what colleagues in other departments need to know or do, allowing them to more quickly diagnose and resolve problems" (Salvato & Vassolo, 2018).

To capture these dialogic dynamics, we advance the following proposition:

Proposition 1. *The value generated out of AI is increased when productive dialogue develops interoperability by (i) aiming at understanding each other's complementarities, (ii) considering data requirements as a priority, and (iii) anticipating organizational constraints.*

4.2. Productive dialogue for nurturing trust

The second category of interactions to enable DCs at the *meso*-level aims at building trust, that is, convincing humans to rely on AI to achieve their goals under conditions of uncertainty (Okamura & Yamada, 2020). AI provides value when it autonomously makes decisions; however, due to its lack of interpretability, humans are generally reluctant to accept it (Berente et al., 2021). In this case, building trust involves interacting with the AI as humans decide the extent to which they confidently cede control and allow the technology to operate autonomously (Hoff & Bashir, 2015). We propose that productive dialogue facilitates the growth of trust by focusing on two issues: highlighting the benefits of AI and maximizing its transparency for the human teammates.

As the benefits of the AI became salient for the domain experts, the team tended to increase both the quantity and the intensity of their collective interactions to support their activities. This, in turn, smoothed the way for sensing and seizing new opportunities for improving processes in the unit, contributing to the transformation of routines in the unit. Previous research has shown that users who appreciate the potential benefits of an application tend to minimize the risk and feel more inclined to adopt it (Hu et al., 2022; Park et al., 2019). We extend this conversation by exemplifying how this perception of value in terms of "what's it in for me" can be realized in the course of productive dialogue among employees and AI, leading to the willingness to adopt a technology that, to be valuable, should be deeply embedded in their work.

Productive dialogue at the *meso*-level also cultivates trust by increasing transparency. This has been among the most studied topics in the field (Holmström & Hällgren, 2022; Shin & Park, 2019; Weber et al., 2022). Algorithm aversion due to opaqueness has been a matter of academic concern for every AI-based practice (Chowdhury, Joel-Edgar, et al., 2023; Vössing et al., 2022). Transparency grew when the human-AI team engaged in intensive interactions to understand, as much as possible, both the process and outcomes of the algorithm as it was integrated into the decision-making system of the unit, and became progressively involved in a candid interaction where the critical points that demanded more transparency were consistently raised.

Based on these arguments, we propose the following:

Proposition 2. *The value generated out of AI is increased when productive dialogue builds trust by (i) making the benefits of the technology salient and (ii) incrementing transparency.*

4.3. Productive dialogue for mutual learning

The third category of interactions that facilitate the creation of DC at the *meso*-level should make the most of the collaboration by producing mutual knowledge (Weiss & Spiel, 2022). The literature on *meso*-level DC creation states that employees' knowledge should be amplified to foster and extend changes to the macro- or firm level (Salvato & Vassolo, 2018). While learning is connatural to AI as it is the essence of its efficient operation, humans must try to become proficient in working with AI to extract maximum value out of the collaboration with the technology. This involves identifying the difficulties in making explicit the contextual factors that determine human decisions, so that the technology can integrate them over its learning process, minimizing biases (Tambe et al., 2019). Our research points to three issues of productive dialogue to produce mutual learning: creating a base of specialized resources in the unit, socializing new knowledge as it is created, and fostering a data-driven culture.

Again, the manager's individual decision to specialize resources (even on a part-time basis) for teaming with the developers formally reinforced closed collective interactions within the team. It also supported the maintenance of a long-term view of the benefits of the technology, thus intensifying the willingness to collaborate. Consequently, as humans become more knowledgeable on interacting with AI, productive dialogue is reinforced, opening new opportunities for projects that are then propelled by the specialists to the rest of the unit.

Productive dialogue for mutual human-AI learning should not only aim at correcting potential AI flaws but should also help improve the good judgement of both agents in decision-making. Quality interactions allow domain experts to leverage the learning opportunities through awareness of their unconscious biases and sharing reflections on alternative courses of action out of the inputs received from the AI's outcomes. This constitutes an indispensable source of opportunities to revise their routines and transform decision-making processes to fine-tune the unit's performance. Productive dialogue should also include actions to socialize these learnings to expand the group's problem-solving abilities, thus reinforcing the *meso*-level of interactions, in turn augmenting the entire unit's capabilities and strengthening the system of collaboration among employees, which is key to enabling change at the macro-level of DC creation (Chowdhury, Dey, et al., 2023; Salvato & Vassolo, 2018).

Finally, the team's productive dialogue should crystalize into a culture of data-driven reasoning to prevent humans from reverting to the earlier routines and consolidate the reconfiguration of resources catalyzed by the changes created by the team. A data-driven culture is characterized by a system of values, beliefs, and assumptions that support firms' competitive advantage by creating analytics, data management, and governance capabilities (Chatterjee et al., 2021). By adopting such values and beliefs, the team motivated the reconfiguration of resources and consolidated new routines in which AI was fully integrated into the department's operations.

Based on these arguments, we propose the following:

Proposition 3. *The value generated out of AI is increased when productive dialogue creates mutual knowledge by (i) specializing resources, (ii) fostering the socialization of learnings and (iii) nurturing a data-driven culture.*

5. Managerial implications

The experience of the TA department of Santander Bank demonstrates that the integration of AI applications in business settings demands managers' strategic vision as well as an explicit drive to transform their organizations and create value through productive dialogue between organizational employees and the technology, which constitutes the basis of effective and sustainable human-AI teaming. A set of recommendations for managers in terms of "dos and don'ts" is shown in Table 3.

First, our findings show that managers, first, should invest time in understanding what human-AI teaming involves, establishing the type and quantity of organizational resources and requirements before starting the development of an AI-based application. This previous exploration is critical to setting the basis for an effective interoperability between experts and developers, involving team dynamics as well as the assessment of the actual state of the database that will input ML and the additional resources that will be required (Weber et al., 2022).

Second, to operate successfully, AI requires much more than "final users." It requires professional wisdom from various angles to learn and correct itself through continuous improvement. Thus, people engagement in a project is key, and managers should create a climate of transparency in which team members exchange their experiences and build trust in AI and its potential benefits. Along these lines, managers will have to leverage team members who are more prone to AI, as well as make visible the value that the department will derive from the AI outcome throughout the project and communicate how it will compensate for the effort invested.

Finally, substantial benefits can be gained from implementing AI-based applications; however, business constraints can refrain managers from capitalizing on them (Hasija & Esper, 2022). Therefore, managers should regularly critically examine the learnings that are being produced in the process through the outcome of the development. Such learnings should serve to train the AI application to the best of its capabilities and minimize automatic rational-judgement biases. Meanwhile, to make the most of the project, mutual learning through interaction with the AI should help revisit the team's expertise—refining individual and group biases and augmenting decision-making—and improve the process and resource optimization within the department.

Table 3
Human-AI teaming: Recommendations for managers.

	Dos	Don'ts
Structural level: Interoperability	Invest time in understanding what human-AI teaming involves, making sure about the type, quantity of organizational resources and requirements before starting the development of an AI-based application.	Don't see the development of an AI-based application as one more technological implementation – the nature of the project is completely distinct and should be approached in its own way.
	Be very clear and transparent about the rules of the game with all the team from the beginning to avoid false expectations.	Don't assume that AI applications can be acquired as off-the-shelf products. They require significant investments in resources for trainiing and integrating the technology.
	Anticipate potential additional stakeholders that will be needed along the project.	Don't take anything for granted as regards roles, tasks and responsibilities. Clarify with the team all the terms of development and integration work.
	Stay flexible to be able to manage contingencies which are normal when exploring new terrains.	
Relational level: Trust	Engage every member of your team all along the process, by creating a psychologically safe environment as far as AI is concerned.	Don't separate the developers from the rest of the unit; create opportunities for them to socialize with the whole team so that they can appreciate the complementarities and benefits of the technology as well.
	Foster the creation of ambassadors of the technology that socialize the benefits and value of AI for the whole unit.	Don't presume that people will be more or less engaged with the technology. Trust is fragile and depends on multiple factors that cannot be controlled easily. Monitor the evolution of the project carefully to control for potential reluctancies.
	Manage the communication about the project in a way that makes as salient as possible the benefits of the use of AI for the daily activities of the team.	
Cognitive level: Mutual knowledge production	Visualize the potential of human-AI teaming in terms of learnings, innovation and revision of the current processes, beyond the impact of the isolated technological delivery and in the context of a mid-term run.	Don't isolate the project from the rest of the department – AI should be seen from the outset of any implementation as a new member of the team
	Make the most of the implementation for opening new scopes of improvement in the unit.	Don't assume that the learnings are limited to a particular implementation. It is the general capability of the department to team with AI that matters.
	Use AI as a catalyst for change through its potential to challenge the ordinary routines of the team.	

6. Limitations and future research directions

Our study was based on a single case. As Yin (2018) states, when using case studies, we can only generalize the theoretical propositions and not the results to the entire population. In this sense, although our findings can be context-specific, our framework and propositions offer insights to open new examinations on critical aspects that organizations must anticipate if they want to fully capitalize on the value of AI, which remains an understudied research field (Ångström et al., 2023b; Holmström & Hällgren, 2022; Weber et al., 2022).

Furthermore, our case is based on a very specific type of AI, an ML classification algorithm, and research has already established differences in the engagement of humans with different AI applications—e.g., according to AI's embodiment forms (Glikson & Woolley, 2020). However, concerning the form and quality of human-AI interactions, our study sets the basis for further research on how to team with other technological development fields such as robotics or generative AI. In this sense, future studies should build on this exploratory work to collect data from multiple source in search of patterns of productive interactions between humans and AI that capture the maximum value from organizational investments in this technology.

Adding to the former points, the present study proposes a framework and derives a set of principles for human-AI teaming in organizational contexts, from which we can infer future directions for research focused on three main streams related to AI. The first one is the analysis of the *meso*-level of DC development, an understudied field so far. Scholars should look into what is the most effective configuration of a human-AI hybrid team to engage in social action and cognition, and under which organizational contingencies these collective interactions are more effective to enable the transformation of routines and therefore the creation of new DCs for the organization. Process-based studies that consider the time dimension and different levels simultaneously to monitor collective interactions are encouraged. Relatedly, the development of measures of such *meso*-level interactions are also needed to structure research designs.

Consistent with the literature, our propositions revolve around the assertion that interactions at the *meso*-level depend on the creation of productive dialogue among the members, and this constitutes another relevant human-AI teaming relevant research area. Further scholar work should look into the underlying mechanism of productive dialogue, what are its main drivers in the case of this particular partnership, and under which conditions the interaction of humans with AI render create more value for companies.

Finally, we invite researchers to explore the three categories of interactions that conform our framework, specifically discussing the dynamics of their interaction to facilitate the cycles of sensing, seizing and transforming that ultimately lead to DC development. Although studies have already examined different aspects of interoperability, trust and mutual learning in the interaction between human and AI-based agents, it is the combination of the three interacting over time that lead to the creation of a solid partnership between so distinct agents. We have inducted from our case study a set of factors that increase the creation of value within each category. Future research should aim to look into each of them in more detail and complement them insofar as they are key to make the most of opportunities, anticipate challenges and maximize the investments in AI that organizations are growingly making to augment their capabilities and increase their performance.

CRediT authorship contribution statement

Cristina Simón: Writing – original draft, Investigation, Formal analysis, Conceptualization. **Elena Revilla:** Validation, Formal analysis, Conceptualization. **Maria Jesús Sáenz:** Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

Aaltonen, A., Alaimo, C., & Kallinikos, J. (2021). The making of data commodities: Data analytics as an embedded process. *Journal of Management Information Systems, 38*(2), 401–429.

Adner, R., & Helfat, C. E. (2003). Corporate effects and dynamic managerial capabilities. *Strategic management journal, 24*(10), 1011–1025.

Akter, S., Wamba, S. F., Mariani, M., & Hani, U. (2021). How to build an AI climate-driven service analytics capability for innovation and performance in industrial markets? *Industrial Marketing Management, 97*, 258–273.

Ambrosini, V., & Bowman, C. (2009). What are dynamic capabilities and are they a useful construct in strategic management? *International Journal of Management Reviews, 11*(1), 29–49.

Ångström, R. C., Björn, M., Dahlander, L., Mähring, M., & Wallin, M. W. (2023). Getting AI implementation right: Insights from a global survey. *California Management Review, 66*(1), 5–22.

Balasubramanian, N., Ye, Y., & Xu, M. (2022). Substituting Human Decision-Making with Machine Learning : Implications for Organizational Learning. *Academy of Management Review, 47*(3), 448–465.

Berente, N., Gu, B., Recker, J., & Santhanam, R. (2021). Managing Artificial Intelligence. *MIS Quarterly, 45*(3), 1433–1450.

Berg, J., Raj, M., & Seamans, R. (2023). Capturing value from Artificial Intelligence. *Academy of Management Discoveries, 9*(4), 424–428.

Berkovich, I. (2014). Between person and person: Dialogical pedagogy in authentic leadership development. In *Academy of Management Learning and Education* (Vol. 13 (2, pp. 245–264). George Washington University.

Bezrukova, K., Griffith, T. L., Spell, C., Rice, V., Jr, & Yang, H. E. (2023). Artificial intelligence and groups: Effects of attitudes and discretion on collaboration. *Group & Organization Management, 48*(2), 629–670.

Bingham, C. B., Heimeriks, K. H., Schijven, M., & Gates, S. (2015). Concurrent learning: How firms develop multiple dynamic capabilities in parallel. *Strategic Management Journal, 36*(12), 1802–1825.

Brau, R., Aloysius, J., & Siemsen, E. (2023). Demand planning for the digital supply chain: How to integrate human judgment and predictive analytics. *Journal of operations management, 69*(6), 965–982.

Campesato, O. (2020). *Artificial Intelligence*. Machine Learning and Deep Learning Account: Mercury Learning & Information.

Chatterjee, S., Chaudhuri, R., & Vrontis, D. (2021). Does data-driven culture impact innovation and performance of a firm? An empirical examination. *Annals of Operations Research*, 1–26.

Chatterji, A., & Patro, A. (2014). Dynamic capabilities and managing human capital. *Academy of Management Perspectives, 28*(4), 395–408.

Chirumalla, K. (2021). Building digitally-enabled process innovation in the process industries: A dynamic capabilities approach. *Technovation, 105*, 1–24.

Choudhury, P., Starr, E., & Agarwal, R. (2020). Machine learning and human capital complementarities: Experimental evidence on bias mitigation. *Strategic Management Journal, 41*, 1381–1411.

Chowdhury, S., Dey, P., Joel-Edgar, S., Bhattacharya, S., Rodriguez-Espindola, O., Abadie, A., & Truong, L. (2023). Unlocking the value of artificial intelligence in human resource management through AI capability framework. *Human Resource Management Review, 33*(1), Article 100899.

Chowdhury, S., Joel-Edgar, S., Dey, P. K., Bhattacharya, S., & Kharlamov, A. (2023). Embedding transparency in artificial intelligence machine learning models: Managerial implications on predicting and explaining employee turnover. *International Journal of Human Resource Management, 34*(14), 2732–2764.

Day, G. S., & Schoemaker, P. J. (2016). Adapting to fast-changing markets and technologies. *California Management Review, 58*(4), 59–77.

Denford, J. S. (2013). Building knowledge: Developing a knowledge-based dynamic capabilities typology. *Journal of Knowledge Management, 17*(2), 175–194.

Dorton, S. L., & Harper, S. B. (2022). A Naturalistic Investigation of Trust, AI, and Intelligence Work. *Journal of Cognitive Engineering and Decision Making, 16*(4), 222–236.

Drydakis, N. (2022). Artificial Intelligence and Reduced SMEs' Business Risks. A Dynamic Capabilities Analysis During the COVID-19 Pandemic. *Information Systems Frontiers, 24*(4), 1223–1247.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., & Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management, 57*.

Easterby-Smith, M., Lyles, M. A., & Peteraf, M. A. (2009). Dynamic capabilities: Current debates and future directions. *British Journal of Management, 20*, S1–S8.

Eisenhardt, K. M. (1989). Building Theories from Case Study Research. *Academy of Management Review, 14*(4), 532–550.

Eisenhardt, K. M., & Graebner, M. (2007). Theory building from cases: Opportunities and challenges. *Academy of Management Journal, 50*(1), 25–32.

Endsley, M. R. (2023). Supporting Human-AI Teams:Transparency, explainability, and situation awareness. *Computers in Human Behavior, 140*.

Endsley, M. R., Cooke, N., McNeese, N., Bisantz, A., Militello, L., & Roth, E. (2022). Healthcare. In. *Journal of Cognitive Engineering and Decision Making, 16*(4), 179–181. Special Issue on Human-AI Teaming and Special Issue on AI in.

Enholm, I. M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2022). Artificial Intelligence and Business Value: A Literature Review. *Information Systems Frontiers, 24*, 1709–1734.

Fainshmidt, S., Pezeshkan, A., Lance Frazier, M., Nair, A., & Markowski, E. (2016). Dynamic capabilities and organizational performance: A meta-analytic evaluation and extension. *Journal of management studies, 53*(8), 1348–1380.

Feitosa, J., Grossman, R., Kramer, W. S., & Salas, E. (2020). Measuring team trust: A critical and meta-analytical review. *Journal of Organizational Behavior, 41*(5), 479–501.

Felin, T., & Powell, T. C. (2016). Designing organizations for dynamic capabilities. *California management review, 58*(4), 78–96.

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals, 14*(2), 627–660.

Harvey, J. F., Bresman, H., Edmondson, A. C., & Pisano, G. P. (2022). A Strategic View of Team Learning in Organizations. *Academy of Management Annals, 16*(2), 476–507.

Harvey, J. F., Bresman, H., Edmondson, A., & Pisano, G. (2020). *Team Learning and Superior Firm Performance: A Meso-Level Perspective on Dynamic Capabilities* (pp. 19–059). Harvard Business School Technology & Operations Mgt. Unit Working Paper.

Hasija, A., & Esper, T. L. (2022). In artificial intelligence (AI) we trust: A qualitative investigation of AI technology acceptance. *Journal of Business Logistics, 43*(3), 388–412.

Hassija, V., Chamola, V., Mahapatra, A., Singal, A., Goel, D., Huang, K., Scardapane, S., Spinelli, I., Mahmud, M., & Hussain, A. (2023). Interpreting Black-Box Models: A Review on Explainable Artificial Intelligence. *Cognitive Computation*, 1–30.

Hauptman, A. I., Schelble, B. G., McNeese, N. J., & Madathil, K. C. (2023). Adapt and overcome: Perceptions of adaptive autonomous agents for human-AI teaming. *Computers in Human Behavior, 138*.

Helfat, C. E., & Peteraf, M. A. (2009). Understanding dynamic capabilities: Progress along a developmental path. *In Strategic Organization, 7*(1), 91–102.
Helfat, C. E., & Peteraf, M. A. (2015). Managerial cognitive capabilities and the microfoundations of dynamic capabilities. *Strategic Management Journal, 36*(6), 831–850.
Hocken, E., & King, G. (2023). AI in the hiring process. *Strategic HR Review, 22*(3), 81–84.
Hoff, K. A., & Bashir, M. (2015). Trust in automation: Integrating empirical evidence on factors that influence trust. *Human Factors, 57*(3), 407–434.
Holmström, J., & Hällgren, M. (2022). AI management beyond the hype: Exploring the co-constitution of AI and organizational context. *AI and Society, 37*(4), 1575–1585.
Hu, P., Lu, Y., & Wang, B. (2022). Experiencing power over AI: The fit effect of perceived power and desire for power on consumers' choice for voice shopping. *Computers in Human Behavior, 128*, 1–12.
Jacobides, M. G., Brusoni, S., & Candelon, F. (2021). The evolutionary dynamics of the artificial intelligence ecosystem. *Strategy Science, 6*(4), 412–435.
Johnson, C. J., Demir, M., McNeese, N. J., Wolff, A. T., & Cooke, N. J. (2021). The Impact of Training on Human-Autonomy Team Communications and Trust Calibration. *Human Factors, 65*(7), 1554–1570.
Johnson, M., & Vera, A. H. (2019). No Ai is an island: The case for teaming intelligence. *AI Magazine, 40*(1), 16–28. https://doi.org/10.1609/aimag.v40i1.2842
Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons, 62*(1), 15–25. https://doi.org/10.1016/j.bushor.2018.08.004
Karimi, J., & Walter, Z. (2015). The role of dynamic capabilities in responding to digital disruption: A factor-based study of the newspaper industry. *Journal of Management Information Systems, 32*(1), 39–81.
Keeling, D. I., Keeling, K., de Ruyter, K., & Laing, A. (2021). How value co-creation and co-destruction unfolds: A longitudinal perspective on dialogic engagement in health services interactions. *Journal of the Academy of Marketing Science, 49*(2), 236–257.
Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals, 14*(1), 366–410.
Kemp, A. (2023). Competitive Advantage through Artificial Intelligence: Toward a Theory of Situated AI. *Academy of Management Review*, (ja), amr-2020.
Kinkel, S., Baumgartner, M., & Cherubini, E. (2022). Prerequisites for the adoption of AI technologies in manufacturing – Evidence from a worldwide sample of manufacturing companies. *Technovation, 110*.
Kor, Y. Y., & Mesko, A. (2013). Dynamic managerial capabilities: Configuration and orchestration of top executives' capabilities and the firm's dominant logic. *Strategic management journal, 34*(2), 233–244.
Kozlowski, S. W. J. (2015). Advancing research on team process dynamics: Theoretical, methodological, and measurement considerations. *Organizational Psychology Review, 5*(4), 270–299.
Kozlowski, S. W. J., & Ilgen, D. R. (2006). Enhancing the effectiveness of work groups and teams. *Psychological Science in the Public Interest, 7*(3), 77–124.
Krakowski, S., Luger, J., & Raisch, S. (2023). Artificial intelligence and the changing sources of competitive advantage. *Strategic Management Journal, 44*(6), 1425–1452.
Langley, A., Smallman, C., Tsoukas, H., & Van De Ven, A. H. (2013). Process studies of change in organization and management: Unveiling temporality, activity, and flow. *Academy of Management Journal, 56*(1), 1–13.
Laurano, M. (2022). The evolution of Talent Acquisition technology. *Aptitude Research.* https://www.aptituderesearch.com/evolution-of-ta-tech/.
Lee, J. D., & See, K. A. (2004). Trust in automation: Designing for appropriate reliance. *Human Factors, 46*(1), 50–80.
Li, J., Huang, J., Liu, J., & Zheng, T. (2022). Human-AI cooperation: Modes and their effects on attitudes. *Telematics and Informatics, 73*.
Lindebaum, D., & Ashraf, M. (2023). The Ghost In The Machine, Or The Ghost In Organizational Theory? A Complementary View On The Use Of Machine Learning. *Academy of Management Review*, (ja), amr-2021.
Lockett, A. (2005). Edith Penrose's Legacy to the resource-based view. *Managerial and Decision Economics, 26*(2), 83–98.
Lui, A. K. H., Lee, M. C. M., & Ngai, E. W. T. (2022). Impact of artificial intelligence investment on firm value. *Annals of Operations Research, 308*(1–2), 373–388.
Madni, A., & Madni, C. (2018). Architectural Framework for Exploring Adaptive Human-Machine Teaming Options in Simulated Dynamic Environments. *Systems, 6*(4), 44.
McNeese, N. J., Schelble, B. G., Canonico, L. B., & Demir, M. (2021). Who/What is My Teammate? Team Composition Considerations in Human-AI Teaming. *IEEE Transactions on Human-Machine Systems, 51*(4), 288–299.
Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information and Management, 58*(3).
Molloy, J. C., & Barney, J. B. (2015). Who captures the value created with human capital? A market-based view. *Academy of Management Perspectives, 29*(3), 309–325.
Moser, C., Den Hond, F., & Lindebaum, D. (2022). Morality in the age of artificially intelligent algorithms. *Academy of Management Learning and Education, 21*(1), 139–155.
Musick, G., O'Neill, T. A., Schelble, B. G., McNeese, N. J., & Henke, J. B. (2021). What Happens When Humans Believe Their Teammate is an AI? An Investigation into Humans Teaming with Autonomy. *Computers in Human Behavior, 122*.
Okamura, K., & Yamada, S. (2020). Adaptive trust calibration for human-AI collaboration. *PLoS ONE, 15*(2).
O'Neill, T. A., McNeese, N. J., University, C., Carolina, S., & Barron, A. (2022). Human-Autonomy Teaming: A Review and Analysis of the Empirical Literature. *Human Factors, 64*(5), 904–938.
Pan, Y., Froese, F., Liu, N., Hu, Y., & Ye, M. (2022). The adoption of artificial intelligence in employee recruitment: The influence of contextual factors. *International Journal of Human Resource Management, 33*(6), 1125–1147.
Park, J., Amendah, E., Lee, Y., & Hyun, H. (2019). M-payment service: Interplay of perceived risk, benefit, and trust in service adoption. *Human Factors and Ergonomics In Manufacturing, 29*(1), 31–43.
Patton, M. Q. (2015). *Qualitative research and evaluation methods: Integrating theory and practice*. Sage Pub.
Peeters, M. M. M., van Diggelen, J., van den Bosch, K., Bronkhorst, A., Neerincx, M. A., Schraagen, J. M., & Raaijmakers, S. (2020). Hybrid collective intelligence in a human–AI society. *AI and Society*, 1–27.
Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of management review, 46*(1), 192–210.
Revilla, E., Saenz, M. J., Seifter, M., & Ma, Y. (2023). Human-Artificial Intelligence Collaboration in Prediction: A Field Experiment in the Retail Industry. *Journal of Management Information Systems, 40*(4), 1071–1098.
Rubin, H. J., & Rubin, I. S. (2012). *Qualitative Interviewing: The Art of Hearing Data*. Sage Pub.
Saenz, M. J., Revilla, E., & Simón, C. (2020). Designing AI Systems With Human-Machine Teams. *MIT Sloan Management Review, 61*(3), 1–5.
Salvato, C. (2021). Dynamic Capabilities and Routine Dynamics. In M. S. Feldman, B. T. Pentland, L. D'Adderio, K. Dittrich, C. Rerup, & D. Seidl (Eds.), *Cambridge Handbook of Routine Dynamics* (pp. 460–480). Cambridge University Press.
Salvato, C., & Vassolo, R. (2018). The sources of dynamism in dynamic capabilities. *Strategic Management Journal, 39*(6), 1728–1752. https://doi.org/10.1002/smj.2703
Sarker, I. H. (2021). Machine Learning: Algorithms, Real-World Applications and Research Directions. *SN Computer Science, 2*(3).
Schelble, B. G., Lopez, J., & Freeman, G. (2022). Towards ethical AI: Empirically investigating dimensions of AI ethics, trust, repair and performance in human-AI teaming. *Human factors*, 1872082211169-187208221116952.
Schoemaker, P. J. H., Heaton, S., & Teece, D. (2018). Innovation, dynamic capabilities, and leadership. *California Management Review, 61*(1), 15–42.
Sharma, G., & Bansal, P. (2020). Cocreating rigorous and relevant knowledge. *Academy of Management Journal, 63*(2), 386–410.
Shin, D., & Park, Y. J. (2019). Role of fairness, accountability, and transparency in algorithmic affordance. *Computers in Human Behavior, 98*, 277–284.
Soleimani, M., Intezari, A., & Pauleen, D. J. (2022). Mitigating cognitive biases in developing ai-assisted recruitment systems: A knowledge-sharing approach. *International Journal of Knowledge Management, 18*(1).
Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and A path forward. *California Management Review, 61*(4), 15–42.
Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal, 28*, 1319–1350.
Teece, D. J. (2014). The foundations of enterprise performance: Dynamic and ordinary capabilities in an (economic) theory of firms. *Academy of Management Perspectives, 28*(4), 328–352.
Teodorescu, M. H. M., Morse, L., Awwad, Y., & Kane, G. C. (2021). Failures of fairness in automation require a deeper understanding of human–ml augmentation. *MIS Quarterly: Management Information Systems, 45*(3), 1483–1499.
Tjosvold, D., Wong, A. S. H., & Feng Chen, N. Y. (2014). Constructively Managing Conflicts in Organizations. In *Annual Review of Organizational Psychology and Organizational Behavior* (Vol. 1, pp. 545–568).
Tsoukas, H. (2009). A dialogical approach to the creation of new knowledge in organizations. *Organization Science, 20*(6), 941–957.
Tsoukas, H. (2017). Don't Simplify, Complexify: From Disjunctive to Conjunctive Theorizing in Organization and Management Studies. *Journal of Management Studies, 54*(2), 132–153.
Tsoukas, H., & Chia, R. (2002). On organizational becoming: Rethinking organizational change. *Organization Science, 13*(5), 567–582.
van de Wetering, R., Milakef, P., & Dennehy, D. (2022). Artificial Intelligence Ambidexterity, Adaptive Transformation Capability, and Their Impact on Performance Under Tumultuous Times. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics, 13454 LNCS*, 25–37.
Van Den Broek, E., Levina, N., & Sergeeva, A. (2022). In Pursuit of Data: Negotiating Data Tensions Between Data Scientists and Users of AI Tools. *Academy of Management Proceedings, 2022*(1).
van Zoelen, E. M., van den Bosch, K., & Neerincx, M. (2021). Becoming Team Members: Identifying Interaction Patterns of Mutual Adaptation for Human-Robot Co-Learning. *Frontiers in Robotics and A, I, 8*.
Verleye, K. (2019). Designing, writing-up and reviewing case study research: An equifinality perspective. *Journal of Service Management, 30*(5), 549–576.
Vial, G., Jiang, J., & Giannelia, T. (2021). The Data Problem Stalling AI. *MIT Sloan Management Review, 62*(2), 47–53.
Vössing, M., Kühl, N., Lind, M., & Satzger, G. (2022). Designing Transparency for Effective Human-AI Collaboration. *Information Systems Frontiers, 24*(3), 877–895.
Wang, D., Churchill, E., Maes, P., Fan, X., Shneiderman, B., Shi, Y., & Wang, Q. (2020, April 25). From human-human collaboration to Human-AI collaboration: Designing AI systems that can work together with people. *Conference on Human Factors in Computing Systems - Proceedings*.
Weber, M., Engert, M., Schaffer, N., Weking, J., & Krcmar, H. (2022). Organizational Capabilities for AI Implementation—Coping with Inscrutability and Data Dependency in AI. *Information Systems Frontiers*.
Weiss, A., & Spiel, K. (2022). Robots beyond Science Fiction: Mutual learning in human–robot interaction on the way to participatory approaches. *AI and Society, 37*(2), 501–515.

Werder, K., Seidel, S., Recker, J., Berente, N., Gibbs, J., Abboud, N., & Benzeghadi, Y. (2020). Data-Driven, Data-Informed, Data-Augmented: How Ubisoft's Ghost Recon Wildlands Live Unit Uses Data for Continuous Product Innovation. *California Management Review, 62*(3), 86–102.

Xiong, W., Wang, C., & Ma, L. (2023). Partner or subordinate? Sequential risky decision-making behaviors under human-machine collaboration contexts. *Computers in Human Behavior, 139*.

Yang, X. J., Schemanske, C., & Searle, C. (2023). Toward Quantifying Trust Dynamics: How People Adjust Their Trust After Moment-to-Moment Interaction With Automation. *Human Factors, 65*(5), 862–878.

Yin, R. K. (2018). *Case study research an applications: Design and methods*. Sage Pub.

Zhang, D., Pee, L. G., & Cui, L. (2021). Artificial intelligence in E-commerce fulfillment: A case study of resource orchestration at Alibaba's Smart Warehouse. *International Journal of Information Management, 57*, Article 102304.

Zhang, Q., Lee, M. L., & Carter, S. (2022, April 29). You Complete Me: Human-AI Teams and Complementary Expertise. *Conference on Human Factors in Computing Systems - Proceedings*.

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