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Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance

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ABSTRACT

Artificial intelligence (AI) has been heralded by many as the next source of business value. Grounded on the resource-based theory of the firm and on recent work on AI at the organizational context, this study (1) identifies the AI-specific resources that jointly create an AI capability and provides a definition, (2) develops an instrument to capture the AI capability of the firms, and (3) examines the relationship between an AI capability and organizational creativity and performance. Findings empirically support the suggested theoretical framework and corresponding instrument and provide evidence that an AI capability results in increased organizational creativity and performance.

1. Introduction

Artificial intelligence (AI) has emerged as a top technological priority of organizations over the past few years, largely fueled by the availability of big data and the emergence of sophisticated techniques and infrastructure [1]. A recent report by Gartner indicated that the number of organizations implementing AI grew 270 % in the past four years and has tripled in the last year [2]. While there is much excitement about the potential business value that AI can deliver, organizations that are beginning to adopt AI solutions are facing numerous challenges which prevent them from realizing performance gains [3,4]. In a 2019 global executive study published in the MIT Sloan Management Review, seven out of 10 companies reported that AI has delivered minimal to no business impact so far [5]. Despite the large potential that AI technologies hold, Brynjolfsson et al. [6] highlight that we are dealing with a modern productivity paradox. According to the authors, one of the main reasons AI has yet to deliver expected outcomes is due to implementation and restructuring lags. Organizations, therefore, need to invest in complementary resources to be able to leverage their AI investments. Understanding what complementary resources need to be developed and implementing them is imperative in the quest of realizing performance gains from AI. In other words, it is time to examine how organizations build an AI capability.

Within the IS literature we know that firms achieve competitive performance gains by building unique, and hard to imitate capabilities, which emerge by combining and deploying several complementary firm-level resources [7–10]. Building on this stream of research, this study considers AI technologies as one such resource, which is necessary, but not sufficient to develop an AI capability. Essentially this means that AI techniques alone will be unlikely to deliver any competitive gains by their own right, as they are easily acquired in the market and are subject to replication. In addition, the data used to fuel these techniques alone will be insufficient to create distinct AI capabilities. Early reports from leading firms in terms of AI adoption highlight that organizations require a unique blend of physical, human, and organizational resources to create an AI capability, which can deliver value by differentiating it from that of competitors [11,1,4]. Despite a growing number of popular press articles—most of which are written by technology consultants and vendors—underscoring the importance of some key aspects organizations must consider, there is little theoretically grounded knowledge about how to build AI capabilities.

This study draws on the resource-based theory (RBT) of the firm and seeks to examine the resources that are required to build an AI capability. Findings from past studies have shown that the RBT is an appropriate theoretical lens for dynamic and turbulent environments, particularly when resource complementarity is fostered, and

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organizations develop distinctive capabilities around their respective resources [12]. We therefore provide the following definition:

"An AI capability is the ability of a firm to select, orchestrate, and leverage its AI-specific resources."

In developing the notion of an AI capability, we draw on past IT capability literature, and on recent studies on AI in the organizational context. The IS research is rich in understanding the enablers and effects of different types of IT capabilities, such as social media capabilities [13], social commerce capabilities [14], and business analytics capabilities [8,15–17]. Nevertheless, as with any new technology, such as that of AI, organizations need to develop a unique set of resources to effectively leverage their investments to generate business value. By building on these past studies and on recent research on AI in the organizational context, we identify several key types of resources and then categorize them into tangible, human skills, and intangibles resources. In addition, this study develops a survey instrument to quantify these resources and measure an organization's AI capability. To do so, we adhere to established guidelines for scale development in the management information systems (MIS) literature [18]. Thus, we used an expert panel to establish the content validity of the measures, and in sequence, through a large-scale survey study using a sample of 143 senior technology managers with knowledge of AI initiatives in their organizations, examined the psychometric properties of all measures. We also examined the nomological validity of the AI capability scale by testing its relationship with organizational creativity and organizational performance.

The rest of the paper is organized as follows. In the next section we briefly introduce the relevant literature around the RBT of the firm, as well as that on AI. Next, in Section 3 we describe the different resources that create an AI capability. In Section 4, we introduce the process by which we arrive at the AI capability instrument, as well as the methods used to validate it. The paper then discusses the theoretical and practical implications of this research, as well as some important limitations.

2. Background

2.1. The RBT of the firm

The RBT of the firm has become one of the most widely applied theoretical perspectives in explaining how the resources that an organization owns or has under its control can lead to differences in performance in the same industry [19]. Grounded in strategic management literature, the RBT posits that firms compete based on the resources that they have under their control, which providing are valuable, rare, difficult to imitate, and non-substitutable can generate performance gains [7]. Later work on the RBT makes a distinction between resource-picking and capability building, two distinct central facets of the theory. Amit and Schoemaker [20] define resources as tradable and non-specific firm assets, and capabilities as non-tradable firm-specific abilities to integrate, deploy, and utilize resources within the firm. As such, resources represent the input of the production process, while a capability is the potential to deploy these resources to improve productivity and generate rents [21,22]. By adopting this perspective, there is an inherent assumption that firms' capabilities are dependent and developed based on the available set of organizational resources [23]. Therefore, the strength of a firm's capabilities is determined by the resources on which they are developed [24].

The RBT has been a central theoretical perspective in understanding how information technology (IT) investments produce value and enable firms to attain performance gains [25]. This theoretical perspective is also highly relevant in the context of our study since knowing which AI resources firms must develop is crucial in generating rents from investments. Past studies applying the RBT have highlighted the fact that apart from the technology itself, other human and complementary organizational resources are required to leverage investments [8,26]. Empirical evidence from these and other past studies consistently demonstrate the strength of the RBT in explaining the relationship between organizational resources and firm performance. Within the MIS field, numerous studies have applied the RBT to examine if, and what combination of IT and other complementary resources drive performance gains [7].Melville et al. [27] argue that the RBT allows researchers to develop empirically testable propositions, an assessment of which will enable us to advance our understanding of the value of different IT resources and their role in affecting organizational performance. Similarly, Wade and Hulland [25] advocate that the RBT provides a cogent framework to evaluate the strategic value of information system resources.

The value of the RBT in explaining organizational-level phenomena is evident by the fact that it is a well-accepted theory in other business disciplines including those of operations management [28], supply chain management [29], and marketing [30] among others. More than three decades of empirical testing have thus established the RBT as a prevailing paradigm for developing theoretical arguments and empirically examining the effect that organizational resources have on firm performance [31]. The RBT has also been suggested as an appropriate theoretical lens in turbulent and frequently changing business environments, as resource complementarity, and developing distinctive and hard-to-imitate capabilities has been long linked to competitive success [32].

Since the aim of this study is to identify the necessary organizational resources that will enable firms to develop their AI capabilities, which in turn are argued to result in performance gains, the choice of the RBT as the underlying theoretical framework of this study is deemed as appropriate. Doing that through the RBT lens, we are not only able to theorize about the strategic importance of organizational resources, but also to develop associations about the effect of these resources, as independent variables, on firm performance as a dependent variable. The central premise which studies that adopt the RBT build on is that the bundling of resources facilitates the formation of organizational capabilities, which, in turn, drive performance gains [33].

Several studies have put forth the different types of resources that are required for the development of organizational capabilities that drive performance [34]. One of the most widely used classifications is that proposed by Grant [35], who makes a distinction between tangible (e.g., physical and financial resources), human skills (e.g., knowledge and skills of employees), and intangible (e.g., synergy, coordination, and strategic orientation). This categorization of resources into tangible, human skills, and intangible has been used extensively in the IS literature [7,8]. Following this stream of literature, we adhere to the same classification to categorize resources that form an AI capability. We discuss these in the following sections.

2.2. Artificial intelligence

Despite the fact that AI has been a topic of interest for several decades, there is still a lack of a universally accepted definition throughout the literature. This lack of a definition to ground empirical studies on AI has led to a fundamental problem of understanding AI in its entirety [36]. In order to build a coherent understanding of AI, it is necessary to first explore the notion of "intelligence", before ascribing this concept to machines and defining the compound term "artificial intelligence". To measure the intelligence of diverse technologies, such as those encompassed under the umbrella term AI, we must take a step back from the specifics of systems and establish the underlying fundamentals of what it is we are attempting to capture through the term "intelligence". Grounded on a series of prior definitions, Legg and Hutter [37] develop an integrated definition of intelligence, explicating it as "the ability to interact, learn, adopt, and resort to information from experiences, as well as to deal with uncertainty". In combination with the above, the notion "artificial" pertains to the idea of something being made by humans, which is a copy or replica of something natural [38]. Building on the meaning of these two core notions, it is crucial that we develop a more sophisticated understanding of the term AI. To enable a more holistic and comprehensive understanding of what AI is, we identified and selected five definitions of AI from relevant articles, which are presented in Table 1.

From these definitions, all address the issue of human-like behavior being replicated or enacted by machines. The underlying theme in all is the attempt of AI to reproduce human cognitive processes in order to address different situations. An emphasis on all definitions is the focus of AI on emulating human learning mechanisms, processing information, as well as dealing with states that require problem-solving. The only exception is the definition provided by Poole and Mackworth [44] who describe the properties of the agents without attributing any characteristics to human-like characteristics. Building on these definitions, as well as on the delineation of the two comprising terms that form the overall notion, we provide an integrative definition of AI that is used throughout this article. Our goal in doing so is not to provide yet another definition of AI, but one that is relevant in the context of information systems research. Providing such a definition is in response to several calls by editorials and recent studies on the role of AI in the organizational setting [45]. Hence, we provide the following definition:

AI is the ability of a system to identify, interpret, make inferences, and learn from data to achieve predetermined organizational and societal goals.

In line with this definition, our understanding of an AI application is that of any form of manufactured system that can autonomously generate insights and/or take action based on these, to reach a set of objectives. These objectives are narrowed to those that are directly or indirectly relevant to the directions set out by organizations and societies. We purposefully avoid making any inference to human-like abilities, as many AI applications that are used in the organizational setting exhibit complementary characteristics to those of humans [46]. Also, we avoid describing AI as emerging directly from human programming, since many AI applications are developed and tuned by other AI applications [47]. As such, our definition diverges slightly from those presented in Table 1 and is limited in scope toward the study of management and information systems–related phenomena. By developing this definition, it is thus easier to identify what does and what does not constitute an AI within the organizational setting.

2.3. The business value of artificial intelligence

AI has been hailed by many academics and practitioners as a revolutionary and game-changing set of technologies in the business world [4,45]. Nevertheless, there are to date very few empirical studies examining the effects that structured adoption of AI has on key performance indicators. In addition, there is a large discussion about how AI can fuel creativity in organizations [48]. The reasoning in such claims is that by automating many manual tasks, humans will have more time on their hands to engage in creative activities. Also, through certain applications of AI, human capabilities can be augmented, through what is termed augmented intelligence [46]. The main idea is that specific AI techniques can use large data-sets to assist professionals in creative tasks, such as engineering, design, and the arts, by enhancing their input information, and provide suggestions that would otherwise be hard to develop [49]. An example of such applications of AI can be found in the latest designs of Philippe Starck, who in early 2020 introduced a new series of chairs that were designed with the aid of AI. Through specialized software provided by Autodesk, in their Fusion 360 software package, the designer was able to overcome his biases developed over the years and come up with new creative concepts [50]. Similar cases are gradually emerging in different professions, documenting some of the potential benefits that AI may have on the creativity of individuals, and as an extension, on organizations.

Apart from enhancements in creativity, AI has also been suggested to lead to improvements in various key performance indicators at an organizational level. For example, applications that enable better customer segmentation and facilitate better knowledge and interaction with profitable segments, are suggested to improve market share and customer retainment [51]. Other applications of AI have been argued to increase the speed of processing data, thus reducing bottlenecks and improving overall operational efficiency [52]. In their recent article, Davenport and R. Ronanki [1]. provide several examples of areas where AI can be applied to automate processes, ranging from “reading” legal and contractual documents to extract provisions, to replacing lost credit or ATM cards and handling customer communications. Finally, by enabling access to insight that would be impossible to uncover otherwise, AI is argued to facilitate better decision-making by expanding the range of insight top-management and other key decision-makers usually have access to. Such insight can have significant effects on key performance outcomes enabling organizations to slice-costs, expand their products and/or services, and provide more personalized offerings to customers [53].

Table 1
Sample definitions of Artificial Intelligence.

Author(s)	Definition
Kaplan and Haenlein [39]	A system’s ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation
Russel and Norvig [40]	Systems that mimic cognitive functions generally associated with human attributes such as learning, speech, and problem solving
Dwivedi et al. [41]	The increasing capability of machines to perform specific roles and tasks currently performed by humans within the workplace and society in general
Knowles [42]	The theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages
McCarthy [43]	The science and engineering of making intelligent machines
Poole and Mackworth [44]	Computational agents that act intelligently and perceive their environments in order to take actions that maximize chances of success

3. Conceptualizing an AI capability

Although the published research on the business value and use of AI in the organizational setting is still quite limited, there are some studies that have identified obstacles when it comes to successful deployments of AI projects [54]. A large proportion of these studies have been from practice-based press, which nevertheless draws on samples from leading organizations in terms of AI adoption and use. For instance, a study by Ransbotham et al. [54] finds that a lack of technology competence is one of the biggest inhibitors of deriving value from AI. Specifically, their findings highlighted the fact that almost one in five organizations do not understand the data requirements when it comes to AI, and the corresponding technological infrastructure required to store and transport it. Another recent study by Davenport and Ronanki [1] noted that the difficulty in integrating AI projects with existing processes and systems was the main issue for derailing AI initiatives. In the context of the public sector, Mikalef et al. [55] find that the primary issue is the inability to integrate systems and data, as well as to ensure that quality data are utilized to train AI. Evidently, novel technological solutions are required to address the new challenges that are caused by characteristics of data needed for AI. Nevertheless, there have been great strides in the progress of AI-related technologies in the last few years.

Although the AI-specific technology required to support initiatives is forecasted to mature very fast, it is equally as important to focus on other organizations resources that need to be fostered besides the technology. These complementary organizational resources are what is needed to build firm-specific, and hard-to-imitate AI capabilities [56]. We define AI capability as *the ability of a firm to select, orchestrate, and leverage its AI-specific resources*. An indicative example of the complementary organizations resources that are required in order to realize business value from AI investments is that provided in the study of Ransbotham et al. [4]. The authors of the study who note that one of most important barriers in realizing value is the lack of leadership to support AI, while Davenport and Ronanki [57] highlight that in more than a third of the surveyed organizations, managers do not understand AI technologies and how they work. Several practice-based studies have emphasized the importance of such complementary resources. For instance, Fountaine et al. [3] underscore the importance of fostering inter-departmental coordination, developing cross-functional teams with a mix of skills and perspectives. By having analytics experts work together with business and operational people, organizations can ensure that AI initiatives address broad organizational priorities, and not just isolated business issues. Doing so will also ensure that the developed AI applications are better aligned with regard to operational needs. Another challenge noted by several studies relates to the AI-specific skills that companies need to develop, as working with AI requires a completely new type of skill-set for both technical and managerial personnel [11].

The studies discussed so far, as well as several other academic publications and business reports highlight the diversity of resources that organizations need to foster in order to derive business value from their AI investments. Nevertheless, there is a lack of theoretically grounded research about how organizations can create an AI capability. This is an important gap for both research and practice, as it can indicate the core areas that organizations should steer their focus toward when deploying AI initiatives and provide a notion upon which to gauge the potential business value and mechanisms of value creation. Building on the theoretical underpinnings of the RBT [19,35,58], on empirical work adopting the RBT in the IS domain [7,25,59], as well as on recent studies that outline the challenges related to AI adoption and value generation [11,60,1,3,4,54,55], we propose eight resources which we argue jointly constitute an AI capability (Fig. 1). These resources can either be directly owned by the focal firm or be acquired through service agreements. The theoretical framing of the RBT allows for such types of resource "ownership" as it essentially underscores the importance of controlling resources. In the context of IT-related resources this is very important as many companies use the support of external IT vendors for solutions that cannot be developed in-house [61,62].

The previously mentioned resources were identified by surveying existing academic studies, analyzing practitioner reports and through a series of unstructured interviews with academics and practitioners through a deductive approach. The identified resources were then grouped into three categories based on the framework of Grant [35]. Tangible resources comprise data, technology, and basic resources, while human resources consist of business and technical skills. Inter-departmental coordination, an organizational change capacity, and risk proclivity are included as three critical intangible resources that are required to build an AI capability. In the sub-sections that follow we

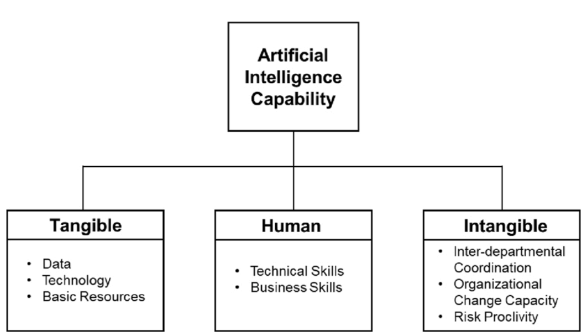


Fig. 1. AI capability and categorization of resources.

discuss each of these resources in detail. The RBT and the identification of important resources in the formation of a capability are also a relevant perspective for practice, as managers and practitioners can develop specific benchmark criteria and quantify their readiness in each of the dimensions. By doing so, they can reveal potential weaknesses that can be addressed through targeted actions.

3.1. Tangible resources

Following the literature on the RBT, tangible resources are considered those that can be sold or bought in a market [34]. For instance, physical assets, such as equipment or facilities, and financial assets, such as debt and equity, are different types of tangible resources. As tangible resources, are to a large extent available in the market for all firms, these resources are not likely to provide a competitive advantage *per se*. Nevertheless, tangible resources are necessary, but not sufficient by themselves to create capabilities

3.1.1. Data

Based on a recently published study by the MIT Sloan Management Review, data are considered by managers as one of the key enablers in leveraging the potential of AI [4]. While organizations have traditionally focused on structured data in order to guide business decisions, today's organizations capture a large diversity of data stemming from multiple sources and in different formats [63]. In fact, the availability of high-quality data is considered critical, as it is used to train the AI algorithms. A recent study by Ransbotham et al. [4] found that pioneering organizations in AI follow a common understanding within their management teams which regards data as a corporate asset. The convergence of big data with AI has emerged as one of the most important developments, and is shaping how firms drive business value from their data resources [64]. When it comes to developing AI applications that can deliver value, the quality of the data that are fed into such algorithms are of great importance. Since AI systems require massive training data-sets, and applications effectively "learn" from available information in a manner similar to the way humans do, there is a high requirement on large amounts of high-quality data. In addition to the issues of quality, many AI applications are developed in a supervised way, which places a heavy focus on appropriate labeling of data [65]. Adding to this issue, skewed data during labeling and training can potentially result in biased AI applications [45]. These alone pose some significant challenges to practitioners in leveraging their data assets into AI applications. Over the past few years a lot has been written about the opportunities of utilizing big data [26], with a multitude of papers specifying its defining characteristics, or the sources from which firms can source data with high value potential [66,67]. The significance of the data resource was even noted in an article in The Economist, referring to data as the new oil which when refined can be a source of competitive advantage [68].

The data that organizations have access to can be broadly categorized into two types, internal and external data [69]. Internal data include all that are created by the organization's internal operations such as accounting, sales, human resource management, and manufacturing/production. Traditionally, internal data represented a large proportion of the overall data organizations were utilizing to base decisions on. Yet, relying on such data to base business decisions on is unlikely to result in a competitive edge. External data refer to that which is not directly related to the firm's operations but can provide novel and deeper insights about the competitive landscape in which contemporary organizations operate. The large volumes of inflowing external and internal data while providing unprecedented opportunities for organizations also pose a great challenge, that of filtering out noisy data and reducing their size into manageable and meaningful sets [70]. However, there needs to be an equilibrium when reducing data through cleansing, as summarized data may obscure some key insights, relationships, and patterns, so that a right degree of granularity is achieved toward desired objectives. Thus, firms interested in leveraging data to enable AI must integrate internal and external data sources, while at the same time manage to cleanse, process, and distribute data throughout organizational boundaries as needed.

3.1.2. Technology

One of the main challenges in leveraging these large, unstructured, fast-moving and complex data sources to build AI applications, concerns the underlying technological infrastructure required to bring them to life. Such novel forms of data call for radically new technologies to store, process, transfer, and secure data through all the stages from acquisition, insight generation, and to training AI applications. Data storage requirements for AI vary significantly according to the application and source material. In addition, the data requirements fluctuate depending on the stage of AI application development and use, which puts a requirement on firms to invest in storage infrastructures that can support the volume and different formats, as well as be scalable depending on the demand [71]. Apart from the flexible data storage, AI technologies also put pressure on organizations to invest in technologies that can quickly process data and run complex algorithms. Common approaches include the use of GPU-intensive clusters and using parallel computing techniques to deal with the processing power required [72]. Many organizations are also adopting cloud-based solutions to deal with the large cost associated with AI infrastructure, while a new market for integrated cloud services that allow complex AI methods to be applied through simple API calls has gained prevalence over the last years [73].

A recent report published by McKinsey highlights that a lack of technological infrastructure is one of the main barriers in adopting AI in organizations [11]. As AI technologies require infrastructure investments at multiple levels, this proves to be a major obstacle for many organizations, particularly those with less slack resources [41]. For instance, deep learning systems, with their ability to retrain themselves as they operate, require a constant feed of updated data. This essentially translates to infrastructure investments being made through the whole pipeline from ingest to inference, from storage, transfer through high bandwidth networks, to processing power. The technological infrastructure is also highly dependent on the type of techniques that are used, which means that organizations can end up having to invest in several different supporting technologies. For instance, applications of computer vision require devices with built-in cameras able to capture images at a high frame-rate, high-bandwidth networks, and hardware designed specifically for handling the processing complexity of image segmentation, object detection, pattern detection, and feature matching [74].

3.1.3. Basic resources

Apart from the investments in data and the technological infrastructure to support AI, organizations need to be able to provide time and financial resources to allow such initiatives to deliver expected outcomes. As most organizations are just now experimenting with AI, the vast majority of initiatives will need some time to mature before being released and yielding value [4]. Adding to time requirements, another important aspect that organizations must invest in is providing adequate financial resources to allow AI applications to develop. In a 2017 study by McKinsey, the majority of respondents reported that less than one-tenth of their digital technology spending was on AI initiatives [11]. However, allocating financial resources for AI projects is essential, as internal budgeting for such initiatives requires that technical and non-technical employees can utilize some of their working hours in developing AI applications and have the necessary technological infrastructure to do so. In fact, the experimentation with proof-of-concept pilots is regarded as a best practice when it comes to AI initiatives, where the organization can test different technologies and methods [1]. For example, the multinational pharmaceutical company Pfizer has over 60 AI projects currently, many of which are just at a pilot stage [75]. Based on these reports on industry, and consistent with prior IS business value research [8,10,76], we argue that investments and time are a group of basic resources which are required to create an AI capability. Schryen [10] in his review paper on IS business value refers to time and financial investments as required resources to realize value. To distinguish these resources from the other resources introduced in this study, we use the label “basic resources”.

3.2. Human resources

The human capital of an organization is often measured by assessing the knowledge, skills, experience, leadership qualities, vision, communication and collaboration competencies, and problem-solving abilities of its employees. Past research on digital capabilities has identified technical and business skills as critical pillars of human resources [7,59]. Following this line of reasoning this study suggests that AI-specific technical and business skills are two important components of a firm’s human AI resources.

3.2.1. Technical skills

When referring to technical AI skills, we mean those that are necessary in order to deal with the implementation and realization of AI algorithms, managing the infrastructure to support such initiatives, as well as those to introduce and ensure AI applications adhere to goals. More specifically, algorithm developers are necessary in order to utilize latest AI research and transform it into repeatable processes through mathematical formulas that can be implemented through hardware and software [77]. It has been suggested that most careers in technical aspects of AI will require individuals with a strong background in statistics, probability, predictions, calculus, algebra, Bayesian algorithms, and logic. In addition, a good background in programming, logic, data structures, language processing, and cognitive learning theory has been highlighted as an essential technical AI skill [78]. A recent article in the MIT Sloan Management Review presents three key roles that will emerge as technical profiles in the age of AI: trainers, explainers, and sustainers [79]. Trainers are concerned with teaching AI systems how they should perform, and include tasks of helping service chatbots, for instance, identify the complexities and subtleties of human communication. Explainers bridge the gap between the technologists and the business managers by providing clarity regarding the inner workings of AI systems to non-technical audiences. Finally, sustainers ensure that AI systems are operating as expected and that any unanticipated consequences are addressed with appropriately. Each of these three roles includes a list of more detailed job functions that are already becoming critical for contemporary organizations. While these skills are currently scarce in the market, it is argued that they will gradually become more common, as higher-education and online training courses are emerging, making this resource a commodity across firms over time [80].

3.2.2. Business skills

One of the most commonly cited barriers in adopting and leveraging AI technologies in the organizational setting is the lack of knowledge of managers regarding how and where to apply such technologies [3]. In fact, in a recent survey published in the MIT Sloan Management Review, a lack of leadership support for AI initiatives was ranked as one of the top hindrances in adopting AI [4]. Realizing business value for AI investments requires a real understanding and commitment on the part of the leaders to drive a large-scale change. In addition, managers need to understand the potential application areas of AI, and how to handle the transition to AI-enabled activities. A striking finding by Davenport and R. Ronanki [1] noted that one in three managers do not understand how AI technologies work. It is therefore imperative that managers become acquainted with the types of AI technologies and their potential uses within different functions of the organization. Another important aspect is the ability of managers to initiate and plan AI deployments [81]. This is particularly important when considering the strong forces that exist within organizations against change, and the threat that AI may replace many of the jobs that are currently held by employees. Thus, it is important that managers develop good working relationships between the technical employees and staff of the line function to minimize frictions and potential forces of inertia, which could delay the adoption of AI and impede business value [82]. Being able to capture the opportunities of the different AI technologies and managing the organizational change that are entailed with AI deployments will likely be a resource that will be difficult to imitate by other firms.

3.3. Intangible resources

From the three main types of organizational resources that have been identified in the RBT [35], intangible resources are regarded as those that are more difficult to replicate by other firms and are of heightened importance in uncertain and volatile markets [83]. Unlike the other two categories of resources, intangibles are much more elusive and difficult to identify within organizations [84]. Nevertheless, despite being difficult to measure, they are also the type of resources that meet the VRIN status of the RBT [85]. This means that no two resources are the same across firms as they are highly heterogeneous and unique. The heterogeneity and non-replicability of intangible resources owe themselves to the fact that they are developed through the unique mixture of organizational history, people, processes, and conditions that characterize organizations. Early reports on the drivers of AI success [11,1,4]) as well as a long history of empirical IS research [7,10,86], highlight the importance of intangible resources in reaping business benefits from adopted technologies. In the context of AI, the resources we have identified are inter-departmental coordination, organizational change capacity, and risk proclivity.

3.3.1. Inter-departmental coordination

The ability to coordinate tasks and share a mutual vision among the different departments of an organization is regarded as a cornerstone of success in cross-disciplinary projects [87]. The role of inter-departmental coordination has long been noted as a key enabler of innovation and creativity in organizations [88]. Inter-departmental coordination has been defined as *"a state of high degrees of shared values, mutual goal commitments, and collaborative behaviors"* [89]. Based on this perspective, what is important are continuous relationships between departments rather than simple transactions between departments [90]. On the same lines, recent studies in AI and business value argue that to unleash the value of AI technologies, organizations must foster a culture of teamwork, collective goals, and shared resources [4].

Fountaine et al. [3] note that AI has the biggest impact when it is developed by cross-functional teams with a mix of skills. By doing so, organizations will ensure that AI initiatives address broad organizational priorities and not just isolated business issues. By fostering inter-disciplinary teams, organizations are also suggested to be able to think through the operational challenges new applications may require, thus improving the overall performance of deployed AI solutions. Finally, enhancing inter-departmental coordination is likely to make organizations more agile and adaptable in deploying AI applications, as a shared language and a common understanding of employees between different departments will lead to reduced times in deploying new AI applications or adapting existing ones when the need arises [91]. The importance of inter-departmental coordination is also noted in a recent study, which highlights that functional silos are one of the most important barriers in deriving business value from AI investments as they constrain end-to-end solutions being developed [11].

3.3.2. Organizational change capacity

The ability of organizations to initiate and follow through execution of plans has long been regarded as a key success factor in digital transformation [92]. Organizational change capacity focuses on the potential problems that may arise due to failure to transition from an old process to a new one. In both management literature and IS studies, developing a capacity that minimizes frictions and inertia associated with change is considered as a key resource of digital transformation capabilities and overall business value [93,94]. Grover et al. [92] note that organizational change capacity entails the ability of breaking the organizational status quo and introducing new practices, new values, and new structures. AI applications introduce significant changes to how organizations perform their key activities, either by replacing traditionally human-executed tasks, or by augmenting existing processes [95]. Being able to plan for and manage such change, at multiple levels within the organization, is suggested to be an important component of realizing value from AI investments [4].

In a recently published article in the Harvard Business Review, one of the main findings on how to make AI deliver business included the ability to overcome unique barriers to change [3]. Each organization will present a unique set of inhibiting factors that delay, or even obstruct change. It is therefore important that managers foster a capacity to anticipate, plan, and execute change at an organizational level. In Appian's Future of Work survey of 500 senior level IT managers [91], the most important barriers in leveraging AI investments were according to respondents, changing the existing IT and business cultures. Similar results were noted in a large-scale study conducted by the MIT Sloan Management Review, which indicated that more than 40 % of respondents faced challenges of cultural resistance to AI approaches, which greatly hindered adoption and business value of AI investments [4]. An organization that is unable to overcome these forces of resistance is unlikely to be able to derive value from AI investments. Even with vast amounts of data, highly skilled technical personnel, and state-of-the-art AI infrastructure, an organization that is unable to leverage these and change its existing way of doing business to incorporate AI advancements will not be able to realize performance gains.

3.3.3. Risk proclivity

In their recent survey of top-level executives in 29 industries and located in 126 countries, Ransbotham et al. [4] found that the organizations that adopt a more risk-oriented approach to new ventures such as AI, reap the benefits much before their competitors or new entrants do. This strategic orientation toward risk-taking has been highlighted in management under different terms (e.g., risk proclivity, entrepreneurial orientation, proactive stance) [96,97], and is associated with typologies that reflect proactive and aggressive initiatives to alter the competitive scene (e.g., prospectors) [98]. This body of research underscores the impact of adopting such a risk-taking and proactive stance, which is commonly associated with higher levels of innovation output and market leadership [99,100]. When it comes to AI adoption, Ransbotham et al. [4] highlight that organizations that embrace risk proclivity deepen their commitments to AI, and in doing so establish their position, which makes it harder for others to catch up. The CIO of Chevron, Bill Braun, notes that AI is one of the most exciting-value-added, and competitive parts of business in the future [4], indicating that risk-takers perceive AI as an opportunity that they must capitalize on before competitors do. The shift of orientation that is required to derive value from AI is also highlighted by Fountaine et al. [3] who argue that organizations must depart from risk-averse strategic orientation and become agile, experimental, and adaptable. The main idea is that companies that are willing to move out of standard practices and adopt new and more ambitious targets are also more likely to see the formation of strong AI capabilities compared to those that adopt a more conservative approach. Based on the above, it is safe to suggest that organizations with a high proclivity toward risky projects are likely to be the first to embrace AI and gain the first-mover advantage. By doing so, they are able to consolidate their position long after, and be within the group of pioneers that enjoys a competitive advantage from leveraging their AI resources toward strategic objectives.

3.4. Impact on organizational creativity and performance

Through the previous argumentation on the role of AI in business, it is clear that a lot of emphasis has been placed on the role that such technologies may play in making organizations more creative and improving their performance. We develop our argumentation on this relationship through the conceptual research model presented in Fig. 2. In fact, there have been several documented cases in different industries where developing an AI capability has resulted in organizational creativity gains [101]. While these cases tend to be rather narrow in scope, they do signal that AI has an impact on the creative process within organizations. Apart from direct effects by augmenting human intelligence, such as in the example of the designer we described earlier, AI can also automate many manual processes that require considerable time and human capital. By freeing up human resources that have the potential to engage in creative processes, firms will be more likely to innovate. Both cases, however, require that AI be deployed beyond an experimental stage, so that it is viable to free up human resources on the long term. As such, local experimental applications of AI need to be scaled up to an organizational-wide AI capability. Adding to the above, when AI technologies are deployed and used toward organizational goals they can enable managers to gain insight that was previously unobtainable by making sense of vast amounts of data and uncovering patterns and relationships [102]. Several such applications of AI have been described in recent articles, where new insight essentially results in new creative solutions within organizational boundaries [103].

Yet, enhancing the creative process is not the only way in which AI can deliver value to organizations. Improving operational inefficiencies and automating tasks through AI have direct effects on different performance indicators, such as reducing costs, improving time-to-respond, slicing down production times and costs, and improving customer relationship management [104]. Being able to derive such value, however, necessitates that AI solutions are deployed as part of organizational efforts and there is a shared vision and understanding of their objective. Early studies have documented that such a structured approach in deploying AI solutions can result in performance gains for firms in a range of industries [105,106]. Applications such as chat-bots, intelligent agents, and even process automating methods of AI have the potential to generate performance gains for organizations. Based on the foregoing argumentation, we can hypothesize the following:

H1. An AI capability will have a positive effect on organizational creativity

H2. An AI capability will have a positive effect on organizational performance

Recent literature in the domain of IT-enabled organizational capabilities posits that the use and deployment of different IT solutions can lead to the generation of certain meta-capabilities [107]. In essence, such deployments of IT often have indirect effects on key performance indicators, by enabling certain key organizational capabilities. For example, Mikalef and Pateli [108] indicate that leveraging IT to enable dynamic capabilities allows firms to attain market capitalizing and operational adjustment agility, which are key components of a competitive advantage. Other studies have documented similar findings, with IT being the driver of increased business flexibility [109], amplifiers of an intrapreneurship culture [110,111], and as a tool to mitigate tradeoffs [112]. Following the same logic, we argue that an AI capability can have indirect effects on organizational performance, through its effect on organizational creativity. Several performance indicators are contingent on the creative solutions that emerge within the organization. Similar to the notion of IT wisdom, as described by Liu et al. [107], we suggested that an AI capability can help generate knowledge within the organizations boundaries, which then can be harnessed to improve performance. Thus, we hypothesize the following:

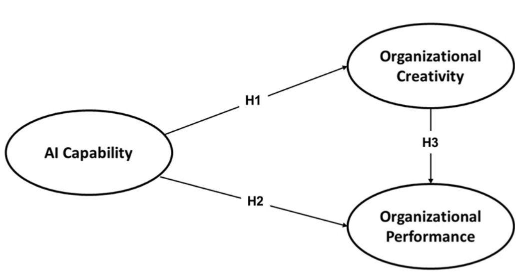


Fig. 2. Conceptual research model.

H3. Organizational creativity will have a positive effect on organizational performance

4. The AI capability instrument

4.1. Conceptualization and measurement of constructs

As introduced earlier, this study defines an AI capability as *a firm's ability to structure, bundle, and leverage its AI-based resources*. In line with this definition, the AI capability construct is conceptualized as a multidimensional third-order formative construct, which is comprised of the following AI-specific dimensions: tangible resources, human skills, and intangible resources. These dimensions are, in turn, conceptualized as second-order formative constructs comprising eight first-order constructs (Table 2).

The measures used to develop the first-order constructs were either adapted or created from existing literature on digital capabilities, while some were based on business reports and expert interviews. As such, the AI capability construct differs significantly from other digital capability constructs such as IT capability as the resources that comprise it are AI-specific. Digital technologies correspond to IT-related resources that support core organizational activities such as computer-supported collaborative work, supply chain management, and human resource management [25,113]. When such digital technologies are combined with other organizational-level resources, they allow the creation of digital capabilities [9,108]. Despite the fact the AI and the data used to develop such applications can be considered digital resources, it is the combination with other AI and organizational-related resources that collectively lead to the emergence of an AI capability. This idea is reflected in the proposed theoretical framework (Fig. 1) and in the items used to capture the first-order constructs, which are related specifically to AI use within organizations (Table 3).

For example, the data construct and the corresponding items capture the degree to which an organization has access to data at the rights level of granularity, and whether the organization can integrate and effectively cleanse data to be suitable for AI applications. Similarly, the technology construct indicates whether an organization has invested in the necessary hardware and software AI technologies to enable flexible data storage (e.g., cloud-based services), analysis (e.g., Microsoft Cognitive Services, Google Cloud Vision), processing (e.g., Parallel computing, CPUs, GPUs), and transfer within and beyond firm boundaries. Through the technical and business skills constructs, we capture the level to which the technical and business staff have AI-specific skills. The inter-departmental coordination construct identifies the extent to which there is a culture of open communication and collaboration between departments, and the degree to which they have a shared vision. Organizational change capacity captures the level to which the organization can agilely adapt to evolving conditions, while risk proclivity measures the degree to which an organization has an attitude of engaging in high-risk projects that can potentially yield high returns. The three later constructs correspond to the intangible organizational resources that firms must possess in order to be successful in the age of AI.

Table 2
Latent constructs and sub-dimensions.

Third-order	Type	Second-order (sub-dimensions)	Type	First-order (sub-dimensions)	Type
AI Capability	Formative	Tangible Resources	Formative	Data	Formative
				Technology	Formative
				Basic Resources	Formative
		Human Resources	Formative	Technical Skills	Reflective
				Business skills	Reflective
		Intangible Resources	Formative	Inter-departmental Coordination	Reflective
				Organizational Change Capacity	Reflective
				Risk Proclivity	Reflective

4.2. Artificial intelligence capability as a higher-order formative construct

In this study, we develop the construct of an AI capability as a higher-order formative construct. Benitez et al. [114] identify two types of formative constructs, composite, and causal-formative constructs. The former is explained nicely through a brewery analogy, where different recipes exist to produce beer, denoting the idiosyncratic nature of capabilities. In essence, this model can be understood as a recipe for how ingredients (the components) should be coalesced to build the artifact [114]. Causal-formative constructs, however, assume that the observed indicators cause the latent variable. In this study we develop the AI capability construct as a composite type as we assume that every organization develops its own unique version of an AI capability through its idiosyncratic means of orchestrating and leveraging the corresponding resources. Based on this emerging stream of research, we proceed to describe the formative nature of the AI capability construct.

Following the IT capability and big data analytics capability literature [7,8,26], which grounds conceptualizations on the RBT, this study conceptualizes the AI capability construct through three main dimensions: tangible resources, human skills, and intangible resources. As this study extend significantly from prior studies that are based on the IT capability literature, we start by examining whether the IT capability construct has been developed as a reflective or formative construct. Within this body of research there is considerable variation, with some studies such as those of Lu and Ramamurthy [115] and Kim et al. [116], developing their conceptualization of IT capability as a higher-order reflective construct, whereas others such as Wang et al. [117] and Ravichandran and Lertwongsatien [59] conceptualizing IT capability as a higher-order formative construct. This divergence in notions that attempt to capture the same underlying concept is an important one to resolve, as the choice of measuring a construct reflectively versus formatively may result in a different overall construct [118].

Adding to the above, although the measure may have the same naming, the indicators that are used to compose a construct will significantly differ if the construct is formative versus reflective [119]. By surveying the existing body of literature in terms of how they develop the notions of IT capability, this difference in measurement and its effects becomes evident. This difference in how similar concepts have been conceptualized and measured essentially has to do with how the researchers have defined the concept at hand and on the theoretical and research objectives of the study [119]. Based on the provided definition of the AI capability notion, and the nature of the underlying dimensions as described in the conceptualization section, we applied four widely accepted decision rules to conceptually assess whether the construct should be developed as a higher-order formative or reflective one [119, 120].

First, from the proposed underlying dimensions (tangible resources, human skills, and intangible resources), there is no single one that can adequately explain the notion of an AI capability. This observation is a strong criterion that tangible, human skills, and intangible resources are core characteristics, rather than manifestations of the AI capability. Extending on this logic, Chen et al. [121] argue that due to the fact that IT capability constructs are quite broad, it is preferable to model capability constructs as formative. This is true also in the case of an AI capability, as the three main dimensions that comprise the construct cover complementary facts of the overall capability.

Second, the three dimensions that comprise the AI capability construct capture very distinct aspects of an organization's AI capability. There is also a minimal degree of overlap between the dimensions. This essentially means that removing one dimension would have a significant impact on the completeness of the overall construct, as the dimensions are not interchangeable. If we were to adopt a reflective conceptualization of the construct, dropping one dimension to satisfy reliability criteria would mean removing a large essential facet of the AI capability construct. In contrast with reflective conceptualizations where items or dimensions are interchangeable, a formative conceptualization dictates that all items or dimensions are essential parts of the whole. In our case, if, for example, we dropped the dimension of human skills, it would be unlikely that the dimensions of tangible or intangible resources would be able to compensate and capture the lost dimension.

Third, in the case of formative constructs there is no requirement of covariation, something which is essential in the case of reflective constructs. Based on the theoretical grounding of the AI capability construct, the three dimensions of tangible, human, and intangible resources do not need to covary [7]. For instance, having developed the tangible dimension does not necessarily entail that an organization has fostered its intangible resources. As an *ex-post* method to ensure that there is no covariation (or multicollinearity) between the dimensions of a formative construct, it is possible to calculate the variance inflation factor (VIF) [122,123]. As part of our empirical analysis, VIF values were calculated to examine if collinearity was an issue for each formative construct. The outcomes of our analysis are presented further in the study.

Fourth, the underlying three dimensions of an AI capability have very different antecedents. For example, tangible resources (i.e., data, technology, and basic resources), human skills (i.e., technical and business skills), and intangible (i.e., inter-departmental coordination, organizational change capacity, and risk proclivity) are developed and dependent on a different set of predictors. Furthermore, the sub-dimensions from which they are composed are very distinct from each other. Therefore, the higher-order AI capability construct satisfies the four decision rules in accordance to the formative methodological literature [118,122,124]. We used the same approach to determine the underlying sub-dimensions (e.g., the conceptualization and measurement approach for data, technology, and basic resources toward their higher-order construct of tangible resources).

4.3. Hierarchical model specification

In specifying our model we used the two-step approach as described by Benitez et al. [125]. To formally specify the hierarchical model, we followed a step-by-step approach in order to represent the relationships between the indicators, sub-dimensions, and the higher-order constructs [126] (Fig. 1). We used the latent variables scores in each step of the estimation after the first. We started by associating the indicators to their corresponding firs-order latent constructs. Data, technology, and basic resources were modeled as mode B "formative", while the remaining first-order constructs were modeled as mode A "reflective".

Table 3
Constructs and measures of AI Capability.

Resource Type	Construct	Items
Tangible	Data	We have access to very large, unstructured, or fast-moving data for analysis
		We integrate data from multiple internal sources into a data warehouse or mart for easy access
		We integrate external data with internal to facilitate high-value analysis of our business environment
		We have the capacity to share our data across business units and organizational boundaries
		We are able to prepare and cleanse AI data efficiently and assess data for errors
		We are able to obtain data at the right level of granularity to produce meaningful insights
	Technology	We have explored or adopted cloud-based services for processing data and performing AI and machine learning
		We have the necessary processing power to support AI applications (e.g., CPUs, GPUs)
		We have invested in networking infrastructure (e.g., enterprise networks) that supports efficiency and scale of applications (scalability, high bandwidth, and low-latency)
		We have explored or adopted parallel computing approaches for AI data processing
		We have invested in advanced cloud services to allow complex AI abilities on simple API calls (e.g., Microsoft Cognitive Services, Google Cloud Vision)
		We have invested in scalable data storage infrastructures
		We have explored AI infrastructure to ensure that data is secured from to end to end with state-of-the-art technology
	Basic Resources	The AI initiatives are adequately funded
		The AI project has enough team members to get the work done
		The AI project is given enough time for completion
Human	Technical Skills	The organization has access to internal and external talent with the right technical skills to support AI work
		Our data scientists are very capable of using AI technologies (e.g., machine learning, natural language processing, deep learning)
		Our data scientists have the right skills to accomplish their jobs successfully
		Our data scientists are effective in data analysis, processing, and security
		Our data scientists are provided with the required training to deal with AI applications
		We hire data scientists that have the AI skills we are looking for
		Our data scientists have suitable work experience to fulfill their jobs
	Business Skills	Our managers are able to understand business problems and to direct AI initiatives to solve them
		Our managers are able to work with data scientists, other employees and customers to determine opportunities that AI might bring to our organization
		Our managers have a good sense of where to apply AI
		The executive manager of our AI function has strong leadership skills
		Our managers are able to anticipate future business needs of functional managers, suppliers and customers and proactively design AI solutions to support these needs
		Our managers are capable of coordinating AI-related activities in ways that support the organization, suppliers and customers
		We have strong leadership to support AI initiatives and managers demonstrate ownership of and commitment to AI projects
Intangible	Inter-Departmental Coordination	*Please indicate to what extent do departments (e.g., marketing, R&D, manufacturing, information technology, and sales) within your organization engage in the following activities:*
		Collaboration
		Collective goals
		Teamwork
		Same vision
		Mutual understanding
		Shared information
		Shared resources
	Organizational Change Capacity	OCC1. We are able to anticipate and plan for the organizational resistance to change
		OCC2. We consider politics of the business reengineering efforts
		OCC3. We recognize the need for managing change
		OCC4. We are capable of communicating the reasons for change to the members of our organization
		OCC5. We are able to make the necessary changes in human resource policies for process re-engineering
		OCC6. Senior management commits to new values
	Risk Proclivity	RP1. In our organization we have a strong proclivity for high risk projects (with chances of very high returns)
		RP2. In our organization we take bold and wide-ranging acts to achieve firm objectives
		RP3. We typically adopt a bold aggressive posture in order to maximize the probability of exploiting potential opportunities

The estimation of reflective constructs was performed using the consistent PLS mode A as it provides a correction for estimates [127]. During the second step, the latent variable scores of the first-order constructs were used to form the second-order corresponding variable. As a result, the latent variable scores of data, technology, and basic resources were used to develop the second-order variable of tangible resources. Similarly, the human skills second-order construct was developed through the latent variable scores of the corresponding first-order dimensions of technical skills and business skills. The intangible resource second-order construct was formed from the latent variable scored of the constructs of inter-departmental coordination, organizational change capacity, and risk proclivity. Finally, the third-order variable, AI capability, was developed by the latent variable scored of the second-order constructs after being re-analyzed.

4.4. Data collection

To ensure that the developed survey instrument was valid and robust, we followed the guidelines suggested by MacKenzie et al. [18]. In accordance with these guidelines, after specifying the measurement model, we proceeded to obtain data in order to examine the psychometric properties of the scale and to evaluate its convergent, discriminant, and nomological validity. As the indicators for the first-order constructs were either adopted or adapted, we assessed their content validity through a group of experts that were required to provide their recommendation as to which questions correspond to each construct. For this step, we used a group of nine experts who had substantial academic and practical experience in the domain of AI. Of the nine experts, six had a background in industry with over 20 years of experience each in the domains of data science and AI, while the three were senior academics whose work was focused on IS in organizations. We provided definitions of each and asked them to map the items onto the corresponding constructs, which they believed they belonged to. Furthermore, we asked them to provide recommendations of questions that were not comprehensive or aspects of questions that could be improved. The feedback provided resulted in some minor modifications and including some examples particularly in the use of technologies. This feedback coupled with the high correct hit ratio of items on their corresponding constructs was a strong indicator that the content validity for the instrument was established.

To ensure that the instrument satisfied convergent, discriminant, and nomological validity, the revised survey instrument was sent out to a sample of C-level technology managers working in firms in the USA. The respondents were members of the *Artificial Intelligence and Business Analytics* group on LinkedIn[1] . We contacted selected respondents through email and asked them to participate only if they were in a high-level technology management position within their organizations. After an initial invitation and three reminders, with a one-week interval between each, a total of 143 responses were received. The responses represented a range of industries (e.g., financial services, manufacturing, high-tech companies), and the job titles of the respondents were primarily chief information officers, chief technology officer, director of IT, IT manager, and chief digital officer. Since we collected data that corresponded to 46 indicators, the first step of our analysis was to conduct an exploratory factor analysis using principal component analysis and varimax rotation. Through this analysis, eight factors emerged (eigenvalues > 1). In addition, all the items loaded to their corresponding factors in accordance to how we had developed them (Tables 4 7 and 9).

To reduce the probability of informant bias, we compared early and late responses to ensure that responses did not differ significantly. We developed two groups of responses, those that replied within the first two weeks, and those that answered during the last two weeks of the data-collection process. For each of the questions used in this study and for corresponding constructs they were used to capture, we run Mann–Whitney U-tests. We did not identify any significant difference in the items and constructs, so late-response bias was not an issue within our sample. Furthermore, from the population of firms that were contacted, no significant differences were observed between responding and non-responding firms in terms of their industry, size-class, and age. Since the collected data were perceptual and came from a single source at one point in time, we also controlled for the common method bias in accordance with the suggestions of Chang et al. [128]. During the invitation email we sent out to the respondents, we assured them that the data collected would remain anonymous and that it would only be analyzed for research purposes. In addition, we made clear that there would be complete confidentiality during the entire process [129]. After the data collection was finalized, we performed Harman's one-factor tests, and entered the study variables into a principal component factor analysis. The outcomes of this analysis revealed that one construct did not account for the majority of variance [130].

Table 4
Sample Characteristics.

	Percentage (N = 143)
Industry	
Technology	25 %
Bank & Financials	20 %
ICT and Telecommunications	13 %
Consulting Services	11 %
Consumer Services	6 %
Media	5 %
Health Care	5 %
Consumer Goods	4 %
Others (Oil & Gas, Transport, Industrials, Basic Materials, etc.)	11 %
Total AI experience	
Less than one year	16 %
1–2 years	19 %
3–4 years	29 %
More than 4 years	36 %
Size-class of the organization	
Micro (1–9 employees)	4%
Small (10–49 employees)	11 %
Medium (50–249 employees)	13 %
Large (250+ employees)	72 %
Respondent position	
Chief Information/Technology/Digital Officer	26 %
IT Director	19 %
Head of IT Department	14 %
Chief Executive Officer	9%
IT Project Manager	8%
Business Analyst	8%
Other (Lead data scientist, Enterprise architect, Operations manager, etc.)	16 %

4.5. Instrument assessment (validity and reliability)

Since the assessment criteria for formative and reflective constructs are different, we used several different criteria to examine their validity and reliability. For the formative measures, we examined the weights of the items and their significance levels. For the *data* construct two indicators were found to be non-significant (D2 and D4), for the *technology* construct two indicators were marked as non-significant (T1 and T5), and for the *basic resources* construct there was one item that was non-significant (BR2). Nevertheless, Cenfetelli and Bassellier [122] highlight that any formative construct with many indicators is likely to have several indicators with non-significant weights. They recommend that non-significant indicators be kept in the model as long as there is a strong theoretical justification for the inclusion, which contrasts the way of approaching reflective indicators. Since the dimensions that are proposed and the corresponding items used to measure them capture different, critical facets, we believe that it was necessary to retain non-significant indicators in the model. This was based on the fact that the expert panel insisted that they are important facets, as well as on several reports and studies documenting their importance toward an AI capability. We therefore deemed it as necessary not to remove any items as each made a distinct contribution to the overall construct it was assigned to.

Next, we followed the recommendations of MacKenzie et al. [18] and Schmiedel et al. [131] and evaluated the validity of the items for the formative constructs by using Edwards' [132] adequacy coefficient (R^2_a). We calculated the R^2_a values by summing the squared correlations between the construct and its dimensions (i.e., indicators) and dividing by the number of dimensions (i.e., indicators). All R^2_a values exceeded the lower threshold of 0.50 (Table 5) suggesting that the majority of variance in the items is shared with the formative construct and are thus valid. We then proceeded to evaluate the higher order constructs with their respective indicators (dimensions) through the same way. All weights from lower-order dimensions to higher-order constructs were positive and significant. We calculated the adequacy coefficient via the same way, and all R^2_a were greater than the 0.50 threshold.

Finally, we assessed whether multicollinearity was an issue between indicators of the formative constructs. Although the presence of

[1] https://www.linkedin.com/groups/62438/

Table 5
Formative construct validation.

Construct	Measures	Weight	Significance	VIF	R^2_a
Data	D1	0.328	$p < 0.001$	1.300	0.59
	D2	0.146	*ns*	1.589	
	D3	0.159	$p < 0.05$	1.797	
	D4	0.011	*ns*	1.635	
	D5	0.423	$p < 0.001$	2.193	
	D6	0.253	$p < 0.01$	2.103	
Technology	T1	0.016	*ns*	2.105	0.68
	T2	0.245	$p < 0.001$	2.461	
	T3	0.136	$p < 0.05$	2.428	
	T4	0.278	$p < 0.001$	3.109	
	T5	0.062	*ns*	2.127	
	T6	0.197	$p < 0.05$	2.777	
	T7	0.273	$p < 0.001$	3.021	
Basic Resources	BR1	0.541	$p < 0.01$	2.028	0.79
	BR2	0.144	*ns*	2.937	
	BR3	0.433	$p < 0.001$	3.090	
Tangibles	Data	0.344	$p < 0.001$	2.395	0.83
	Technology	0.536	$p < 0.001$	2.271	
	Basic Resources	0.235	$p < 0.001$	2.008	
Human	Technical Skills	0.545	$p < 0.001$	1.445	0.83
	Business skills	0.589	$p < 0.001$	1.445	
Intangibles	Inter-departmental Coordination	0.504	$p < 0.001$	1.752	0.81
	Organizational Change Capacity	0.420	$p < 0.001$	2.101	
	Risk Proclivity	0.230	$p < 0.001$	1.796	
AI Capability	Tangibles	0.346	$p < 0.001$	2.045	0.82
	Human	0.410	$p < 0.001$	2.568	
	Intangibles	0.407	$p < 0.001$	1.645	

multicollinearity is desirable among indicators that are modeled as reflective, it is problematic in the case of formative measurements. The thresholds for multicollinearity are typically set at below values of 10 [18], however, Petter et al. [123] recommend a more restrictive cutoff value of 3.3. We examined VIF values for first-order, second-order, and third-order constructs, with all values being below the most conservative cutoff point of 3.3, which demonstrated that multicollinearity was not a concern in this study [122].

To assess the reliability and validity of the reflective constructs we used several analyses at both the item and construct level. For the first-order reflective latent constructs, we assessed their reliability, convergent validity, and discriminant validity. Reliability was gauged at both the construct and item levels. At the construct level, we looked at composite reliability (CR) and Cronbach's alpha (CA) values, and made sure that their values were above the threshold of 0.70 [133]. We determined indicator reliability by examining if construct-to-item loadings were above the threshold of 0.70 (Appendix B). To assess convergent validity, we examined if average variance extracted (AVE) values were above the lower limit of 0.50, with the lowest observed value being 0.58, which exceeds this threshold. To determine if discriminant validity was established we employed two means. First, we tested whether each indicator's outer loading was greater that its cross-loadings with other constructs [134]. Second, we calculated the heterotrait–monotrait ratio (HTMT), which Henseler et al. [135] argue is a more robust criterion to assess discriminant validity. The HTMT is calculated based on the average of the correlations of indicators across constructs measuring different aspects of the model, relative to the average of the correlations of indicators within the same construct [114]. The values we got from the analysis were all below the threshold of 0.85, which is an indication of sufficient discriminant validity (Appendix D). The abovementioned results (Table 6) suggest that first-order reflective measures are valid to work with and support the appropriateness of all items as good indicators for their respective constructs.

For formative constructs, there are, to the best of our knowledge, no established tests to assess the discriminant validity of constructs. Nevertheless, MacKenzie et al. [18]; Benitez et al. [13]; Benitez et al. [136] have put forward some recommendations for formative constructs. Specifically, they highlight that it is important to test for multicollinearity, and examine weights, loadings, and significance levels. We tested for multicollinearity by checking whether the VIF at all levels was below 3.3 (Table 5). The values ranged from 1.300 to 3.109 at the first-order level and from 1.445 to 2.395 at the second-order level, while the range at the third-order level was between 1.645 and 2.568, which is below the stricter threshold. We followed the suggestions of Benitez, et al. [125] who argue that composite indicator and dimensions should be retained irrespective of whether their weight is significant or not. However, loadings are important [123,136]. The analysis showed that five indicators were non-significant. Nevertheless, all first-, second-, and third- order loadings were significant at the 0.001 level. As with reflective constructs, the indicators of formative constructs should load highly on their corresponding constructs in comparison to other constructs [137]. By examining cross-loadings and correlations (Appendix C and Table 5) we can confirm that all reflective and formative constructs satisfy both conditions. Overall, all formative and reflective items demonstrated good psychometric properties, and hence, we proceed to examine the nomological validity by examining the relationship between AI capability and different firm performance measures.

4.6. Nomological validity

4.6.1. Confirmatory composite analysis

The confirmatory composite analysis aims at examining the overall fit of the measurement (saturated) model [114]. In other words, a confirmatory composite analysis helps determine whether it makes sense to create the proposed formative construct and identifies any model misspecifications [138,139]. Based on the guidelines of Benitez et al. [114], the confirmatory composite analysis checks the adequacy of the composite model (i.e., higher-order model) by comparing the empirical correlation matrix with the model-implied correlation matrix. This is done by examining the standardized root means square residual (SRMR), unweighted least squares (ULS) discrepancy (d_{ULS}), and

Table 6
Assessment of reliability, convergent and discriminant validity of reflective constructs.

	Construct	1	2	3	4	5	6	7	8
1	Data	**n/a**							
2	Technology	0.703	**n/a**						
3	Basic Resources	0.667	0.644	**n/a**					
4	Technical Skills	0.627	0.629	0.651	**0.871**				
5	Business skills	0.523	0.448	0.517	0.555	**0.891**			
6	Inter-departmental Coordination	0.434	0.376	0.337	0.384	0.654	**0.854**		
7	Organizational Change Capacity	0.308	0.380	0.273	0.383	0.474	0.630	**0.863**	
8	Risk Proclivity	0.283	0.322	0.477	0.392	0.505	0.542	0.641	**0.947**
	Mean	5.34	5.16	4.53	5.29	4.62	4.82	4.72	4.59
	Standard Deviation	1.68	1.82	1.76	1.51	1.74	1.64	1.62	1.79
	AVE	n/a	n/a	n/a	0.760	0.795	0.730	0.746	0.897
	Cronbach's Alpha	n/a	n/a	n/a	0.947	0.956	0.938	0.932	0.943
	Composite Reliability	n/a	n/a	n/a	0.957	0.964	0.950	0.946	0.963

Table 7
Results of the confirmatory composite analysis.

Discrepancy	Overall saturated model fit evaluation		
	Value	HI_{95}	Conclusion
SRMR	0.037	0.052	Supported
d_{ULS}	0.241	0.588	Supported
d_G	0.053	0.243	Supported

geodesic discrepancy (d_G) to evaluate the goodness of saturated model fit [138]. In sum, the indicators provide empirical support to answer the question if the latent variables exist, or do the indicators form a higher-order construct. To obtain these values, we used the latent variable scores obtained in SmartPLS in the software package ADANCO 2.2.0 Professional for Windows (http://www.composite-modeling.com/) [140]. The SRMR determines the average magnitude of the discrepancies between observed and expected correlations as an absolute measure of model fit criterion. The value of the SRMR was 0.037, which is lower than the threshold of 0.080 [138]. In addition, all discrepancy measures (i.e., d_{ULS} and d_G) were below the 95 % quantile of their corresponding reference distribution (HI_{95}) (Table 7). The results demonstrate that the measurement structure of the composite construct is correct.

4.6.2. Measurement model

As part of examining the nomological validity of the proposed construct, we introduced two performance metrics to capture the suggested effect that an AI capability has at an organizational level. We therefore included organizational creativity (ORC) and organizational performance (ORP), in addition to the existing constructs of the AI capability scale as introduced earlier. The size-class of firms and the industry that they belonged to were also used as controls. Organizational creativity was captured based on the adopted measures from the study of Scheibe and Gupta [141], while organizational performance was operationalized based on the items proposed by Lee and Choi [142]. Both constructs are validated in past empirical studies and reflect different outcomes that have been associated with adoption and use of AI technologies in the organizational boundary. We repeated the same tests to establish that the psychometric properties of the scale are not influenced by the inclusion of outcome variables. We therefore once again examined reliability and validity at the construct level and examined inter-correlations between the latent variables for first-order constructs (Table 8).

4.6.3. Structural model

Having established the psychometric properties of the AI capability scale, we then proceeded to examine the nomological validity of the AI capability construct by assessing its relationship with organizational creative and organizational performance. Consistent with past empirical studies, we define organizational creativity as the degree to which an organization is able to generate new and constructive ideas (or products) in the complex organizational setting [143]. The literature on the value of AI has argued that by automating repetitive processes, or by replacing humans in tasks that do not require creativity, complexity, and dealing with new and unfamiliar situations, human capital can be used in tasks that make use of their creativity and innovation capacities [45]. Adding to this, there are many examples where AI technologies can expand the abilities of human, by amplifying cognitive strengths, embodying human skills to extend physical abilities, and by interacting with customers and employees to free personnel for higher-level tasks [144]. Similarly, following prior literature we define organizational performance as the degree to which organizations achieve their business objectives [142]. As AI has been argued to deliver effects at several different levels within organizational activities [41], it is suggested that it will have an impact on the attainment of key business objectives. For instance [1], highlighted in a recent study that AI can enable firms to pursue multiple objectives, such as enhancing the features, functions, and performance of products, help managers make better decisions, optimize internal business operations, and facilitate external processes such as marketing and sales. As in other studies that examine IT-business value, it is advocated that it is important to make inter-firm comparisons as an appropriate measure for organizational performance [7]. We therefore deem the relative organizational performance measures as appropriate to examine the effect of AI capabilities.

In order to examine the two hypothesized relationships, we used a PLS-SEM analysis and specifically the software SmartPLS 3.0 [145]. The structural model from the PLS analysis is depicted in Fig. 3, where the explained variance of endogenous variables (R^2) and the standardized path coefficients (β) are presented. We verify the structural model by examining the coefficient of determination (R^2) values, effect size of predictor variables (f^2), and the effect size of path coefficients. To obtain the significance of estimates (t-values) we performed a bootstrap

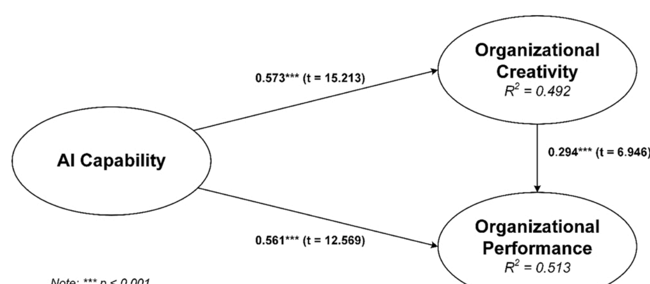


Fig. 3. Results of structural model.

Table 8
Inter-correlations of the latent variables for first-order constructs.

	Construct	1	2	3	4	5	6	7	8	9	10
1	Data	**n/a**									
2	Technology	0.689	**n/a**								
3	Basic Resources	0.673	0.655	**n/a**							
4	Technical Skills	0.631	0.621	0.632	**0.871**						
5	Business skills	0.512	0.451	0.522	0.542	**0.891**					
6	Inter-departmental Coordination	0.430	0.379	0.325	0.383	0.643	**0.854**				
7	Organizational Change Capacity	0.314	0.376	0.282	0.381	0.466	0.621	**0.863**			
8	Risk Proclivity	0.285	0.321	0.466	0.388	0.526	0.537	0.643	**0.947**		
9	Organizational Creativity	0.345	0.289	0.256	0.246	0.421	0.445	0.409	0.488	**0.939**	
10	Organizational Performance	0.310	0.385	0.341	0.401	0.387	0.428	0.436	0.453	0.411	**0.944**
	Mean	5.34	5.16	4.53	5.29	4.62	4.82	4.72	4.59	4.96	4.98
	Standard Deviation	1.68	1.82	1.76	1.51	1.74	1.64	1.62	1.79	1.70	1.71
	AVE	n/a	n/a	n/a	0.760	0.795	0.730	0.746	0.897	0.882	0.892
	Cronbach's Alpha	n/a	n/a	n/a	0.947	0.956	0.938	0.932	0.943	0.931	0.937
	Composite Reliability	n/a	n/a	n/a	0.957	0.964	0.950	0.946	0.963	0.942	0.960

analysis using 500 resamples. As shown in Fig. 3, we found a significant positive effect of AI capability on both organizational creativity ($\beta = 0.573$, t = 15.213, $p < 0.001$) and organizational performance ($\beta = 0.561$, t = 12.569, $p < 0.001$). In addition, we found a significant effect of organizational creativity on organizational performance ($\beta = 0.294$, t = 6.946, $p < 0.001$). We also controlled for firm size and industry; however, only firm size had an impact on organizational performance ($\beta = 0.141$, t = 2.069, $p < 0.05$). The model accounted for 49.2 % of variance with regard to organizational creativity ($R^2 = 0.492$), and 51.3 % of variance for organizational performance ($R^2 = 0.513$).

In addition to examining the R^2, the model is evaluated by assessing the effect size f^2. The effect size f^2 enables us to determine the contribution of an exogenous construct to an endogenous latent variable R^2. All direct values are greater than the thresholds of 0.15 and 0.35, so we can thus conclude that they have moderate to high effect sizes [114]. Moreover, the model fit indicators were established by using ADANCO. Examining model fit in such settings allows us to assess whether we have incorrectly omitted an important effect in the model [114]. The SRMR of the model was 0.036, $d_{ULS} = 0.237$, $d_G = 0.051$, which is an indication of a good model fit. The results from the nomological model provide evidence for a strong, positive relationship between an AI capability and organizational creativity and organizational performance, as well as a highly significant positive effect of organizational creativity on organizational performance.

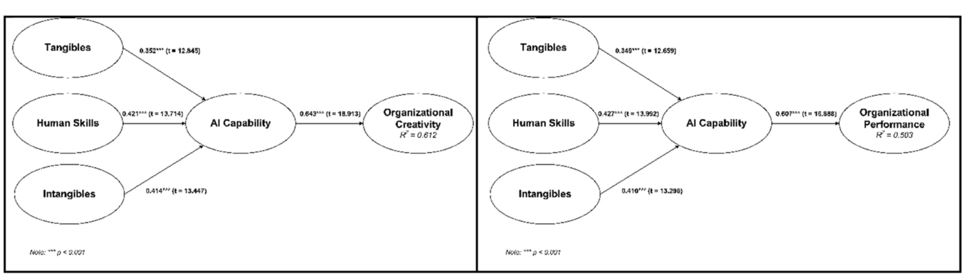
4.7. Comparative test for higher-order factors

Having two paths from our proposed AI capability construct to the organizational creativity (ORC) and organizational performance (ORP) constructs, our model as depicted in Fig. 3 represents a multiple indicator multiple cause (MIMIC) model and therefore satisfies the 2+ emitted paths rule. As such, the formative model presented above is highly unlikely to present interpretational confounding [146]. Nevertheless, to empirically exclude the potential of interpretational confounding in our model, we followed the recommendations of [147] and created two models. Model 1-ORC included organizational creativity as the sole dependent variable, while in Model 2-ORP, organizational performance was the only dependent variable. The weights of the three formative measures that comprise the AI capability construct remained consistent and statistically significant across the two models (see Fig. 4). These results suggest that interpretational confounding was not an issue in this study. Several recent studies including those of Wu et al. [148] and Gupta and George [8] have used this method to empirically validate the formative constructs in their study.

In the next step, we examine the external consistence of the AI capability construct. Based on the guidelines of Kim et al. [147], we developed a test model (TModel) which comprised the three formative indicators of the AI capability construct (tangibles, human skills, and intangibles) and the two endogenous constructs (organizational creativity and organizational performance). The two previously described models—Model 1 and Model 2 were used as the baseline models. External consistency is achieved when the formative measures of a construct have consistent correlation with the measures of the dependent variable in proportion to their correlation with the other construct [8,149]. Therefore, we proceeded by examining two things, 1) comparing the correlations of the three measures of the AI capability construct and the five measures of organizational creativity across Model 1 and the TModel, and 2) comparing the correlations of the three measures of the AI capability construct and the five measures of organizational performance across Model 2 and the TModel. By looking at the differences in correlations between the AI capability measures (i.e., tangibles, human skills, and intangibles) and the measures of organizational creativity and organizational performance across the baseline models and the TModel, we found scores that were close to zero as depicted in Table 9. As such, the issue of weakened external consistency can be excluded in this study.

5. Discussion

Although the interest around the business potential of AI is continuously growing, reports and empirical studies from early adopters indicate that many organizations are struggling to realize business value from their AI investments [1,6]. These findings are quite striking when considering the large number of articles that highlight the business value that can be derived by utilizing AI in core organizational operations [54,144]. This clash of expectations versus reality is nicely described by Brynjolfsson et al. [6] who argue that a lot of the attention AI has gained is from vendors and popular press, which is a cause for false hope. In many occasions AI is put forward as a panacea that can remedy all business-related issues, overinflating expectations about what it can deliver. In addition, many of the reports about the business value of AI have been documented by technology and business consultants, which lack the theoretical basis to consolidate findings.



Model 1—ORC: Organizational creativity as the sole dependent variable

Model 2—ORP: Organizational performance as the sole dependent variable

Fig. 4. Test for interpretational confounding.

Table 9
Test for external consistency (change in correlations).

Formative Indicators	Model 1—TModel					Model 2—TModel				
	ORC1	ORC2	ORC3	ORC4	ORC5	ORP1	ORP2	ORP3	ORP4	ORP5
Tangibles	0.004	0.001	0.004	0.003	0.003	0.003	0.007	0.002	0.001	0.008
Human Skills	0.005	0.008	0.006	0.008	0.000	0.000	0.007	0.004	0.001	0.003
Intangibles	0.009	0.008	0.003	0.010	0.004	0.004	0.006	0.008	0.006	0.001

5.1. Research implications

In this study, we attempted to understand the use of AI in the organizational setting by adopting the theoretical lens of the RBT, a well-established theory in strategic management which has a long tradition of providing useful insights on IT-business value research [7]. The objective of adopting this theoretical perspective was to understand the resources that need to effectively leverage AI technologies and to realize performance gains. While there have been many practitioner-based publications to date highlighting the potential value that AI can deliver, the majority of these do not adopt a theoretical lens that can explain how organizations need to be set up in order to utilize these novel technologies toward organizational goals. In addition, the academic literature that exists to date primarily focuses on the technical elements pertaining to AI, often disregarding the challenges associated with deploying such solutions and aligning them with business objectives. This has led to several commentaries and research studies arguing that it is important to understand the necessary resources that organizations should foster in order to be ready to deploy AI technologies to support their core activities [45].

This study makes an important contribution in the business value of AI literature in three main ways. First, we present a theoretical framework of an AI capability which consists of several technical and nontechnical resources categorized into three categories. Past research has shown that it is important to examine the specific capabilities that are associated with emerging technologies as each creates a unique set of requirements for organizations [8,13,14]. We used the RBT to identify and categorize the different resources that are relevant in the organizational setting of AI, therefore guaranteeing that a holistic perspective is adopted. Further, the identification of resources was performed in a systematic manner that utilized a plethora of approaches to ensure an exhaustive and complete set of AI-related resources that jointly comprise a capability. This was done by surveying business reports, practitioner-based press, research publications, and new releases regarding AI adoption at the organizational level. By performing this review, a large list of important factors emerged, which was then grouped based on the underlying themes and categories as defined in the RBT. After this initial process, a group of practitioners and academics which formed our expert group was asked to evaluate these and highlight if there were any important aspects that were missing. This process was also aided by providing them the definition of AI and AI capabilities upon which we based this study. By doing so we then concluded the main resource categories that jointly comprise an AI capability.

Second, by building on the above-mentioned theoretical framework, this study develops a construct that can be empirically applied to assess the AI capabilities of organizations. We argue that theoretically, the AI capability construct is distinct from other digital capability constructs, such as IT capabilities, and proceed to define based on the extracted dimensions the measures required to capture the concept. By following a rigorous process based on the guidelines of MacKenzie et al. [18] we develop an instrument that captures the AI-specific resources that organizations need to foster. Unlike other constructs and corresponding instruments on different digital capabilities, the questions used to capture the main dimensions are based on the specific AI technologies, skills, and intangible resources. As such, we opted not to focus solely on adapting previous measurements but also to include new ones based on the existing body of research regarding the use of AI and the important elements pertaining to its utilization in organizations. Through our empirical study we demonstrated the reliability and validity of the AI capability construct overall, as well as the underlying dimensions and items. By doing so, we address the recent calls in the IS community concerning the need to define and conceptualize an organizational capacity to leverage AI toward business objectives [15–1736,150].

Third, we demonstrated impact that developing an AI capability has on key organizational performance indicators. Specifically, we assessed the extent to which it impacts organizational creativity and organizational performance. These outcome variables have been suggested to be influenced by the use and deployment of AI in the organizational setting in several practice-based publications [4,54,57], as well as in research commentaries and editorials [45,151]. Nevertheless, there is to the best of our knowledge, no empirical large-scale study linking a theoretically grounded conceptualization of AI with key business indicators. We empirically demonstrate that by developing an AI capability, organizations can realize gains in both creativity and performance. This finding underscores the importance of approaching AI through a holistic manner when deploying in within the organization, as simply focusing on the required data and the technology is insufficient to deliver any substantial business results. The findings also indicate that AI can be of significant value for organizations in achieving and sustain competitive performance gains, as it has an impact on key performance outcomes. From a theoretical standpoint, the outcomes also reveal the strategic potential of AI, as we find support for the idea that AI capabilities can contribute to the creative processes, and perhaps even to the knowledge base and innovation outcomes of firms. These association demonstrate that AI can allow organizations to pursue ambidextrous strategies depending on the type of solutions that are deployed. In addition, we find that organizational creativity, which is directly associated with a firms AI capability, leads to organizational performance gains. These findings combines provide support for the domain of IT-enabled organizational capabilities, whereby strategically leveraging IT organizations can enhance and even develop new organizational capabilities.

Summarizing, following the established theoretical framework provided by the RBT, this study extends the existing body of research in the IS community by adopting it within the context of AI to explain what resources organizations need to develop to realize business value from their AI investments. We follow the reasoning and argumentation of Wade and Hulland [25] who suggest that the RBT can provide benefits to the IS community as, 1) the RBT provides the foundation for specifying firm-level resources, 2) it allows for distinctions between cross-functional, as well as technical and nontechnical firm-level resources, and 3) it enables researchers to systematically test the relationship between the aggregate of resources into capabilities, with key performance outcomes. By building on these strengths of the RBT we have been able to further the explanatory power and generalizability of the RBT to the emerging field of AI.

5.2. Practical implications

By including in our conceptualization of an AI capability aspects that have to do with human skills and other intangible resources, we highlight the importance of expanding the view to incorporate more "soft" factors when designing AI deployment strategies. While to date data, the infrastructure and the techniques used to bring to life AI solutions have mostly dominated practice-based literature, in this study we underscore the significance of more elusive but equally important aspects related to AI success. In fact, we show that making such technically oriented investments alone will most likely not result in substantial performance gains. Rather, managers must develop the structures and culture that enable value generation from their AI investments. For example, interdepartmental coordination if found to be a necessary condition to enable flow of information and data, as well as a means to develop AI solutions that correspond to the business requirements. Unlike many IT solutions, AI applications require lengthy procedures for training, calibrating, and refining, taking into account new sources of data and adapting the models upon which they are developed. Doing so requires that there is a culture of coordination, mutual understanding, and cooperation between the different departments within an organization. In other words, developing an AI orientation within the firm is a necessary precondition for successful deployments.

On a similar note, we highlight the role that skills have in facilitating the mobilization and orchestration of AI within organizations. Our results indicate that practitioners should focus not only on purely technical skills associated with AI, but also on the managerial competencies to direct AI initiatives toward priority areas that generate business value. These findings stress the importance of training technical and business staff with regards to emerging AI techniques and their applications. As AI requires a substantially different skillset compared to other IT solutions, it is critical that organizations are prepared to accommodate their existing employees with the necessary training and educational material to become acquainted with AI tools and techniques. Online resources can be a viable solution as they provide up-to-date knowledge in an environment that facilitates asynchronous learning. In addition, it also serves to highlight what skills would be required in the case of newly hired employees.

Through the intangible dimension of risk proclivity, we also explain the importance of adopting an organizational culture that embraces risk taking and making bold and radical actions. This is a necessary mind-set when it comes to AI projects, as in many successful business cases using AI, going forward with uncertain initiatives that can possibly yield high returns has proven to be instrumental [3,11]. A lot of organizations are risk averse when it comes to implementing new IT solutions and deploying them in operations. However, findings from our study as well as other reports show that it is important to embrace a logic of “high risk high gains” when it comes to AI.

Adding to the above, an important component of becoming an AI-ready organization is being able to self-assess the organizations' strengths and weaknesses. The survey instrument we developed as part of this study can be used by managers in organizations to identify what resources need to be enhanced and which ones are developed to a satisfactory level. For example, the instrument can be applied at local business units, exposing areas such as technical skills, or basic resources such as financing that require further development locally. By distributing it to sub-units, it is also possible to identify which business units are not well connected or have been under-emphasized. This could show imbalances within the organization and units that are not on par with the others or have major weaknesses that could potentially inhibit overall attainment of goals. Given that AI adoption in organizations is still an inaugurating state, such benchmarking attempts could help direct financing and resource allocation more efficiently and help generate business value with fewer uncured costs.

Finally, while the AI capability construct may highlight areas within the organization that practitioners should develop in order to maximize the likelihood of attaining performance outcomes, it must be noted that the value-generating mechanisms are likely to be produced in very dissimilar ways. This has to do both with the types of AI applications that can be developed, as well as on the context in which they are applied. For instance, certain forms of AI can lead to substantial performance gains by automating manual and repetitive tasks, whereas others could be applied to enhance creativity of skilled labor. Since AI applications encompass a broad type of technologies and techniques, it is likely that value will depend on the technologies used, but also on how they are deployed.

5.3. Limitations and future research

As with any research, our study is not without limitations. First, while we outline the main types of resources firms should consider when designing and deploying their AI initiatives, it cannot be considered as a universal model, completely applicable to all organizations. As we are in an initial stage of understanding AI in the business context, providing an exhaustive list of resources driving an AI capability is not easy. It is probable that some organizations may require additional resources to be able to leverage their AI investments based on several contingent aspects, such as industry, size-class, type of AI application, or country of operation. Furthermore, the AI capability construct is by no means exhaustive, so there may be additional important dimensions that we did not manage to capture that future research could examine.

Second, while we identify and describe the main pillars of an AI capability through the tangible, human skills, and intangible dimensions, we do not delve into a process-based perspective of how AI initiatives unfold and what dynamics shape final outcomes. It is highly probable that organizations follow different trajectories when it comes to how they plan and deploy AI solutions, and in doing so face a different set of challenges and hindrances. By adopting an interpretivist approach, it would be possible to uncover the forces that influence choices around AI deployments, the tensions that unfold between involved stakeholders, as well as what the influences of frameworks and governance choices are in impacting the attainment of set goals [21,22].

Third, our study used respondents that worked in companies based in the United States. It is likely that organizations from different regions, or the ones that are laggards in adopting AI technologies may do so in a different manner. For instance, organizations that have less slack financial resources to invest in developing AI solutions may opt to selecting applications from vendors that just require minimum configurations to be operational. In this case, outsourcing solutions would mean a lower need for mobilizing and developing internal resources. Surveying companies from different geographical areas and at different stages of AI deployments could uncover new, equally effective patterns of utilizing AI for organizational purposes.

Finally, while we relied on senior technology professionals within firms, the choice of a single respondent could potentially include some bias in results. A way to remedy this would be to opt for survey designs that collect data from multiple respondents within firms. Another way in which business value can be assessed would be to use objective, rather than subjective performance indicators, time-lagged based on when AI solutions were first deployed.

6. Conclusion

This study has been motivated by the surge of interest in the AI phenomenon by practitioners and academics, particularly over the past five years. Although there has been considerable contribution in literature from practitioners [60,152], within the academic community only within the last couple of years has the topic gained some traction. As a result, there has been much discussion about the business potential of AI, without clearly defining what AI means in the IS context, and with an absence of a concrete definition of an organization's AI capability. In this study, we took insight from the RBT, prior IT studies, and recently published work on using AI in the organizational setting. Through this approach and grounded on input from a group of experts and a large-scale survey-based study, we developed and validated a conceptualization of an AI capability. We argue that eight types of complementary resources must be developed, and which jointly contribute to the emergence of an overall AI capability. Specifically, the tangible resources comprise of data, technology, and basic resources, human skills consist of technical and business skills, while intangible resources that are critical include the presence of inter-department coordination, an organizational change capacity, and risk proclivity. Finally, this study developed a survey instrument to measure an organization's AI capability, which was empirically validated, demonstrating that by fostering an AI capability firms can realize gains in terms of organizational creativity and performance.

CRediT authorship contribution statement

Patrick Mikalef: Conceptualization, Methodology, Software, Writing - original draft, Writing - review & editing. **Manjul Gupta:** Conceptualization, Methodology, Investigation, Methodology, Project administration, Writing - original draft, Writing - review & editing.

Appendix A. AI Capability Instrument

Measure	Item
AI Capability	
Tangible	
	D1. We have access to very large, unstructured, or fast-moving data for analysis
- Data	D2. We integrate data from multiple internal sources into a data warehouse or mart for easy access
	D3. We integrate external data with internal to facilitate high-value analysis of our business environment
	D4. We have the capacity to share our data across business units and organizational boundaries
	D5. We are able to prepare and cleanse AI data efficiently and assess data for errors
	D6. We are able to obtain data at the right level of granularity to produce meaningful insights
- Technology	T1. We have explored or adopted cloud-based services for processing data and performing AI and machine learning
	T2. We have the necessary processing power to support AI applications (e.g. CPUs, GPUs)
	T3. We have invested in networking infrastructure (e.g. enterprise networks) that supports efficiency and scale of applications (scalability, high bandwidth, and low-latency)
	T4. We have explored or adopted parallel computing approaches for AI data processing
	T5. We have invested in advanced cloud services to allow complex AI abilities on simple API calls (e.g. Microsoft Cognitive Services, Google Cloud Vision)
	T6. We have invested in scalable data storage infrastructures
	T7. We have explored AI infrastructure to ensure that data is secured from to end to end with state-of-the-art technology
	BR1. The AI initiatives are adequately funded
- Basic Resources	BR2. The AI project has enough team members to get the work done
	BR3. The AI project is given enough time for completion
Human Skills	
	TS1. The organization has access to internal and external talent with the right technical skills to support AI work
- Technical Skills	TS2. Our data scientists are very capable of using AI technologies (e.g. machine learning, natural language processing, deep learning)
	TS3. Our data scientists have the right skills to accomplish their jobs successfully
	TS4. Our data scientists are effective in data analysis, processing, and security
	TS5. Our data scientists are provided with the required training to deal with AI applications
	TS6. We hire data scientists that have the AI skills we are looking for
	TS7. Our data scientists have suitable work experience to fulfill their jobs
	BS1. Our managers are able to understand business problems and to direct AI initiatives to solve them
- Business skills	BS2. Our managers are able to work with data scientists, other employees and customers to determine opportunities that AI might bring to our organization
	BS3. Our managers have a good sense of where to apply AI
	BS4. The executive manager of our AI function has strong leadership skills
	BS5. Our managers are able to anticipate future business needs of functional managers, suppliers and customers and proactively design AI solutions to support these needs
	BS6. Our managers are capable of coordinating AI-related activities in ways that support the organization, suppliers and customers
	BS7. We have strong leadership to support AI initiatives and managers demonstrate ownership of and commitment to AI projects
Intangible	
	Please indicate to what extent do departments (e.g., marketing, R&D, manufacturing, information technology, and sales) within your organization engage in the following activities:
- Inter-Departmental Coordination	IC1. Collaboration
	IC2. Collective goals
	IC3. Teamwork
	IC4. Same vision
	IC5. Mutual understanding
	IC6. Shared information
	IC7. Shared resources
- Organizational Change Capacity	OCC1. We are able to anticipate and plan for the organizational resistance to change
	OCC2. We consider politics of the business reengineering efforts
	OCC3. We recognize the need for managing change
	OCC4. We are capable of communicating the reasons for change to the members of our organization
	OCC5. We are able to make the necessary changes in human resource policies for process re-engineering
	OCC6. Senior management commits to new values
- Risk Proclivity	RP1. In our organization we have a strong proclivity for high risk projects (with chances of very high returns)
	RP2. In our organization we take bold and wide-ranging acts to achieve firm objectives
	RP3. We typically adopt a bold aggressive posture in order to maximize the probability of exploiting potential opportunities

Appendix B. Performance Measures

Construct	Item
Organizational Creativity	
	ORC1. Our organization has produced many novel and useful ideas (services/products).
	ORC2. Our organization fosters an environment that is conductive to our own ability to produce novel and useful ideas (services/products).
	ORC3. Our organization spends much time for producing novel and useful ideas (services/products).
	ORC4. Our organization considers producing novel and useful ideas (services/products) as important activities.
	ORC5. Our organization actively produces novel and useful ideas (services/products).
Organizational Performance	
	ORP1. Compared to our key competitors our organization is more successful.
	ORP2. Compared to our key competitors our organization has a greater market share.
	ORP3. Compared to our key competitors our organization is growing faster.
	ORP4. Compared to our key competitors our organization is more profitable.
	ORP5. Compared to our key competitors our organization is more innovative

Appendix C. Cross-Loadings

	D	T	BR	TS	BS	IC	OCC	RP
D1	**0.740**	0.463	0.542	0.491	0.345	0.246	0.123	0.210
D2	**0.699**	0.413	0.347	0.311	0.287	0.372	0.273	0.116
D3	**0.767**	0.497	0.414	0.356	0.417	0.505	0.379	0.338
D4	**0.721**	0.367	0.297	0.227	0.380	0.378	0.256	0.238
D5	**0.868**	0.641	0.583	0.577	0.521	0.337	0.258	0.251
D6	**0.792**	0.590	0.492	0.471	0.312	0.294	0.224	0.143
T1	0.383	**0.753**	0.394	0.486	0.313	0.195	0.200	0.171
T2	0.587	**0.835**	0.551	0.521	0.375	0.263	0.257	0.187
T3	0.564	**0.776**	0.439	0.369	0.399	0.399	0.367	0.301
T4	0.605	**0.877**	0.618	0.640	0.434	0.331	0.377	0.302
T5	0.377	**0.759**	0.452	0.465	0.375	0.286	0.257	0.300
T6	0.619	**0.850**	0.507	0.492	0.378	0.301	0.324	0.291
T7	0.677	**0.906**	0.568	0.569	0.322	0.332	0.315	0.287
BR1	0.586	0.608	**0.907**	0.560	0.443	0.293	0.232	0.432
BR2	0.613	0.546	**0.885**	0.612	0.426	0.266	0.182	0.354
BR3	0.603	0.544	**0.881**	0.599	0.499	0.325	0.281	0.444
TS1	0.659	0.645	0.651	**0.759**	0.429	0.189	0.251	0.253
TS2	0.638	0.568	0.620	**0.866**	0.471	0.266	0.222	0.230
TS3	0.509	0.518	0.578	**0.919**	0.524	0.304	0.324	0.341
TS4	0.617	0.595	0.503	**0.895**	0.443	0.380	0.325	0.345
TS5	0.438	0.505	0.493	**0.868**	0.463	0.394	0.412	0.377
TS6	0.480	0.489	0.525	**0.888**	0.475	0.312	0.367	0.357
TS7	0.515	0.543	0.614	**0.900**	0.571	0.474	0.423	0.468
BS1	0.466	0.363	0.413	0.440	**0.902**	0.587	0.396	0.389
BS2	0.426	0.325	0.405	0.432	**0.931**	0.595	0.430	0.453
BS3	0.364	0.301	0.385	0.389	**0.888**	0.510	0.377	0.387
BS4	0.485	0.440	0.435	0.607	**0.747**	0.409	0.307	0.355
BS5	0.489	0.400	0.510	0.513	**0.933**	0.657	0.401	0.499
BS6	0.548	0.470	0.506	0.489	**0.943**	0.693	0.482	0.519
BS7	0.466	0.475	0.552	0.577	**0.881**	0.608	0.545	0.529
IC1	0.498	0.323	0.423	0.397	0.603	**0.859**	0.537	0.483
IC2	0.401	0.328	0.298	0.326	0.553	**0.863**	0.530	0.448
IC3	0.454	0.363	0.375	0.418	0.592	**0.875**	0.568	0.489
IC4	0.366	0.335	0.206	0.244	0.535	**0.873**	0.586	0.435
IC5	0.319	0.340	0.248	0.299	0.562	**0.864**	0.545	0.483
IC6	0.272	0.277	0.198	0.290	0.586	**0.849**	0.483	0.427
IC7	0.273	0.276	0.264	0.319	0.478	**0.796**	0.513	0.478
OCC1	0.303	0.341	0.295	0.373	0.499	0.646	**0.857**	0.666
OCC2	0.297	0.369	0.236	0.387	0.334	0.502	**0.879**	0.495
OCC3	0.261	0.379	0.243	0.387	0.356	0.467	**0.840**	0.475
OCC4	0.246	0.351	0.213	0.345	0.395	0.522	**0.891**	0.514
OCC5	0.252	0.309	0.133	0.247	0.365	0.529	**0.870**	0.540
OCC6	0.233	0.230	0.288	0.250	0.487	0.577	**0.843**	0.610
RP1	0.245	0.287	0.424	0.294	0.481	0.518	0.575	**0.921**
RP2	0.297	0.319	0.489	0.410	0.494	0.514	0.622	**0.968**
RP3	0.262	0.310	0.442	0.407	0.461	0.510	0.626	**0.952**

D – Data, T – Technology, BR – Basic Resources, TS – Technical Skills, BS – Business skills, IC – Inter-Departmental Coordination, OCC – Organizational Change Capacity, RP – Risk Proclivity

Appendix D. Heterotrait-Monotrait Ratio (HMTM)

	(4)	(5)	(6)	(7)	(8)
(4) Technical Skills					
(5) Business skills	0.581				
(6) Inter-Departmental Coordination	0.403	0.688			
(7) Organizational Change Capacity	0.407	0.496	0.669		
(8) Risk Proclivity	0.411	0.530	0.577	0.680	

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