Conceptualizing a Capability-Based View of Artificial Intelligence Adoption in a BPM Context

Aleš Zebec[1[0000-0003-4469-3665]] and Mojca Indihar Štemberger[2[0000-0002-2154-5750]]

[1] School of Economics and Business, University of Ljubljana, Kardeljeva ploščad 17, SI-1000 Ljubljana, Slovenia
ales.zebec@student.uni-lj.si

[2] School of Economics and Business, Academic Unit for Business Informatics and Logistics, University of Ljubljana, Kardeljeva ploščad 17, SI-1000 Ljubljana, Slovenia
mojca.stemberger@ef.uni-lj.si

Abstract. Advances in Artificial Intelligence (AI) technologies are creating new opportunities for organizations to improve their performance; however, as with other technologies, many of them have difficulties leveraging AI technologies and realizing performance gains. Research on the business value of information technology (IT) suggests that the adoption of AI should improve organizational performance, though indirectly, through improved business processes and other mediators, but research so far has not extensively empirically investigated the way AI creates business value. The paper proposes a capability-based view of AI adoption based on the conception that, with the adoption of AI, an organization develops AI-enabled capabilities – abilities to mobilize AI resources to effectively exploit, create, extend, or modify its resource base. This leads to higher organizational performance through cognitive process automation, innovation, and organizational learning. The first step in this research is to clarify the AI adoption construct. The goal of the paper is thus to provide a conceptual definition, and deeper insights into the components of the AI adoption construct at the organizational level.

Keywords: Artificial Intelligence, Adoption, Conceptualization, Business Process Management, Business Value

1 Introduction

Artificial Intelligence is driving intelligent automation, augmentation, and innovation as well as transforming every aspect of society at individual, organizational, and societal levels [1]. Although it has no single accepted definition, we understand AI as *a simulation of human cognitive functions using intelligent agents*. Intelligent agents are capable of receiving percepts from the environment and performing actions [2]. AI is likely to be a general-purpose technology [3], characterized by pervasiveness, inherent potential for technical improvements, and innovational complementarities [4].

Although AI has been around since the 1960s, it has reemerged on the stage as a key technology that will likely play a central role in realizing performance and competitive value for organizations [5]. Vast amounts of data (Big Data), cloud computing, data management, programming frameworks, and AI services provide a readily available platform for adopting AI technology.

However, organizations have difficulties with leveraging AI technologies and realizing performance gains [6]. There is much research on the business value of IT, but AI is a distinct kind of technology because it can perform cognitive tasks usually performed by humans. This ability opens up a lot of possibilities and opportunities for innovation [5]. The key characteristics of the value proposition of AI are speed, scale, granularity, learning (accuracy), and AI-assisted decision-making [7, 8]. Furthermore, AI is highly dependent on data and domain knowledge, making it challenging to integrate and align with existing business processes [9]. The literature on this topic is scarce. There is a lack of empirical research on how AI adoption impacts the performance of business processes and organizations.

To address the gap, we draw from the concept of IT capability [10]. Researchers have shown that an organization's ability to effectively leverage its IT investments by developing a strong IT capability can lead to improved organizational and process performance. The concept has been adapted for technologies such as Business Analytics, Business Intelligence, and Big Data Analytics [11-13]. We posit that AI-specific ability to create intelligent agents capable of self-learning and decision-making can enable significant performance gains [14].

The motivation behind this study was to define a concept that would capture all components of AI adoption at an organizational level in the context of Business Process Management (BPM). The concept is an important and foundational element that will support and enhance efforts to measure the impact and value of AI technology. The conceptualization procedure included literature identification and nine in-depth semi-structured interviews to confirm and refine the definition. Interviews included managers, academics, and experts from financial services, insurance, government organization, AI technology providers, and the energy sector. The concept would then be operationalized as a measurement scale to conduct empirical research. In the paper, we describe AI adoption *as the successful deployment and use of AI resources (data, AI infrastructure, skills, competencies, etc.) in business processes*. The level (success) of adoption is measured by the development of AI-enabled capabilities (components of AI adoption), which represent *the ability to mobilize AI resources for specific business needs through the successful implementation of AI applications, tools, or technology*.

The remainder of the paper is structured as follows. In the next section, we present the adoption of AI in the BPM context. In section 3, we describe the conceptualization procedure and the detailed results of the capability-based view of AI adoption and its dimensions. Finally, we summarize our study and discuss future work.

2 Adoption of AI and BPM Context

Our exploratory research (Table 1) shows that organizations can achieve significant performance gains when aligning AI adoption with business processes. Findings from empirical studies generally suggest that organizational processes mediate IT's impact on organizational performance [13, 15-17]. Thus, we adapted the integrative model of IT Business Value [18] to analyze the impact of AI adoption at the process and organizational level. We study the adoption of AI in the setting of BPM, focusing on operational and dynamic capabilities developed to manage and improve business processes. Based on a literature review [5, 6, 8, 14, 19-21] and in-depth exploratory interviews on the topic of AI and BPM, we identified three key ways AI can generate business value: 1) Cognitive Business Process Automation, 2) Business Process Innovation, 3) Organizational learning and by extension improved Decision-Making Performance. These capabilities comprise the BPM context and process level, through which AI adoption impacts organizational performance.

Cognitive automation is recognized as one of the key ways AI adoption can produce business value [5, 22]. The aim of cognitive automation has often been to speed up information flow and to provide decision support [23]. However, automation systems lack many of the human cognitive skills now made possible by AI technologies.

Cockburn, Henderson, and Stern present AI as an enabler of innovation, with the ability to spawn complementary innovations [3]. AI adoption affects business process innovation mainly by modifying underlying process models through self-learning [24] and by organizational learning's ability to spark innovation [22]. Numerous cases show the impact of AI on innovation – for example, in reducing unconscious bias during the hiring process (Harver[1]), modeling a person's immune process system for drug development (CyroReason[2]), performing a visual search in e-commerce, personalizing clothing and accessories (Stitch Fix[3]), or optimizing agricultural performance (Agtech[4]).

Various authors present evidence of AI's ability to enable double-loop learning and promote organizational learning through human-computer collaboration [6, 25-27]. Aydiner et al. [19] report that technological infrastructure and related systems affect decision-making performance. We conclude that as AI includes cognitive decision-support capabilities, adoption of it will directly or indirectly (through organizational learning) affect decision-making performance, reducing the time and effort required to make a decision. Faster decision-making has a significant positive impact on business process performance [19].

This view incorporates both AI-enabled strategies of automation and augmentation. The following figure (Fig. 1) presents the contextualization of the IT Business Value Generation Process model [18], outlining the impact of AI adoption on business processes. This view identifies the areas where AI can be applied and supports the conceptualization of AI adoption.

---

1 https://harver.com/
2 https://www.cytoreason.com/
3 https://www.stitchfix.com/
4 https://www.valuer.ai/blog/best-agtech-startups-in-europe#top_EU_startups

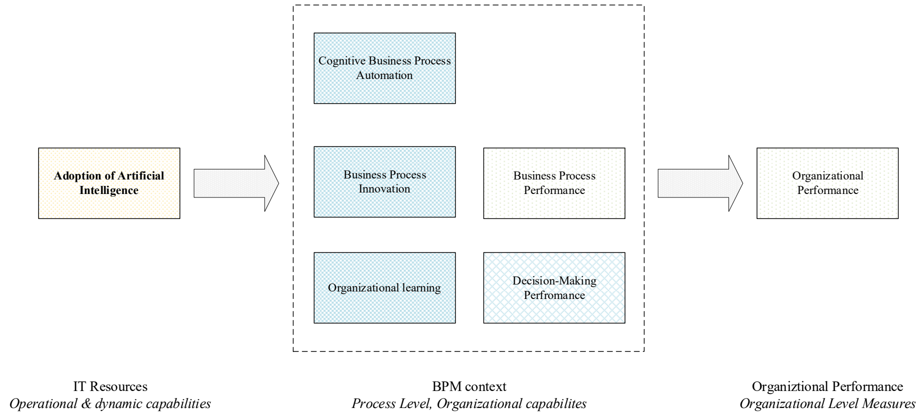

Fig. 1. AI adoption and Business Value Framework

3 Conceptualization of Capability-Based View of AI Adoption

The conceptualization followed the recommended literature guidelines for the development of conceptual definitions [28, 29]. The definition of "adoption of artificial intelligence" was developed in three stages:

1. collecting possible attributes of the "adoption of artificial intelligence" construct by examining and assembling a set of definitions from the literature and in-depth semi-structured interviews,
2. compiling the key potential attributes and generating a preliminary definition of "adoption of artificial intelligence," and
3. refining the definition of "adoption of artificial intelligence."

3.1 Literature Identification

To identify any existing definitions, we conducted a review of information systems literature (SCOPUS and Web of Science). The literature review included papers on AI adoption constructs and models at the organizational level. We identified two empirical studies using diffusion of innovations (DOI) theory and the technology-organization-environment (TOE) framework [30, 31]. AI adoption constructs and measurement scales we found measured the adoption related to antecedents and determinants of readiness for adoption, the process of adoption, and adoption intention. Since we found no constructs assessing AI adoption level as an exogenous, component-based (unlike antecedents or determinants) variable related to the level of deployment, actual use, or utilization of specific applications and technologies, we deemed it necessary to develop a new construct.

To conduct a component-based conceptualization, we separately examined the concepts of "adoption" and "Artificial Intelligence." We followed the recommendations of Podsakoff et al. [28] and implemented several techniques to collect potential attributes and generate an illustrative set of definitions for the focal construct. The procedure included examining the definitions from dictionaries and antonyms of both concepts, a literature review, and in-depth semi-structured interviews with subject matters experts and practitioners.

We examined definitions of "adoption" in dictionaries and top MIS journals to extract common attributes centered on actual use after the adoption of the technology. The common attributes were *implementation*, *integration*, *deployment*, *use*, and *exploitation*. We discarded attributes centered on the adoption process: *investment decision*, *acceptance*, *selection*, *planning*, and *configuration*.

We examined definitions of "Artificial intelligence" in dictionaries and information systems literature. AI has no single accepted definition, and definitions are very general, focusing mostly on two key attributes: *learning* and *perception*. Some definitions emphasize computer capacity to mimic human intelligence; others are more precise, defining AI as the technologies enabling the simulation of human cognitive functions. The term *intelligent agent* is often presented as the central unifying theme [2]. The AI Group of Experts at the OECD [32] defined an intelligent agent or AI system as *a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments. It does so by using machine and/or human-based inputs to 1) perceive real and/or virtual environments, 2) abstract such perceptions into models through analysis in an automated manner (e.g., with ML, or manually), and 3) use model inference to formulate options for information or action. AI systems are designed to operate with varying levels of autonomy.* To identify more specific characteristics and uncover conceptual themes of AI adoption, we further investigated AI types, AI features, AI technologies, and AI application domains.

We expect AI to have promising capabilities that enable or facilitate the transformation or redesign of business processes [1]. Thus we analyzed and extracted attributes from definitions of specific AI technologies, including *Biometrics, Collaborative Systems, Computer Vision, Deep Learning, Expert Systems, Generative Adversarial Networks, Image Analysis, Image Recognition, Knowledge Engineering, Knowledge Representation, Automated reasoning, Planning, Optimization, Verification, Logic Networks, Machine Learning, Natural Language Generation, Natural Language Processing, Natural Language Understanding, Neural Networks, Ontology Creation, Pattern Recognition, Robotic Process Automation (RPA), Robotics & Smart Robotics, Speech Recognition, Text Analysis, Video Analysis,* and *Virtual Agents*.

To organize the extracted attributes in conceptual themes, we used the lens of business capabilities or application domains rather than technological capabilities [5]: *Robotics and cognitive automation*, *Enhanced process automation*, *Cognitive insights*, *Cognitive engagement*, *Cognitive interaction*, and *Cognitive Decision Support*.

3.2 Exploratory Research

According to established guidelines [28, 29], the findings from the literature review were supplemented with interviews to extract additional definitions and attributes from experts. Organizations and experts were selected because of their work with AI or on

AI-related projects. During all of the nine in-depth semi-structured interviews, we discussed the broader scope of AI adoption and the interviewees' experiences with AI implementation, deployment, and use. We aligned their views on the technology with the extracted conceptual themes (presented application domains), as these were the classifications experts and practitioners were most comfortable with. We present the excerpt of the results in Table 1.

Table 1. Excerpt of the main findings from the interviews.

Findings	Theme
Financial Services; 5900 employees; Chief Data Officer (CDO)	
AI adoption emerged in the analytics department. The organization adopted a new business strategy that relied on advanced techniques for pattern recognition to gain customer insights. The goals were to increase process performance and generate revenue based on AI capabilities. The new business strategy defined data as a critical resource. They appointed a CDO to manage a data management sector. The organization is dealing with automation in the scope of the Lean initiative, improving business processes by creating more value with fewer human resources. Are focused on processes where decisions are not deterministic (e.g., credit scoring). Integrated AI with their products (e.g., in personal finance management and in automating classification of revenue and expenses).	Business insights, Data management, Automated decision-making, Engagement, AI techniques
Insurance company; 5200 employees; head of the team responsible for developing DWH/BI/AI solutions	
Are integrating chatbots for customer support. Organization-wide deployment of advanced AI functionalities for decision support (e.g., a model for automated detection of insurance policy renewal). Are focused on automation and optimization of processes. They identified several opportunities for RPA. They are developing a central data repository to eliminate data silos and are gathering publicly available data from the environment. After data is available in the data warehouse, they search for opportunities with Business Intelligence and AI methods.	Human–computer interaction, Decision support, AI technology, Data acquisition
Financial services; 1010 employees; head of Analytics Department	
Implemented and deployed a next-best-offer solution for salespeople. The organization is using machine learning and decision trees in marketing. They are mostly concerned with the propensity to buy and with churn management, and they see the most value in AI-enabled predictive analytics. They are focused on ensuring high-quality data.	Decision support, AI techniques, Business insights, Data management

3.3 Five-Dimensional Conceptualization

Based on the example of Sonenshein et al. [33], we organized the extracted attributes into a smaller set of themes and then aggregated them into dimensions. As indicated in Figure 2, we organized the attributes into 17 related themes and five dimensions: *Data Acquisition and Preprocessing*, *Cognitive Insights*, *Cognitive Engagement*, *Cognitive*

Decision Assistance, and *Cognitive Technologies*. The construct derived from the conceptual definition is a multidimensional, second-order construct, reflective – reflective type I [34].

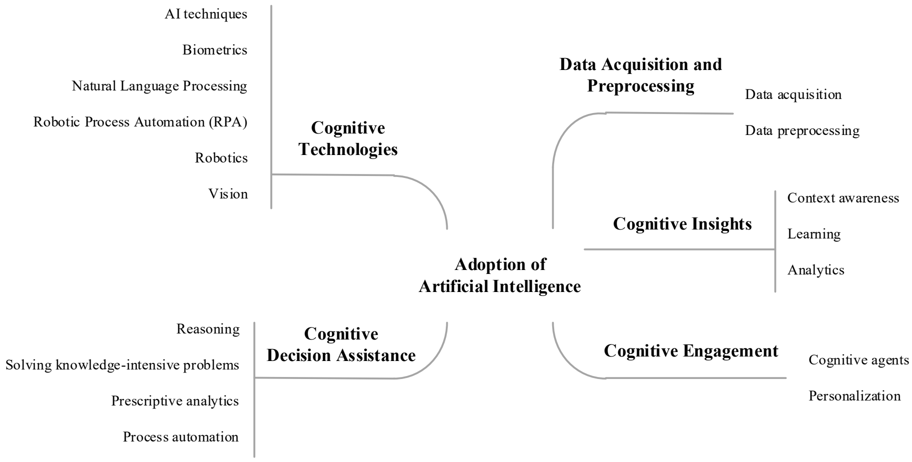

Fig. 2. Organizing attributes into common conceptual themes and dimensions.

In the last stage of the conceptual analysis, we refined the conceptual definition of the examined construct by discussing it with subject matter experts and peers to examine the definition and solicit questions about the concept. As a result, we modified the scope of the definition. Next, we present the resulting definition.

The conceptual definition of the focal construct: "the s*uccessful deployment and use of AI resources in business processes."* We use the term AI resources for AI-related elements that must be brought together to ensure the successful deployment and use of AI technology. Key AI-related elements are scalable infrastructure, AI assets (data, trained models, etc.), AI skills, domain knowledge, expertise, capabilities, partnerships, AI talent, processes, privacy policies, etc. The definition of a construct must incorporate the "property" the concept characterizes and the "entity" to which that property relates [29]. We defined the property for "Adoption of Artificial Intelligence" as "*the organization's ability to develop a set of distinct AI-enabled capabilities (the ability to mobilize AI resources to exploit strategic assets and achieve innovative changes), through the successful implementation of AI applications, tools, or technology.*" The property applies to the entity of an organization.

AI is primarily concerned with data, which is exploited, examined, renewed, or reconfigured through AI-enabled capabilities. We argue that AI, by itself, cannot be a capability. AI becomes a part of a capability when it is applied to a problem and given a goal. AI needs goals; otherwise, it cannot learn. This characteristic is not so different from one of humans; we cannot learn anything without a goal either. Without a goal, there is no frame of reference for evaluating performance and, thus, no way to improve. By conceptualizing "Adoption of Artificial Intelligence," we describe the level of the adoption through the development levels of five distinct and progressive AI-enabled capabilities (components of AI adoption). In a broader scope, these capabilities not only support business processes but become an integral part of an organization's ability to generate value from its data. Next, we present conceptualized dimensions.

Data Acquisition and Preprocessing: "*the organization's ability to extract data from structured and unstructured sources, new and legacy systems, and internal and external sources and to prepare it for analysis*." The three basic routines are data extraction, data preprocessing, and continuous ensuring of data quality. Their purpose is to deal with Big Data (ever-increasing volume, variety, and velocity of data) collected from internal and external sources. Preprocessing includes consolidation, organization, validation, cleaning, transformation, reduction, summarization, labeling, and loading into a data warehouse, data lake, NoSQL database, relational database (RDBMS), or other applications. High-quality data is an important business resource and asset and has tremendous impact on an entity's performance [35]. We propose to measure the dimension by assessing the successful deployment and use of data management applications and tools (e.g., Information propagation, Data warehousing/Data Lake, Data capturing system IoT/SCADA, Content Creation, Discovery, Creation, Computational Creativity, etc.).

Cognitive Insight: "*the organization's ability to use AI to detect patterns in data and interpret their meaning.*" This dimension is conceptualized around themes of context awareness, learning, and analytics. AI enables a recognition of patterns or clusters of data that would be otherwise invisible to a human [36]. It can interpret events and contextualize recognized patterns to derive their true meanings. The learning aspect of AI allows for making predictions on the basis of past experiences [37] and, by the continuous learning process, for improving insight over time [5]. Cognitive analytics (Knowledge representation, Inference, Reasoning, Learning & adaptation, Hypothesis generation & validation, Domain cognitive models, and Machine learning, or Deep learning) offer better results in terms of speed, scale, accuracy, and granularity. We propose to measure the dimension by assessing the successful deployment and use of AI-analytics applications and tools (e.g., Predictive Sales, Churn Management, Fraud Detection, Risk Management, etc.).

Cognitive Engagement: "*the organization's ability to support AI-enhanced human–computer interaction and collaboration*." Engagement consists of several key elements, including understanding, perception of intention, and domain knowledge [38]. Understanding encompasses natural language processing, natural language understanding, automated speech recognition, and text-to-speech conversion. Leveraging contextual information about humans to develop human-like empathy and communication skills in human–computer interaction or collaboration applications involves perception of intention, tone, sentiment, emotional state, environmental conditions, and the strength and nature of a person's relationships [5]. All the elements are used for reasoning through the total of all structured and unstructured data to determine the optimal approach for engaging a person [39]. This ability enables automated interactions to reliably support customers' activities and prompt their engagement [40] in customer-facing business processes. Organizations are also increasingly using cognitive engagement to interact with employees (to support routine activities), augment information, improve knowledge acquisition/exploration/understanding, and to support the collaborative formulation of goals and decisions [5]. We propose to measure the dimension by assessing the successful deployment and use of AI-enabled applications and tools related to user engagement (e.g., Virtual assistants, Chatbots, Avatars, Recommendation systems, etc.).

Cognitive Decision Assistance: "*the organization's ability to use AI in decision-making processes*." AI technologies and techniques enable AI-assisted decision-making and render decision support more intelligent. Some common abilities descriptive of AI's capability are as follows: to speed up information flows, to provide predictive and adaptive decision support, to utilize automated reasoning to solve knowledge-intensive problems, to make sense out of ambiguous or contradictory messages in large data sets, to recognize the relative importance of different elements in a situation, to respond quickly and successfully to a new situation, and to apply knowledge to manipulate the environment [41]. We propose to measure the dimension by assessing the successful deployment and use of AI-assisted decision-making applications and tools (e.g., AI-enabled Decision Support System, Expert Systems, Fuzzy logic systems, Optimization, Knowledge Engineering, etc.).

Cognitive Technologies: "*the organization's ability to integrate AI technologies with other IT resources, services, and devices.*" This dimension was isolated by the conceptualization process for cases where organizations do not deploy and use AI in a specific application domain as a particular application or a tool. *Cognitive Technologies* AI-enabled capability is the highest level of adoption, when AI is not merely used, but utilized (implying innovation or creative use beyond the intended use). AI technologies can radically transform data utilization and processing within existing value-creating processes. Their ability to learn and adapt continuously due to self-awareness and input from actors (with whom it interacts) and contexts (in which it is embedded) amplifies the resourcefulness of AI technologies [40]. The summative effects can be seen in the interactions between the knowledge of the AI-enabled device or service and the knowledge and actions of a human. We propose to measure the dimension by assessing the successful integration of AI technologies in other IT resources, services, and devices. The AI technologies most suitable for integration include Machine learning, Deep learning, and neural networks, Natural language processing, Genetic programming, Sensor networks, Augmented reality, Computer Vision, Speech recognition, and RPA [22].

We posit the presented dimensions impact all of the proposed ways (automation, innovation, organizational learning, decision-making) of business value generation, although to a different extent.

4 Discussion and Future Work

AI has the potential to change the workforce positively: automating repetitive tasks and freeing up workers to be more creative and productive with augmenting human capabilities. Although there is widespread consensus about the potential of AI [9], the technology and its impact on the workforce and by extension process performance is not fully understood. Organizations have difficulties leveraging AI technologies and extracting business value. A review of relevant studies and exploratory interviews by us confirmed that organizations are mostly at an early stage of AI adoption. Studies [9, 42] have reported that only 5 percent of organizations have extensively incorporated AI and that 20 percent have partially used it. Most are in the phase of evaluating a proof of concept and identifying business cases on which to apply the technology. There are no real "out of the box" solutions. AI is about data and domain knowledge. The results of our interviews show that organizations struggle with data management – especially data governance – and with the organization-wide deployment of AI. Thus, the study sought to identify the key AI-enabled capabilities to deploy and use the technology effectively. Building on these capabilities, organizations can realize opportunities that AI offers.

The objective of this study was to conceptualize AI adoption and capture specific dimensions that are potentially responsible for generating business value. Following Podsakoff's [28] guidelines, we developed dimensions based on extracted attributes and properties of the concept. Conceptualization was guided by the purpose of uncovering the details of the process of generating business value through AI. The goals were to assess adoption level, define AI adoption components as AI-enabled capabilities, and identify the most promising AI applications and technologies. The result is the refined definition of AI adoption as "the s*uccessful deployment and use of AI resources in business processes*." Five developed progressive levels of AI-enabled capabilities include 1) *Data Acquisition and Preprocessing*; 2) *Cognitive Insight*; 3) *Cognitive Engagement*; 4) *Cognitive Decision Assistance*; and 5) *Cognitive technologies*.

The next step of the research will be to operationalize the proposed dimensions to be able to assess the total level of AI adoption. Based on the proposed framework, we plan to develop a measurement model and conduct a comprehensive study using a questionnaire survey. The results will validate the proposed model and provide empirical evidence as well as a more detailed view of the business value generation process of AI technology.

Researchers can use the concept of AI adoption or its specific dimensions in different contexts to assess the level of adoption, uncover management strategies, and understand the impact and value of AI. (e.g., moving from organizational to the process level and assess the impact on specific process types, BPM goals, or specific organizational and environmental dimensions).

References

1. Bawack, R.E., Fosso Wamba, S., Carillo, K.: Artificial Intelligence in Practice: Implications for IS Research. (2019)
2. Russel, S., Norvig, P.: Artificial intelligence: a modern approach. Pearson Education Limited (2016)
3. Cockburn, I.M., Henderson, R., Stern, S.: The impact of artificial intelligence on innovation. National bureau of economic research (2018)

4. Bresnahan, T.F., Trajtenberg, M.: General purpose technologies 'Engines of growth'? Journal of econometrics 65, 83-108 (1995)
5. Davenport, T.H., Ronanki, R.: Artificial intelligence for the real world. Harvard business review 96, 108-116 (2018)
6. Mishra, A.N., Pani, A.K.: Business value appropriation roadmap for artificial intelligence. VINE Journal of Information and Knowledge Management Systems (2020)
7. Agrawal, A., Gans, J., Goldfarb, A.: What to expect from artificial intelligence. MIT Sloan Management Review (2017)
8. Mikalef, P., Fjørtoft, S.O., Torvatn, H.Y.: Developing an Artificial Intelligence Capability: A Theoretical Framework for Business Value. In: International Conference on Business Information Systems, pp. 409-416. Springer, (Year)
9. Chui, M.: Artificial intelligence the next digital frontier? McKinsey and Company Global Institute 47, (2017)
10. Santhanam, R., Hartono, E.: Issues in Linking Information Technology Capability to Firm Performance. MIS Quarterly 27, 125-153 (2003)
11. Mikalef, P., Krogstie, J., Pappas, I.O., Pavlou, P.: Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. Information & Management 57, 103169 (2020)
12. Shanks, G., Bekmamedova, N.: Achieving benefits with business analytics systems: an evolutionary process perspective. Journal of Decision Systems 21, 231-244 (2012)
13. Krishnamoorthi, S., Mathew, S.K.: Business analytics and business value: A comparative case study. Information & Management 55, 643-666 (2018)
14. Wamba-Taguimdje, S.-L., Wamba, S.F., Kamdjoug, J.R.K., Wanko, C.E.T.: Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects. Business Process Management Journal (2020)
15. Marie Burvill, S., Jones-Evans, D., Rowlands, H.: Reconceptualising the principles of Penrose's (1959) theory and the resource based view of the firm: The generation of a new conceptual framework. Journal of Small Business and Enterprise Development 25, (2018)
16. Bhatt, G.D., Grover, V.: Types of information technology capabilities and their role in competitive advantage: An empirical study. Journal of management information systems 22, 253-277 (2005)
17. Kim, G., Shin, B., Kim, K.K., Lee, H.G.: IT capabilities, process-oriented dynamic capabilities, and firm financial performance. Journal of the association for information systems 12, 1 (2011)
18. Melville, N., Kraemer, K., Gurbaxani, V.: Review: Information Technology and Organizational Performance: An Integrative Model of IT Business Value. MIS Quarterly 28, 283-322 (2004)
19. Aydiner, A.S., Tatoglu, E., Bayraktar, E., Zaim, S.: Information system capabilities and firm performance: Opening the black box through decision-making performance and business-process performance. International Journal of Information Management 47, 168-182 (2019)
20. Liao, S.-H., Wu, C.-c.: System perspective of knowledge management, organizational learning, and organizational innovation. Expert systems with Applications 37, 1096-1103 (2010)
21. Jiménez-Jiménez, D., Sanz-Valle, R.: Innovation, organizational learning, and performance. Journal of business research 64, 408-417 (2011)
22. Zasada, A.: How Cognitive Processes Make Us Smarter. (2019)

23.Frohm, J.: Levels of Automation in production systems. Chalmers University of Technology Göteborg (2008)
24.Hull, R., Motahari Nezhad, H.R.: Rethinking BPM in a Cognitive World: Transforming How We Learn and Perform Business Processes. pp. 3-19. Springer International Publishing, (Year)
25.Bohanec, M., Robnik-Šikonja, M., Borštnar, M.K.: Organizational learning supported by machine learning models coupled with general explanation methods: A Case of B2B sales forecasting. Organizacija 50, 217-233 (2017)
26.Samek, W., Wiegand, T., Müller, K.-R.: Explainable artificial intelligence: Understanding, visualizing and interpreting deep learning models. arXiv preprint arXiv:1708.08296 (2017)
27.Banasiewicz, A.D.: Organizational Learning in the Age of Data. (2019)
28.Podsakoff, P.M., MacKenzie, S.B., Podsakoff, N.P.: Recommendations for creating better concept definitions in the organizational, behavioral, and social sciences. Organizational Research Methods 19, 159-203 (2016)
29.MacKenzie, S.B., Podsakoff, P.M., Podsakoff, N.P.: Construct Measurement and Validation Procedures in MIS and Behavioral Research: Integrating New and Existing Techniques. MIS Quarterly 35, 293-334 (2011)
30.Alsheibani, S., Cheung, Y., Messom, C.: Artificial Intelligence Adoption: AI-readiness at Firm-Level. Artificial Intelligence 6, 26-2018 (2018)
31.Chen, H.: Success Factors Impacting Artificial Intelligence Adoption---Perspective From the Telecom Industry in China. (2019)
32.OECD: Artificial Intelligence in Society (2019)
33.Sonenshein, S., DeCelles, K.A., Dutton, J.E.: It's not easy being green: The role of self-evaluations in explaining support of environmental issues. Academy of Management Journal 57, 7-37 (2014)
34.Jarvis, C.B., MacKenzie, S.B., Podsakoff, P.M.: A critical review of construct indicators and measurement model misspecification in marketing and consumer research. Journal of consumer research 30, 199-218 (2003)
35.Appelbaum, D., Kogan, A., Vasarhelyi, M., Yan, Z.: Impact of business analytics and enterprise systems on managerial accounting. International Journal of Accounting Information Systems 25, 29-44 (2017)
36.Burgess, A.: AI Capabilities Framework. The Executive Guide to Artificial Intelligence, pp. 29-54. Springer (2018)
37.Bawack, R.E., Wamba, S.F.: Where Information Systems Research Meets Artificial Intelligence Practice: Towards the Development of an AI Capability Framework. (2019)
38.Roeglinger, M., Seyfried, J., Stelzl, S., Muehlen, M.z.: Cognitive Computing: What's in for Business Process Management? An Exploration of Use Case Ideas. pp. 419-428. Springer International Publishing, (Year)
39.Kelly, J.E.: Computing, cognition and the future of knowing. Whitepaper, IBM Reseach 2, (2015)
40.Mele, C., Spena, T.R., Peschiera, S.: Value creation and cognitive technologies: Opportunities and challenges. Journal of Creating Value 4, 182-195 (2018)
41.Phillips-Wren, G.: Ai Tools in Decision Making Support Systems: A Review. International Journal on Artificial Intelligence Tools 21, (2012)
42.Sam Ransbotham, S.K., Ronny Fehling, Burt LaFountain, and David Kiron: Winning With AI. MIT Sloan Management Review (2019)