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AI organizational capabilities: A proposal for a comprehensive taxonomy

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Abstract

This article proposes an expanded taxonomy of AI capabilities that updates the widely used framework by Davenport and Ronanki (2018), which omitted essential aspects of the decision-making process. By integrating Herbert Simon's (1960) model with the three analytical levels of business analytics (descriptive, predictive, and prescriptive), this research reconfigures AI functionalities into a higher-order construct. This refined framework encompasses process automation, AI-enabled decision-making, and cognitive engagement. Ultimately, this approach transcends narrow technological classifications, providing a structured lens to understand how AI drives strategic value, optimizes resources, and fosters advanced human-technological interaction in the modern business environment.

Keywords: *Artificial Intelligence, AI Organizational Capabilities Taxonomy, Decision-Making, Process Automation, Cognitive Engagement, Predictive Analytics*

1. Introduction

In today's turbulent business landscape, Artificial Intelligence (AI) has emerged as the most significant disruptive force, driving digitalization across organizations and transforming business models. However, fully realizing AI's business value requires a rigorous synthesis of strategic, economic, and organizational theories (Borges et al., 2021; Caballar, 2024). Understanding how to create sustained value necessitates addressing a critical research question: what specific organizational capabilities does AI generate, and how can they be measured?

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This article proposes a taxonomy to classify AI organizational capabilities, defined as the resources, competencies, and skills that allow a firm to integrate and leverage AI within its processes, decision-making, and stakeholder relationships, with a specific focus on business applications. Our approach is grounded in a comprehensive literature review, building upon the classification by Davenport and Ronanki (2018), which has been widely adopted in subsequent studies (Borges et al., 2021; Nishant et al., 2024; Yu et al., 2024).

Davenport and Ronanki's taxonomy identifies three fundamental capabilities: process automation, cognitive insight, and cognitive engagement. This framework is particularly relevant to our work, as it transcends a purely technological perspective and emphasizes the application of AI within organizational contexts. While the Davenport and Ronanki (2018) model provides a solid foundation, it also has inherent limitations, primarily stemming from a narrow view of the support it offers for decision-making. Consequently, this study adopts a holistic approach to refine and expand this initial taxonomy, providing a more robust classification tailored to contemporary organizational needs.

2. Theoretical framework

The study of organizational capabilities in Management has shaped the theory and practice of strategic management. The Resource and Capabilities View (RCV), commonly known as the Resource-Based View (RBV) (Barney, 1991), has become a foundational framework in business management, emphasizing that an organization's valuable, rare, inimitable, and non-substitutable internal resources and capabilities constitute the primary source of sustained competitive advantage. Subsequent developments, such as those by Teece et al. (1997), address the limitations of the RBV in highly dynamic environments and propose the Dynamic Capabilities (DC) perspective, which focuses on the firm's ability to adapt and reconfigure its resource and capability sets as the key to maintaining a sustained competitive advantage.

AI organizational capabilities refer to the organizational competencies and resources that enable a company to integrate, apply, and leverage AI in its processes, decision-making, and interactions with employees and customers (Davenport & Ronanki, 2018; Mikalef et al., 2021). From the perspective of Dynamic Capabilities (DC), these act as lower-order resources that, by reconfiguring organizational structures, enable the development of higher-order capabilities and the generation of measurable business value.

3. AI organizational capabilities taxonomy

The classification proposed by Davenport and Ronanki (2018) has been widely accepted in previous studies (Borges et al., 2021; Nishant et al., 2024; Yu et al., 2024). This taxonomy,

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consisting of process automation, cognitive insight, and cognitive engagement, aligns with our proposed focus on business applications, as it goes beyond a purely technological perspective.

Herbert Simon (1960) proposed a decision-making model with three stages: intelligence, design, and choice. Additionally, business analytics literature links these stages to descriptive, predictive, and prescriptive levels of data analysis. We identified a significant gap because cognitive insight is mainly associated with the intelligence phase (descriptive analysis). The framework by Davenport and Ronanki (2018) does not explicitly include the design and choice phases, thereby limiting its ability to fully represent the entire decision-making process.

To address this limitation, we referred to more recent studies, such as that of Sjödin et al. (2023), who include these phases in their classification. Specifically, these authors refer to perceptive and prescriptive capabilities, previously recognized as fundamental pillars of business analytics, alongside descriptive capability (intelligence).

This review led us to incorporate the AI-enabled decision-making capability identified by Cao et al. (2024) into our taxonomy. This element, absent in previous frameworks, aligns with Simon's (1960) model. Its inclusion enables a more comprehensive and applicable taxonomy for the business environment, facilitating a structured approach for analyzing and implementing AI capabilities within organizational decision-making.

The following section outlines the definitive configuration of this taxonomy for AI organizational capabilities, based on its business applications.

3.1 Process automation

Automating digital and physical tasks, particularly administrative and financial activities, has significantly advanced thanks to robotic process automation (RPA) technologies. Unlike traditional business process automation tools, RPA employs "robots" (i.e., server-executed code) that mimic human behavior in inputting and consuming information from multiple IT systems. This technology automates many tasks, including data transfer, credit card replacement, reconciliation of missed payments, and document reading. By improving operational efficiency and reducing manual intervention, RPA represents a key advancement in organizations' digital transformation (Borges et al., 2021; Davenport & Ronanki, 2018).

Therefore, process automation can be defined as an AI organizational capability focused on operational efficiency that integrates RPA technologies to execute repetitive tasks autonomously. This approach minimizes human intervention in rule-based workflows, enabling the reallocation of critical resources toward higher-value strategic activities. The applicability of this taxonomy is reflected in leading corporate solutions; for instance, in process automation, JPMorgan Chase employs COIN to analyze documents efficiently.

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3. 2 AI-enabled decision-making capability

According to Simon (1960), decision-making integrates key managerial functions such as planning, organizing, and controlling. AI serves as a valuable tool by identifying patterns in historical data, facilitating a precise interpretation of the business environment, and enabling more informed decision-making (Sharda et al., 2024). In this sense, AI-based organizational capabilities can significantly enhance and support decision-making. In this domain, the literature has yet to reach consensus on the required levels of competence (Madanaguli et al., 2024). Additionally, it is crucial to recognize that AI effectiveness depends on the availability of structured data and a robust analytical infrastructure (Sjödin et al., 2023).

To address these issues, we will leverage the existing business analytics framework (descriptive, predictive, and prescriptive). This framework allows us to evaluate how AI tools optimize decision-making and improve managerial effectiveness (Borges et al., 2021; Cao et al., 2024; Sjödin et al., 2023) by distinguishing among the three aforementioned levels of analysis, which differ in complexity and value. Strengthening these levels through AI enables significant process optimization. The following section details three specific AI capabilities that enhance decision-making by automating and improving data analysis.

3.2.1 AI-enabled descriptive capability

According to Turban et al. (2021), AI-enabled descriptive or perceptive capability involves identifying problems or opportunities, gathering relevant information, and establishing objectives and evaluation criteria. This enables the generation of structured summaries of historical data, facilitating the extraction of useful information and preparing the data for more advanced analysis.

This capability provides a comprehensive understanding of business dynamics, serving as a foundation for future strategies. Descriptive analytics focuses on answering “What has happened?” and “What is happening?” The systematic collection of data facilitates the identification of patterns, trends, and critical elements that guide the interpretation of the organizational environment (Sharda et al., 2024), enabling the detection of emerging trends and supporting contextual decision-making (Rainer & Prince, 2020).

This functionality aligns with the cognitive insight capability described by Davenport and Ronanki (2018), defined as the ability to extract deep, actionable knowledge through the intensive processing of large data volumes. According to the authors, this approach transcends traditional analysis by enabling the interpretation of complex trends and the discovery of hidden opportunities, thereby enhancing human cognitive capacity.

Finally, Sjödin et al. (2023) reinforce this view, noting that these perceptive capabilities allow organizations to gain precise insights into how their products are used in real operational environments, particularly in industrial contexts. Thus, organizations can identify underlying

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patterns, opportunities, and processes that would otherwise remain invisible without deep, automated data analysis.

Therefore, this work define AI-enabled descriptive capability as an AI-based organizational capability that transforms unstructured historical data into actionable insights by systematically identifying patterns and trends.

3.2.2 AI-enabled predictive capability

According to Turban et al. (2021), predictive capability defines courses of action to solve problems or capitalize on opportunities by analyzing alternatives and evaluating them against established criteria. Technically, it employs data analysis methods to build models that anticipate future events.

Sjödin et al. (2023) emphasize that the effectiveness of this AI capability depends on both the quantity and quality of data. Predictive AI enables multidimensional analysis of large-scale data to optimize resource allocation (Caballar, 2024; Z. Cao et al., 2024; Sjödin et al., 2023). While detecting anomalies and anticipating environmental changes are often linked to descriptive capabilities, predictive AI integrates machine learning algorithms with statistical analysis to forecast behaviors, facilitating more accurate decision-making models.

Furthermore, this capability enables organizations to operate with more granular datasets without sacrificing accuracy, thereby improving resource-allocation efficiency in response to shifts in demand or market conditions. Overall, integrating the predictive capability into business processes enables better-informed decisions, the anticipation of future scenarios, and proactive resource optimization, all of which directly contribute to greater operational efficiency and organizational competitiveness (Sjödin et al., 2023).

Consequently, in the proposed taxonomy AI-enabled predictive capability is conceptualized as an AI-based organizational competence that anticipates future behaviors, events, or scenarios through the technical integration of machine learning algorithms and advanced statistical analysis. Regarding decision-making, GE's Predix platform exemplifies this predictive capability in industrial maintenance, demonstrating how these analytical models anticipate equipment failures to optimize operational performance.

3.2.3 AI-enabled prescriptive capability

AI-enabled prescriptive capability focuses on selecting the optimal course of action among various alternatives, considering known parameters (Turban et al., 2021). This process involves searching for, evaluating, and recommending solutions based on criteria of feasibility and profitability (Sharda et al., 2024). Through mathematical models that account for multiple variables and scenarios, this approach provides concrete recommendations for strategic decision-making (Sharda et al., 2024).

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Sjödin et al. (2023) define prescriptive AI as that which generates solutions to optimize product use and maximize sustainable value. Through advanced simulations, this capability identifies optimal strategies and suggests informed actions, improving operational efficiency and reducing costs, for instance, within manufacturing processes or supply chains. This approach combines predictive modeling with mathematical optimization techniques to deliver high-value strategic recommendations. Human intuition remains fundamental under uncertainty. Jarrahi et al. (2023) emphasize that while AI excels at probabilistic analysis, human judgment remains irreplaceable in critical, unfamiliar situations.

Accordingly, it is proposed that AI-enabled prescriptive capability is a high-level organizational competence that uses optimization algorithms to determine the optimal course of action. Its value lies in the ability to simultaneously evaluate multiple variables and constraints, transforming predictions into actionable recommendations that maximize operational efficiency and strategic value. For instance, ORION (UPS) illustrates this prescriptive capability by optimizing global logistics routes, demonstrating how complex data translates into superior strategic decisions.

3.3 Cognitive engagement

Cognitive engagement is a strategic approach oriented toward facilitating direct interaction between the organization and its key stakeholders, primarily employees and customers, through advanced technologies such as natural language processing, chatbots, intelligent agents, and machine learning (ML), as proposed by Borges et al. (2021). This model transcends mere technical optimization by focusing on how these technologies transform the quality and depth of communication and service engagement (Davenport & Ronanki, 2018; Nishant et al., 2024; Yu et al., 2024)

This approach is consistent with the AI democratization framework defined by Sjödin et al. (2021). The goal is to make AI accessible across the entire organization, involving not only specialists but also a diverse network of participants, including partners and suppliers. AI democratization fosters the inclusion of these actors in the utilization of technological tools, thereby promoting an organizational culture based on innovation and continuous operational optimization.

Finally, implementing a model based on cognitive engagement leads to a "network-type" system where partners, employees, suppliers, and clients interact fluidly and effectively. This ecosystem enhances collaboration, information exchange, and value generation through technology, ultimately consolidating a sustainable competitive advantage for the organization.

Therefore, cognitive engagement is conceptualized as the organizational capacity to democratize access to AI, thereby optimizing service quality and the depth of communication while effectively linking the organization with its stakeholders. Finally, cognitive engagement

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is materialized in recommendation engines, such as those used by Netflix or the Aura assistant by Telefónica, which personalize interactions through AI. These cases demonstrate that such capabilities act as strategic enablers, transforming traditional operations into data-driven business models.

4. Conclusion

This study makes a relevant contribution by proposing a taxonomy of AI organizational capabilities, with a clear focus on business applications rather than a purely technical perspective, a perspective currently absent in the literature. By integrating economic and technological dimensions, this framework establishes an objective metric to evaluate how AI generates strategic business value. Grounded in Dynamic Capabilities Theory, we posit that AI capabilities function as lower-order resources. The main novelty of this paper lies in formalizing this taxonomy, which provides a foundation for future validation. These results will support subsequent research into AI business value creation, exploring both direct effects and indirect impacts on higher-order capabilities, such as organizational resilience. Ultimately, this research positions AI as a fundamental mechanism for organizations to navigate uncertainty. Furthermore, this work is part of a larger project in which subsequent stages will focus on developing and empirically validating a measurement scale for these AI capabilities.

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