Creating AI business value through BPM capabilities

Aleš Zebec and Mojca Indihar Štemberger
School of Economics and Business, University of Ljubljana, Ljubljana, Slovenia

Received 24 July 2023
Revised 29 October 2023
Accepted 21 February 2024

Abstract

Purpose – Although businesses continue to take up artificial intelligence (AI), concerns remain that companies are not realising the full value of their investments. The study aims to provide insights into how AI creates business value by investigating the mediating role of Business Process Management (BPM) capabilities.

Design/methodology/approach – The integrative model of IT Business Value was contextualised, and structural equation modelling was applied to validate the proposed serial multiple mediation model using a sample of 448 organisations based in the EU.

Findings – The results validate the proposed serial multiple mediation model according to which AI adoption increases organisational performance through decision-making and business process performance. Process automation, organisational learning and process innovation are significant complementary partial mediators, thereby shedding light on how AI creates business value.

Research limitations/implications – In pursuing a complex nomological framework, multiple perspectives on realising business value from AI investments were incorporated. Several moderators presenting complementary organisational resources (e.g. culture, digital maturity, BPM maturity) could be included to identify behaviour in more complex relationships. The ethical and moral issues surrounding AI and its use could also be examined.

Practical implications – The provided insights can help guide organisations towards the most promising AI activities of process automation with AI-enabled decision-making, organisational learning and process innovation to yield business value.

Originality/value – While previous research assumed a moderated relationship, this study extends the growing literature on AI business value by empirically investigating a comprehensive nomological network that links AI adoption to organisational performance in a BPM setting.

Keywords Artificial intelligence, IT business value, Firm performance, Business process automation, Business process innovation, Organisational learning, BPM capabilities, Business process performance

Paper type Research paper

1. Introduction

While Artificial Intelligence (AI) technology emerged in the 1960s, only recently has it gained considerable traction due to its potential business applications. This study defines AI as *"the simulation of human cognitive functions using intelligent agents"* (Russel and Norvig, 2016). Vast amounts of structured and unstructured data (Big Data), cloud computing, data management, programming frameworks, and AI services have contributed to the new wave of AI, providing a readily available platform for adopting AI technology. In the last few years, organisations have increasingly turned to AI to realise business value through sustained competitive advantage (Krakowski *et al.*, 2023). AI has quickly developed to the point where it

The authors disclosed receipt of the following financial support for the research, authorship, and publication of this article: The research presented in this article was financially supported by the Business Intelligent Systems Research Group registered by the Slovenian Research Agency under No. 3258-001 and the research program No. P2-0037—Future internet technologies: concepts, architectures, services, and socioeconomic issues.

Business Process Management Journal
Vol. 30 No. 8, 2024
pp. 1-26
Emerald Publishing Limited
1463-7154
DOI 10.1108/BPMJ-07-2023-0566

can undergo transformations that enable intelligent automation and augmentation and create opportunities for ongoing digital innovation (Grewal *et al.*, 2020, May *et al.*, 2020, Abbad *et al.*, 2021; Enholm *et al.*, 2021; Trocin *et al.*, 2021; Akter *et al.*, 2022; Johnson *et al.*, 2022). Nonetheless, organisations continue to struggle with how to adopt and leverage AI technologies and realise performance gains (Mishra and Pani, 2020).

Despite extensive research on IT Business Value (De Haes *et al.*, 2020), coherent understanding of how AI technologies create business value is still missing (Enholm *et al.*, 2021). Prior research posited the adoption of AI had a partial indirect influence on performance by mediating the organisational capabilities of creativity and agility (Mikalef and Gupta, 2021; Wamba, 2022; Chen *et al.*, 2022). However, these studies did not consider the role played by Business Process Management (BPM) in how AI creates value. BPM is recognised as one of the most central and sustainable management approaches (Rosemann *et al.*, 2004). Its structured and strategic approach complements AI's innovative capabilities (Ng *et al.*, 2021), prompting investigations into AI adoption in a BPM context. Wamba-Taguimdje *et al.* (2020a) examined the mediating effect of process-oriented dynamic capabilities and emphasised the process-level impact (Wamba-Taguimdje *et al.*, 2020b). Still, the ways that AI generates business value, specifically via BPM capabilities, have yet to receive sufficient attention (Ahmad and Van Looy, 2020). The study contributes to the existing discourse by considering the research question: *"How do AI technologies create business value through BPM capabilities?"*. To that end, a holistic understanding of the value-generation process is needed.

The proposed extended AI Business Value Framework includes AI-enabled capabilities as components of AI adoption, mediating the capabilities and effects of BPM on process and organisational levels. Duality in using AI to augment and automate human capabilities to create value is already recognised (Raisch and Krakowski, 2021). The automation–augmentation perspective is integrated by introducing business process automation as a mediator. The considerable innovation potential of AI, i.e. innovation ambidexterity, is incorporated through continuous and radical process improvements. Connections are also drawn between organisational learning and innovation ambidexterity based on AI's ability to impact both the exploration and exploitation of process innovation (Mishra and Pati, 2020). The outcomes were deconstructed into lower- and higher-order effects, representing process- and organisational-level impacts to better understand the ways AI contributes to performance. Considering the mediating effect of lower-order measures, the analysis explores market and operational performance through the lens of process and decision-making performance. The aim of this approach is to provide a more detailed understanding of the value-generation process.

A components-based view of AI adoption and Business Process Automation (BPA) has been conceptualised and operationalised. Both AI adoption and BPA are regarded as essential and foundational elements in efforts to measure the impact and value of AI. The established guidelines of Podsakoff *et al.* (2016) for the concept, scale development, and validation were followed. Finally, the newly developed measures for AI adoption and BPA were merged with existing measures in a structured questionnaire, representing the operationalised research model. The developed questionnaire was used in an EU-wide research study involving 448 organisations based in the EU (hereafter: "EU organisations") that use AI technology in their business processes.

The remainder of the paper is structured as follows. The next section introduces the theoretical basis of the hypotheses and the proposed AI Business Value Framework. Section 3 describes the research methods, before presenting the study results. Finally, a discussion and conclusion are provided along with the theoretical contributions, managerial implications, limitations, and future research suggestions.

2. Theoretical background and hypotheses

To align this study with existing research (Table 1) on the adoption of AI, the Resource-Based View (RBV) was selected as the theoretical framework. Earlier research in the broader Information Systems (IS) domain applied the RBV extensively, positioning it as the central theoretical perspective for understanding how IS resources produce value and enable organisations to attain performance gains (Patas *et al.*, 2012).

As business goes digital, data becomes a vital resource. It helps capture, harness and understand business operations, enabling organisations to improve and adapt to the changing environment (Aydiner *et al.*, 2019b). AI leverages data as a core resource through AI-enabled capabilities, thereby improving performance.

The greater frequency of environmental dynamism and complexity in business operations means that organisations operate in environments with considerable unpredictability (Wamba *et al.*, 2020). The Dynamic Capabilities View (DCV) was applied to address the vital role of capabilities in coping with a highly volatile environment (Haarhaus and Liening, 2020). Existing research suggests that IS resources may have many attributes of dynamic capabilities and thus be particularly useful for organisations in rapidly changing environments (Steininger *et al.*, 2022). The RBV and DCV are, accordingly, deemed appropriate for this study's theoretical framework.

2.1 AI and firm performance

In this paper, AI is understood as the "simulation of human cognitive functions using intelligent agents" (Zebec and Štemberger, 2020) or AI systems, i.e. *"machine-based systems that can, for a given set of human-defined objectives, make predictions, recommendations, or*

Author	Scope	Theory	Findings
Wamba-Taguimdje *et al.* (2020a)	150 AI-related case studies	RBV, DCV	(+) AI capability → Process-driven Dynamic Capabilities, Firm performance
Mikalef and Gupta (2021)	Survey, 143 senior US firm managers	RBV, DCV	(+) AI capability → Organisational Creativity and Organisational performance
Wamba (2022)	Survey, 205 US firm managers	RBV, DCV	(+) AI assimilation → Organisational agility, Customer agility, Firm performance
Chen *et al.* (2022)	Survey, 394 e-commerce entrepreneurs	RBV, DCV	(+) AI capability → Firm creativity, AI Management, AI-driven decision-making, Firm performance
Rammer *et al.* (2022)	Germany Community Innovation Survey (CIS) 2018		(+) AI → Innovation performance
Bag *et al.* (2021)	306 senior executives in South Africa	KBV	(+) Big data-powered artificial intelligence → Knowledge Management Process, Decision-Making Style, Firm performance
Mishra *et al.* (2022)	10-K data from US firms		(+) AI focus → Firm performance
Kim *et al.* (2022)	395 US-listed firms using AI between 2000 and 2018		(+) AI adoption → Firm performance, (+) AI adoption → Automation
Lui *et al.* (2022)	62 US-listed firms between 2015 and 2019		(−) AI adoption announcements → Firm market value (−) AI adoption announcements → Abnormal market returns

Note(s): (+) Positive impact; (−) Negative impact; RBV, Resource-Based View; DCV, Dynamic Capabilities View; KBV, Knowledge-Based View
Source(s): Authors own work

Table 1. Current empirical studies on AI and firm performance

decisions influencing real or virtual environments. AI systems are designed to operate with varying levels of autonomy" (OECD, 2019).

Researchers have demonstrated a robust IT capability can enable an organisation to improve its processes and overall performance (Santhanam and Hartono, 2003). Recent empirical research shows that the adoption of AI impacts organisational capabilities and can improve performance (Table 1). It is argued in this study that AI-specific ability to create intelligent agents facilitating the automation–augmentation of decision-making and transformation (improvement and redesign) of business processes can unlock considerable Organisational Performance (OP) gains. First, a test is conducted for the direct effect to confirm the proposed full or partial mediation. This leads to formulation of the following hypothesis:

H1. AI adoption positively influences OP.

Lui *et al.* (2022) state that AI adoption projects are challenging, and organisations must consider how their AI investment will affect their business value. This means a holistic understanding of the value-generation process is needed to predict outcomes and reduce the associated risk.

2.2 AI business value model

The aligning of AI adoption with business processes can bring significant performance gains, as confirmed by exploratory research and suggested by previous studies on IT business value (Schryen, 2013). For this purpose, the integrative IT business value model (Melville *et al.*, 2004) was adopted to study AI adoption in the BPM setting. The model provides an appropriate holistic perspective on the AI business value-generation process, integrating AI resources, BPM capabilities, business processes, process performance, organisational performance, and the external environment.

Prior research (Table 1) established that the impact of AI is mediated by particular organisational capabilities. Three capabilities were identified by aligning the AI resources with BPM capabilities (Kerpedzhiev *et al.*, 2020): BPA, Organisational Learning (OL) and Business Process Innovation (BPI), i.e. an ambidextrous innovation view that combines the operational capability of incremental process improvements (BPII) and the dynamic capability of radical process improvements (BPIR). Consistent with the IT business value model, outcomes on the process level were examined, considering Business Process Performance (BPP) and Decision-making Performance (DMP), and the model was extended to the OP level.

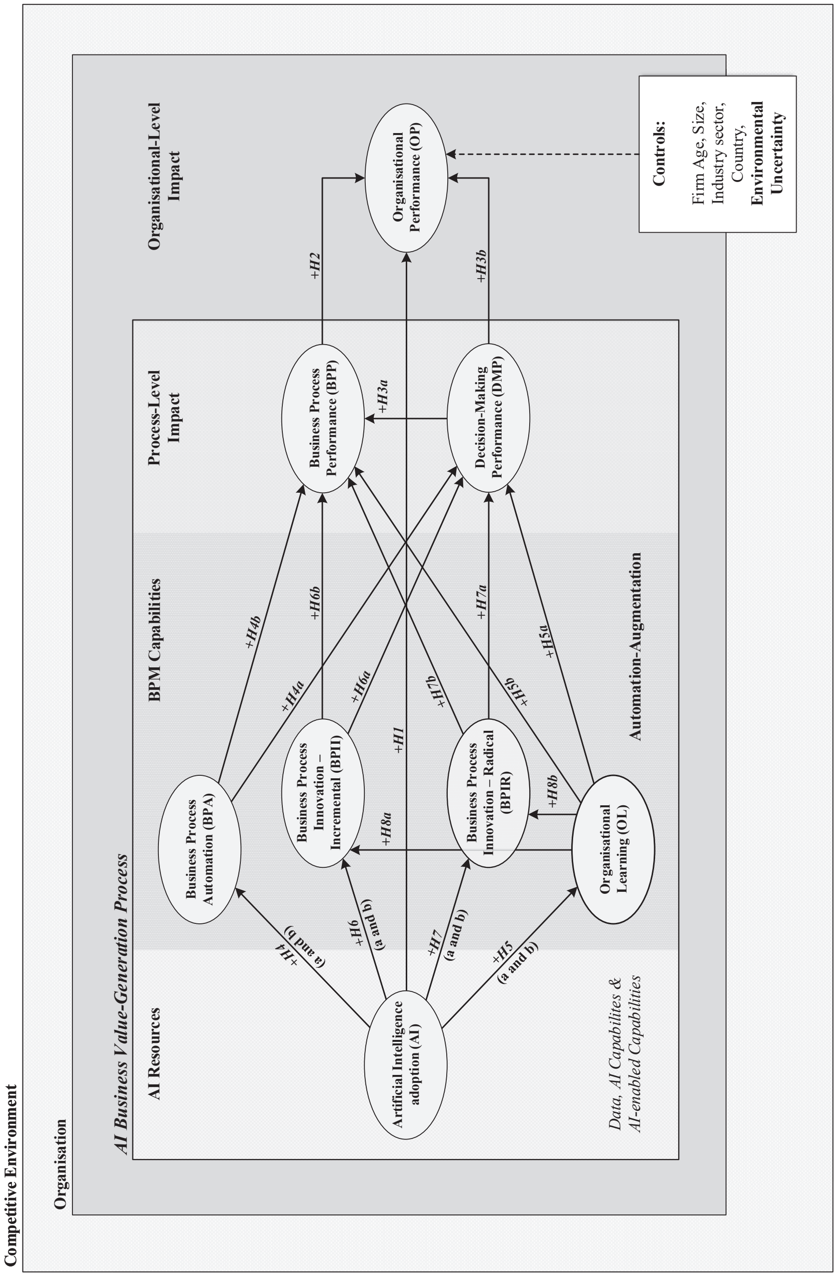
The individual relationships are presented below.

While aligning AI resources with BPM capabilities (Kerpedzhiev *et al.*, 2020), three capabilities were identified: BPA, Organisational Learning (OL) and Business Process Innovation (BPI). This perspective integrates the operational capability of incremental process improvements (BPII) with the dynamic capability of radical process improvements (BPIR), reflecting an ambidextrous innovation view.

The IT business value-generation process model was refined for AI technology using the guidelines of Hong *et al.* (2014) for context-specific theorising. AI adoption is the central focus of this study. Figure 1 depicts the conceptual framework and relationships among the main constructs.

2.3 A components-based view of AI adoption

Drawing from Aydiner *et al.* (2019b), AI adoption is described as *"the implementation, deployment, and use of AI resources (data, AI infrastructure, skills, competencies)"*. The level of adoption is measured by the development of AI-enabled capabilities (components of AI



Source(s): Authors own work

Figure 1.
Proposed research model

adoption), which represent *"the ability to mobilize AI resources for specific business needs through the implementation, deployment, and use of AI applications, tools, or technology"*. This perspective stresses the operational aspects of AI rather than examining the factors that contribute to its development or influence its adoption (like antecedents or determinants). By adopting the components-based view, researchers and practitioners analyse the tangible components to be effectively employed and utilised in real-world contexts. Such a perspective provides a more transparent and academic lens (precision and specificity, empirical examination, technological considerations, application-oriented analysis) for understanding AI's practical implications and impact in various domains. The conceptualisation, based on previous research, outlines five progressive levels of AI-enabled capabilities that support business processes and contribute to an organisation's data-driven value generation (Zebec and Štemberger, 2020).

Data Acquisition and Pre-processing (DACQ) dealing with Big Data manipulation: *"the organisation'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"*.

Cognitive Insight (CI): *"the organisation's ability to use AI to detect patterns in data and interpret their meaning"*. This dimension is conceptualised around context awareness, learning, and analytics themes.

Cognitive Engagement (CE): "the organisation'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 (Russel and Norvig, 2016; Roeglinger *et al.*, 2018). This ability enables automated interactions to support customers' activities and prompt their engagement reliably (Mele *et al.*, 2018) in customer and employee-facing business processes.

Cognitive Decision Assistance (CDA): *"the organisation's ability to use AI in decision-making processes"*. AI technologies and techniques enable AI-assisted decision-making and render decision support more intelligent.

Cognitive Technologies (CT): *"the organisation's ability to integrate AI technologies with other IT resources, services, and devices"*. This dimension was isolated for organisations that do not deploy and use AI in a specific application domain as a particular application or tool. The Cognitive Technologies capability is the highest level of adoption where AI is not merely used but utilised (implying innovation or creative use beyond its intended use).

2.4 Mediating role of business process performance

According to Melville *et al.* (2004), performance encompasses both business process and organisational performance. The IT Business Value Framework Model separates the operational efficiency of business processes from overall organisational performance, expecting business process benefits to lead to improved organisational performance (Tallon *et al.*, 2000). Drawing on their conclusion, it is argued that AI resources assist organisations in creating value through their impact on business processes. The key characteristics of the AI value proposition, including speed, scale, granularity, learning (accuracy of prediction), problem-solving and decision-making (Agrawal *et al.*, 2017; Roeglinger *et al.*, 2018), are aligned with the lead indicators of process efficiency (time, cost), effectiveness (quality), and flexibility (Dumas *et al.*, 2013) to examine the impact on process performance.

H2. BPP positively influences OP.

2.5 Decision-making performance

DMP is an organisation's ability to make decisions efficiently and effectively. AI systems are used to replace human decision-makers in the context of structured or semi-structured decisions (automation) or as a decision-support tool on the organisational strategic level or the process level (augmentation) (Duan *et al.*, 2019). AI-assisted decision-making can significantly boost operational efficiency and productivity to achieve superior performance (Ashaari *et al.*, 2021). Business processes involve numerous decisions that directly impact performance (Ghattas *et al.*, 2014), in turn influencing various aspects like effectiveness, efficiency and flexibility. The decision-making components within a business process play a crucial role in accomplishing process objectives and add significantly to its overall outcomes (Raghu and Vinze, 2007). An effective decision-making process guides business processes towards early adoption of successful innovations, improved business models, efficiency-gaining technologies, and proactive collaborations that yield cost savings and knowledge synergies (Robert Baum and Wally, 2003). The following hypothesis formalises the relationship:

H3a. DMP positively influences BPP.

The decision-making process on the organisational level requires understanding of business growth trends and patterns (Keding, 2021), which is only feasible with accurate data. Besides providing practical insights, data are also used to implement strategic business decisions. Managerial decision-making is largely knowledge-based (Wiklund and Shepherd, 2008). AI-enabled knowledge-based information systems (i.e. Knowledge Engineering and Expert Systems, Decision Support Systems) are valuable tools enabling evidence-based decision-making and problem-solving in intricate business situations. Several authors assert that AI-based decision-making directly impacts organisational performance (Ashaari *et al.*, 2021; Rahman *et al.*, 2021; Chen *et al.*, 2022). This leads to the following hypothesis:

H3b. DMP positively influences OP.

2.6 Automation–augmentation

To increase performance, automation and augmentation are two principal use cases for the adoption of AI (Enholm *et al.*, 2021; Raisch and Krakowski, 2021). Automation involves machines taking over tasks from humans, leading to performance gains via resource, cost and information-processing efficiencies. In contrast, augmentation involves humans collaborating with machines, enhancing both human and machine skills and productivity. Automation and augmentation lie on either end of the human–machine collaboration spectrum (Raisch and Krakowski, 2021), with automation ranging from fully manual (i.e. human) to fully automatic (Parasuraman *et al.*, 2000). Blending automation and augmentation creates synergies, providing varied benefits and improving overall performance (Raisch and Krakowski, 2021; Grønsund and Aanestad, 2020).

Adapted from Dwarkanhalli *et al.* (2018) and Zasada (2019), the concept of BPA is defined as *"the automation of knowledge-intensive processes"*. The concept is essential for understanding the impact of adopting AI. BPA is an operational capability, i.e. an organisation's ability to perform functional activities using purposefully chosen groups of resources (Saunila *et al.*, 2020). Wu *et al.* (2012) state that operational capabilities are primarily studied from the outcome's perspective, including cost, quality, dependability, speed and flexibility. Indeed, automated processes benefit the most from cost efficiencies, faster execution, and enhanced information processing (quality) (Berruti *et al.*, 2017; Ansari *et al.*, 2019; Rocha *et al.*, 2017). Nevertheless, some authors hold more pessimistic views on cognitive automation (Daugherty and Wilson, 2018; Raisch and Krakowski, 2021). They claim a real digital cognitive mediator (full automation) does not yet exist (Rouse and Spohrer, 2018), meaning that partial automation or augmentation should be prioritised. To examine the impact of automation, the concept is generally defined as *"The organisation's ability to automate knowledge-intensive (unpredictable, non-repeatable, highly flexible, complex) business processes to simulate knowledge work and collaboration activities"*. The focus is placed on two dimensions: the level of automation (*Manual, Decision support, Decision selection, Supervisory control, Full automation*) (Sindhgatta *et al.*, 2020) and the extent of automation (*Structured, Structured with ad hoc exceptions, Unstructured with predefined fragments, Loosely structured and Unstructured processes*) (Szelagowski and Lupeikiene, 2020). According to the theorising of Raisch and Krakowski (2021) and Karan *et al.* (2021), a bigger impact on decision-making and less on process performance are expected following increased automation. Given this, an effect on the effectiveness and efficiency of BPP and DMP can be presumed. The following hypotheses are thus formulated:

H4a. BPA mediates the positive impact of AI adoption on DMP.

H4b. BPA mediates the positive impact of AI adoption on BPP.

2.7 Organisational learning

OL represents a constant effort to create organisational knowledge. Further, it contributes to an organisation's ability to adapt effectively to changes in its business environment (Bohanec *et al.*, 2017). OL refers to the developing of new, incremental knowledge or updating of existing knowledge. This study defines OL as *"the acquisition, creation, integration, and distribution of information and knowledge"* (Wang and Ellinger, 2011; Templeton *et al.*, 2002). Learning and knowledge in different fields are essential for several BPM capabilities in the People and Culture areas (Kerpedzhiev *et al.*, 2020; Helbin and Van Looy, 2021). OL can accordingly also be considered to be a BPM capability.

Creating and utilising technology-based knowledge has become an integral part of business operations because it plays a significant role in competitiveness (Banasiewicz, 2019). AI holds considerable potential to explicate the organisational knowledge base, provided that it is represented in Big Data. Machine and deep-learning-based AI systems greatly enhance analytical capabilities by allowing existing knowledge resources to be transformed into new capabilities, enriching the learning process within an organisation (Jarrahi *et al.*, 2022).

OL's ultimate purpose is to add to the informational efficacy of decision-making (Banasiewicz, 2019). In a knowledge-centric economy, staying competitive requires new and effective methods for generating and utilising decision-guiding knowledge (Banasiewicz, 2019). AI opportunities can be exploited for augmentation, encompassing analytic data techniques and codified knowledge to enhance human decision-makers' intelligence (intelligence amplification). While these techniques do not replace decision-makers, they may help make complex decisions through well-designed human–AI system learning interactions (Wijnhoven, 2022). These considerations lead to the following hypotheses to test the mediating effect of OL via DMP on BPP.

H5a. OL mediates the positive impact of AI adoption on DMP.

H5b. OL mediates the positive impact of AI adoption on BPP.

OL represents the augmentation potential of AI. As a dynamic capability, it integrates, builds or reconfigures existing competencies, increasing their ability to adapt to changing environments and support performance improvements (Eisenhardt and Martin, 2000; Senge, 1998).

2.8 Ambidextrous innovation and organisational learning

Digitalisation and automation impact innovation processes (Helbin and Van Looy, 2021). AI gives possibilities to address two specific innovation barriers. First, information processing constraints limit an organisation's potential opportunities and solutions (Williams and Mitchell, 2004). Haefner *et al.* (2021) present two AI abilities to overcome this barrier.

AI systems can extract information from Big Data, identify and evaluate vastly more information, use it to develop ideas (e.g. *Data storytelling, Performance Visualisation, Metasearch, Named Entity Recognition*), while also recognise more problems, opportunities and threats that can be used to generate new ideas (e.g. *Predictive Modelling and Analytics, Anomaly and Deviant Behaviour Detection, Predictive Maintenance*). The second barrier stems from inefficient or locally limited search methods (Katila and Ahuja, 2002) whereby organisations typically search for solutions within their current knowledge base (Posen *et al.*, 2018). Solutions thus often build on existing knowledge, resulting in incremental innovation. Organisations must extensively explore new domains and external data sources to create new opportunities and boost creativity and innovation. AI systems can generate, identify and evaluate more creative/exploratory ideas (e.g. *Generative AI – Generative Design,* Protein *engineering, Material Discovery, Process Mining*).

Researchers argue that ambidextrous organisations can balance both strategies (exploitation and exploration) and avoid the problem of being over-reliant on a single strategy (Aljumah *et al.*, 2021; Benner and Tushman, 2015). Although O'Reilly and Tushman (2011) emphasise the importance of organisations exploring new domains and simultaneously exploiting existing ones to survive and grow, it is also clear that firms often find it difficult to do this (Johnson *et al.*, 2022). Most organisations see AI technology as an opportunity to explore, while others focus on AI's ability to boost efficiency in current operations (Johnson *et al.*, 2022). In the BPM context, an expectation exists to enhance processes through embedded AI technology or an AI-enabled innovation process. Exploitation relates to incremental innovation (BPII), improving business process efficiency, quality and flexibility. In contrast, exploration aims for a radical improvement (BPIR) through new, transformed or redesigned processes (Norman and Verganti, 2014). The argument put forward is that the adoption of AI technology enables ambidextrous innovation to occur. Two pairs of hypotheses are proposed for incremental and radical innovation to test the statements:

H6a. BPII mediates the positive impact of AI adoption on DMP.

H6b. BPII mediates the positive impact of AI adoption on BPP.

H7a. BPIR mediates the positive impact of AI adoption on DMP.

H7b. BPIR mediates the positive impact of AI adoption on BPP.

Research indicates that OL and its output – organisational knowledge – contribute to innovation (Almuslamani, 2022). OL prevents stagnation and encourages continuous innovation by renewing and reinventing technology and production methods (García-Morales *et al.*, 2012). A higher level of innovation requires greater critical capacity, skills, and new and relevant knowledge (Senge, 1998). March (1991) states that an organisation can exploit current knowledge and explore ways to utilise technology, such as AI, to generate new knowledge. However, little empirical evidence shows whether AI-enabled knowledge acquisition, sharing and utilisation (i.e. OL) influence process performance by facilitating innovation. Hypotheses are thus proposed to test the impact:

H8a. OL positively influences BPII.

H8b. OL positively influences BPIR.

3. Research design

3.1 Survey setting

In order to empirically examine the research problem, a survey design was employed. A single primary data source, self-report, and cross-sectional design were used.

An anonymous English-language questionnaire distributed electronically (online) was used to collect the data, treating the organisation as the analytical unit. The design, measurement items, and questionnaire were developed following the guidelines of MacKenzie *et al.* (2011) and Brace (2018).

3.2 Data collection and sample

In 2020, 7% of companies in the EU were using AI applications (Eurostat, 2020). The sample frame was estimated to constitute 8% of active companies, amounting to 2.2 million companies. With a confidence level of 95% and a margin of error of 5%, a minimum sample size of 385 was defined. Proportionate country-stratified random sampling was employed to select the sample.

The participants were sourced from LinkedIn Pro Subscription and ZoneFiles.io Active Business Domains by Country Code. The target demographic included senior business managers and other senior business decision-makers or employees directly involved with executing AI strategies within their respective organisations. Email invites were sent in four waves from March 2022 to June 2022 at the start of each month.

The collected and processed sample included 448 EU organisations. Sample representativeness was ensured in terms of firm size, industry sector, years in business (age) and country. The respondents were mainly executive (76.34%) or middle (18.75%) managers. Respondents came predominantly from medium-sized (89.73%) organisations in the information and communication sector, service (20.98%), scientific, technical (29.02%), financial and insurance activities (7.37%), and manufacturing (5.58%). Among businesses covered, 40.63% were newer, while 25.22% were mature, with almost half from Germany (21.43%), Italy (10.94%), the Netherlands (10.49%) and France (6.92%).

3.3 Non-response and common method bias

An independent samples *t*-test was performed to assess the possible presence of non-response bias (Armstrong and Overton, 1977). Levene's test for equality found no significant variance difference between early and late responses for each variable ($p > 0.136$). Comparing 200 non-respondents with 448 respondents showed no significant differences and minimal organisational-level effects (industry, size, age, revenue). The sample is unaffected by non-response bias. Early and late respondents hence represent the same target population.

Harman's one-factor, Harman's single-factor, and Common latent factor tests were conducted to confirm that common method variance was not a significant issue in the data (Gaskin, 2021).

3.4 Measurement of the variables

The operationalisation of **AI adoption** comprised five underlying sub-constructs: DACQ, CI, CE, CDA and CT. The construct derived from the conceptual definition is a multidimensional second-order construct of reflective–reflective type I (Jarvis *et al.*, 2003). Items were generated from the literature review, interviews with experts, and a review of 1,860 AI-related projects from businesses (MacKenzie *et al.*, 2011). The MacKenzie *et al.* (2011) guidelines for model specification, scale evaluation, refinement, and validation were followed. To assess the content validity of items, a panel of four experts evaluated the relevance of the test domains and the representation of items within those domains. Data obtained in the pilot study (sample size of 80) were used for scale purification and refinement. After the pilot study validation procedure, 15 items were retained, with 3 items representing each sub-construct. Scale validity was further assessed in the main study (sample size of 448). AVE for first- and second-order levels exceeded 0.50. Internal consistency reliability was still greater than 0.70, and the index of construct reliability was greater than 0.70 on first- and second-order levels. Model Fit was adequate: χ^2/df = 2.753, GFI = 0.937, AGFI = 0.909, TLI = 0.948, CFI = 0.959, RMSEA = 0.063, SRMR = 0.0465. A test of nomological validity confirmed a strong, positive relationship between AI adoption and the constructs in the proposed model.

The **BPA** (first-order construct with reflective indicators) was operationalised with items derived from the literature review (Vagia *et al.*, 2016; Di Ciccio *et al.*, 2015), expert interviews, and an examination of existing measures of the construct (MacKenzie *et al.*, 2011). Data obtained in a pilot study were used for scale purification and refinement. After the validation procedure, ten items concerned with the level and extent of automation in business processes were retained. Scale validity was further assessed in the main study (sample size of 448), with AVE at 0.45, internal consistency reliability at 0.75, and the index of construct reliability at 0.88. Model Fit was adequate: χ^2/df = 2.175, GFI = 0.977, AGFI = 0.948, TLI = 0.981, CFI = 0.990, RMSEA = 0.051, SRMR = 0.0258. The confirmed mediating role of BPA in the proposed model establishes nomological validity.

An existing measurement scale developed by Ng *et al.* (2015) was adapted to measure **BPI**, incorporating separate incremental and radical process improvement scales. The scope captured in the individual unidimensional measures emphasises the duality of process exploitation and exploration.

The measurement of OL was based on the four items described by García-Morales *et al.* (2012). The scope captured by the unidimensional measure stresses an organisation's ability to maintain or improve its performance, involving knowledge acquisition, sharing and utilisation (DiBella *et al.*, 1996).

DMP assesses organisational decision-making efficiency and effectiveness. It was measured using six items taken from Aydin Aydiner *et al.* (2019a).

The existing measurement scales of Vukšić *et al.* (2017) and Hernaus (2016) were adopted to measure the **BPP** construct. The scale is based on the Devil's Quadrangle (Dumas *et al.*, 2013).

A measurement scale developed by Wang *et al.* (2012) was used to measure the OP construct. As a second-order construct, it consists of two first-order reflective constructs: Operational Performance and Market Performance.

The firm-specific characteristics were tested with four control variables – firm age, size, industry sector, and country. The industry sector variable was based on NACE-R2 1st-level categories. The country was measured by the organisation's principal place of business, a member state of the EU-27. According to Nielsen and Raswant (2018), multi-country studies often face omitted variable challenges due to complex environmental factors, including political, economic, socio-cultural and institutional contexts. Environmental Uncertainty was therefore included as a control variable, and its measurement was based on eight items proposed by Rowe *et al.* (2017).

4. Data analysis and results

AMOS version 28 with the Maximum Likelihood Method was used for performing the CFA and Path Analysis (i.e. to test the hypotheses in the conceptual model).

4.1 Validation of the measurement model

The CFA was conducted to test the validity of the measurement model. Model Fit was adequate (χ^2/df = 2.082, GFI = 0.930, AGFI = 0.902, TLI = 0.957, CFI = 0.966, RMSEA = 0.049 (p-close = 0.581) and SRMR = 0.0349), confirming the proposed model. Further, all factor loadings showed significance in their variable correspondence ($p < 0.001$).

4.2 Reliability and validity of the constructs

The unidimensionality of the constructs was measured with Cronbach's alpha. Table 2 shows that values vary between 0.744 and 0.890, which exceed the threshold of 0.70 (Hair *et al.*, 2013). Moreover, MaxR(H), which refers to McDonald's Construct Reliability, was estimated and was higher than the 0.70 threshold (Hancock and Mueller, 2001).

Composite reliability estimates in Table 2 show that the values align with the threshold value of 0.70 (Fornell and Larcker, 1981).

Convergent validity was established using Average Variance Extracted (AVE), noting that Table 2 shows the values are above the recommended threshold value of 0.50.

Discriminant validity was established where Maximum Shared Variance was lower than AVE for all of the constructs (Hair *et al.*, 2013). Table 2 indicates that all the values in italic on the diagonal or the square root of AVE values are higher than the inter-construct correlations, satisfying the Fornell-Larcker criterion (Fornell and Larcker, 1981). The discriminant validity was confirmed using the heterotrait–monotrait ratio (Henseler *et al.*, 2015), where the threshold of 0.85 was not exceeded.

Variance inflation factors confirmed the absence of multicollinearity for all predictors on the dependent variables. The results were lower than the threshold of 10. The Tolerance values were also higher than 0.1 (Linton *et al.*, 2020).

4.3 Structural model assessment and hypotheses testing

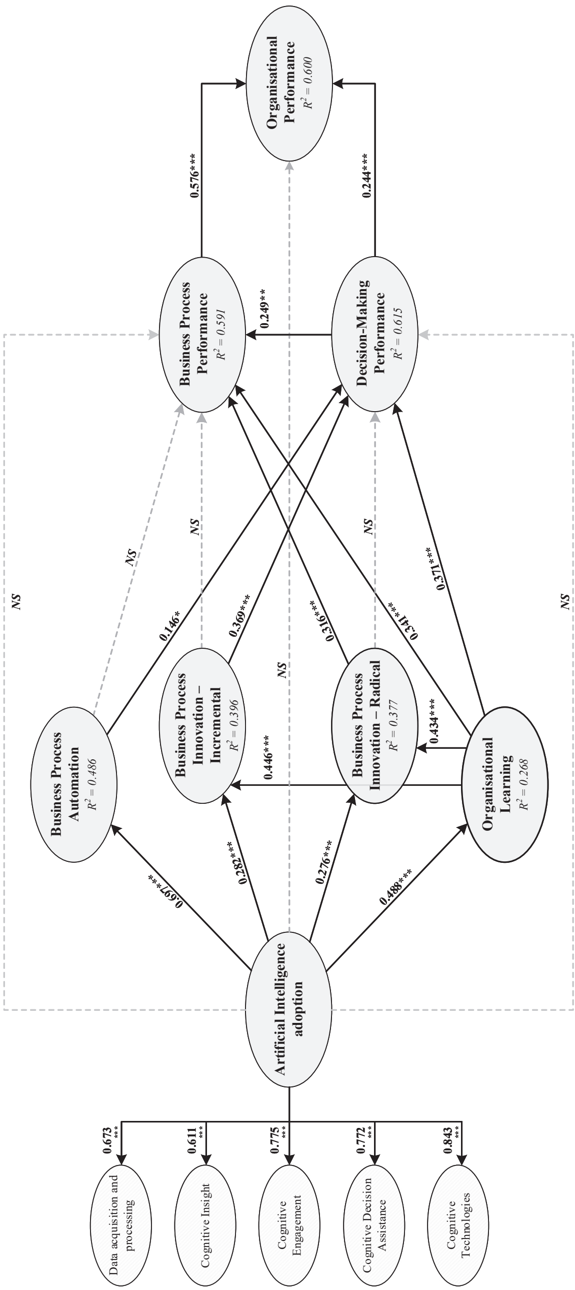
Path analysis was performed to test the conceptual model's hypotheses, considering multiple mediating effects as outlined by Collier (2020). The maximum likelihood method used the bootstrap (bootstrap sample = 5,000 with replacement) method to simulate the sampling distributions of the estimated parameters selected to calculate the model parameters. Post hoc power analysis using semPower (Moshagen and Erdfelder, 2016) confirmed that the sample size was sufficiently powered. Figure 2 shows the results of the analyses.

The fit of the structural equation model is within acceptable levels: χ^2/df = 1.874, GFI = 0.917, AGFI = 0.891, TLI = 0.950, CFI = 0.959, RMSEA = 0.044 (p-close = 0.951) and SRMR = 0.0443 (Collier, 2020). The results confirmed that the model fits the data well.

	Latent variable	1	2	3	4	5	6	7	8
1	AI	*0.731*							
2	BPA	0.705	*0.800*						
3	OL	0.452	0.366	*0.810*					
4	BPII	0.476	0.431	0.584	*0.877*				
5	BPIR	0.469	0.486	0.560	0.584	*0.779*			
6	DMP	0.499	0.471	0.557	0.682	0.557	*0.896*		
7	BPP	0.439	0.361	0.616	0.505	0.616	0.643	*0.823*	
8	OP	0.406	0.355	0.585	0.448	0.516	0.574	0.704	*0.846*
	Mean	2.141	2.377	3.651	3.561	2.792	3.350	3.350	3.093
	Standard Deviation	0.888	0.892	0.926	0.894	0.960	0.844	0.902	0.766
	A	0.842	0.776	0.879	0.867	0.744	0.890	0.855	0.832
	CR	0.849	0.779	0.883	0.869	0.754	0.891	0.862	0.834
	AVE	0.534	0.639	0.655	0.769	0.607	0.803	0.678	0.715
	MSV	0.497	0.497	0.449	0.465	0.379	0.465	0.496	0.496
	MaxR(H)	0.868	0.794	0.898	0.880	0.775	0.891	0.883	0.843

Note(s): α, Cronbach's alpha; CR, Composite Reliability; AVE, Average Variance Extracted; MSV, Maximum Shared Variance; MaxR(H), McDonald Construct Reliability; Diagonal = Fornell-Larcker criteria = $\sqrt{AVE}$
Source(s): Authors own work

Table 2. Inter-correlations, assessment of reliability and validity of the latent variables



Note(s): +: Standardised regression weights are shown.
*$p < 0.05$, **$p < 0.01$; ***$p < 0.001$; NS = Not significant

Source(s): Authors own work

Figure 2.
Structural model results

Examining the direct effects, Figure 2 shows no support for H1 (β = 0.036, t = 0.691, $p > 0.05$), indicating that AI adoption has no direct association with OP. However, the relationship is significant in the absence of the mediating variables. On the contrary, support for H2 (β = 0.576, t = 9.488, $p < 0.001$) is consistent with prior studies that point to BPP as the link to OP (Melville *et al.*, 2004; Aydiner *et al.*, 2019a). Support was also found for H3a (β = 0.249, t = 3.532, $p < 0.001$) and H3b (β = 0.244, t = 4.050, $p < 0.001$), confirming the expected impact of DMP on BPP and OP (Aydiner *et al.*, 2019a; Fredrickson and Mitchell, 1984). Finally, support was found for H8a (β = 0.446, t = 8.442, $p < 0.001$) and H8b (β = 0.434, t = 7.001, $p < 0.001$), revealing that OL has a significant direct association with process innovation, i.e. BPII and BPIR.

Without the mediators, the total effect of AI on OP was tested. The relationship is significant, and the standardised total effect is 0.418 (t = 6.584, $p < 0.001$, 95% CI: LL = 0.314 to UL = 0.521). Model Fit is χ^2/df = 1.719, GFI = 0.977, AGFI = 0.952, TLI = 0.969, CFI = 0.982, RMSEA = 0.040 (p-close = 0.829) and SRMR = 0.0288.

Next, the indirect effects were examined. The indirect effect is quantified as the product of the unstandardised regression weight of mediation paths, as shown in Table 3. Due to Sobel test limitations (Collier, 2020), the preferred mediation testing uses the Bootstrap technique to determine the significance.

The full model was run to identify the mediating, indirect effects. According to the results shown in Table 3, BPA mediates the positive impact of AI adoption on DMP (support for H4a) but not on BPP (no support for H4b). The results in Table 3 reveal OL mediates the positive impact of AI adoption on DMP and BPP (support for H5a and H5b). To test the effects of AI on process innovation, two parallel constructs of BPII and BPIR were inserted, and the relationships were tested. The results in Table 3 show BPII mediates the positive impact of AI adoption on DMP (support for H6a). However, BPII does not mediate the path between AI and

Path	Relations	Unstandardised weights	Indirect effect	Z-score	Mediation
AI → BPA → DMP	AI → BPA BPA → DMP	0.715 (0.063) 0.146 (0.063)	0.104* (0.050)	2.271ξ*	Support for H4ã
AI → BPA → BPP	AI → BPA BPA → BPP	0.715 (0.063) −0.058 (0.073)	−0.042 (0.059)	−0.713ξ	No support for H4b
AI → OL → DMP	AI → OL OL → DMP	0.576 (0.065) 0.321 (0.046)	0.185*** (0.040)	5.482ξ***	Support for H5a
AI → OL → BPP	AI → OL OL → BPP	0.576 (0.065) 0.330 (0.060)	0.190*** (0.045)	4.673ξ***	Support for H5b~
AI → BPII → DMP	AI → BPII BPII → DMP	0.304 (0.058) 0.350 (0.054)	0.106*** (0.034)	4.076ξ***	Support for H6a
AI → BPII → BPP	AI → BPII BPII → BPP	0.304 (0.058) −0.042 (0.067)	−0.013 (0.023)	−0.622ξ	No support for H6b
AI → BPIR → DMP	AI → BPIR BPIR → DMP	0.241 (0.052) 0.086 (0.067)	0.021 (0.023)	1.237ξ	No support for H7a
AI → BPIR → BPP	AI → BPIR BPIR → BPP	0.241 (0.052) 0.413 (0.082)	0.099*** (0.031)	3.410ξ***	Support for H7b

Note(s): + Boot Standard errors are indicated within parentheses. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. ξ2-Tail z-score = $\frac{a * b}{\sqrt{b^2 * SEa^2 + a^2 * SEb^2}}$ for a single mediation effect. ~ The direct effect is not significant
Source(s): Authors own work

Table 3. Results of the single mediation analysis, i.e. indirect effects

BPP (no support for H6b). In contrast, BPIR does not mediate the impact of AI adoption on DMP (no support for H7a) but does on BPP (support for H7b).

Without the BPA, OL, BPII and BPIR mediators, the impact of DMP on BPP and OP is positive and significant. Still, running the full model reveals no significant direct effect of AI adoption on DMP. Table 4 nevertheless shows a positive mediating impact of DMP when positioned as a secondary mediator in serial multiple-mediation relationships. DMP therefore plays a mediating role and is fully mediated.

Similarly, when excluding the BPA, OL, BPII, BPIR and DMP mediators, the impact of AI on OP mediated through BPP is positive and significant, but not when running the entire model. The results in Table 4 indicate a positive BPP mediating effect when situated as a secondary mediator within serial multiple-mediation relationships. BPP accordingly plays a mediating role and is fully mediated.

As presented in Table 4, the distinctive serial (chain) relationships of BPA, OL, BPII, BPIR, DMP and BPP establish the link between AI and OP. The non-significant direct relationship defined by H1 indicates that the relationship between AI and OP is fully mediated.

As for the control variables, only Firm Size significantly influences the OP and OL variables. There was a higher level of performance among larger organisations than among smaller ones. In contrast, the organisational learning of larger organisations was on a lower level. Other control variables were found not to be significant.

Path	Relations	Unstandardised weights	Indirect effect	Z-score
AI → BPA → DMP → OP	AI → BPA	0.715 (0.063)	0.022* (0.012)	1.981ξξ*
	BPA → DMP	0.146 (0.063)		
	DMP → OP	0.215 (0.053)		
AI → BPA → DMP → BPP → OP	AI → BPA	0.715 (0.063)	0.013* (0.008)	
	BPA → DMP	0.146 (0.063)		
	DMP → BPP	0.278 (0.079)		
	BPP → OP	0.455 (0.048)		
AI → OL → DMP → OP	AI → OL	0.576 (0.065)	0.040*** (0.013)	3.261ξξ***
	OL → DMP	0.321 (0.046)		
	DMP → OP	0.215 (0.053)		
AI → OL → DMP → BPP → OP	AI → OL	0.576 (0.065)	0.023** (0.010)	
	OL → DMP	0.321 (0.046)		
	DMP → BPP	0.278 (0.079)		
	BPP → OP	0.455 (0.048)		
AI → OL → BPP → OP	AI → OL	0.576 (0.065)	0.086*** (0.024)	4.191ξξ***
	OL → BPP	0.330 (0.060)		
	BPP → OP	0.455 (0.048)		
AI → BPII → DMP → OP	AI → BPII	0.304 (0.058)	0.023*** (0.010)	2.875ξξ**
	BPII → DMP	0.350 (0.054)		
	DMP → OP	0.215 (0.053)		
AI → BPII → DMP → BPP → OP	AI → BPII	0.304 (0.058)	0.013*** (0.006)	
	BPII → DMP	0.350 (0.054)		
	DMP → BPP	0.278 (0.079)		
	BPP → OP	0.455 (0.048)		
AI → BPIR → BPP → OP	AI → BPIR	0.241 (0.052)	0.045*** (0.016)	3.209ξξ***
	BPIR → BPP	0.413 (0.082)		
	BPP → OP	0.455 (0.048)		

Note(s): + Boot Standard errors are indicated within the parentheses. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.
ξ ξ 2-tail z-score = $\frac{a*b*c}{\sqrt{a^2*b^2*SEc^2+a^2*c^2*SEb^2+b^2*c^2*SEa^2}}$ for serial multiple mediation effect
Source(s): Authors own work

Table 4. Results of the serial multiple-mediation analysis, i.e. supported serial indirect effects

5. Discussion

Although Big Data and AI technology are at the forefront of IT investments, the mechanisms and conditions that produce business value generally remain unexplored in empirical research. Relevant mediating variables are needed to make further progress in understanding the relationship between AI resources, BPM capabilities, and organisational performance.

5.1 Theoretical implications

Using context-specific theorising, the IT business value-generation process model was brought into the context of AI technology. By pursuing a complex nomological framework, several perspectives on realising business value from AI investments could be included, enriching the emerging literature on AI.

First, an alternative concept of AI adoption is presented to capture a more accurate and generalisable view of AI's impact on organisational performance (OP). An exogenous, components-based variable was related to the level of deployment, actual use, or utilisation of specific AI applications and technologies. Second, this study extends the growing literature on AI by providing a nomological network that links the adoption of AI to OP. While prior research posited a partial indirect influence of AI adoption on performance mediated by organisational capabilities related to creativity and agility (Mikalef and Gupta, 2021; Wamba, 2022; Mishra *et al.*, 2022; Kim *et al.*, 2022), the findings show that this impact is contingent upon BPM capabilities, decision-making, and process performance. Third, positioning automation as an important mediator, Business Process Automation (BPA) was conceptualised and operationalised. With respect to the BPM context, focussing on measuring the level and extent of automation, this study recognises it as the organisation's ability to automate knowledge-intensive business processes. Finally, the positive impact of AI adoption on performance was empirically demonstrated with a large-scale EU study.

Various authors (Raisch and Krakowski, 2021) have theorised that the full automation of complex decision-making processes is made challenging by technical and social limitations. The results reveal that the adoption of AI indeed mostly leads to the augmentation and improvement of decision-making processes. Notably, decision-making is fully mediated by process automation and organisational learning, two inherent characteristics of AI, decision-making and knowledge engineering. The findings show that AI adoption impacts incremental and radical innovation equally and thus is suitable for establishing a balanced and ambidextrous set up to drive the exploration and exploitation of knowledge and technology. As broadly acknowledged in the literature, empirical evidence confirms that incremental improvements impact decision-making performance, whereas radical improvements benefit process performance significantly.

5.2 Managerial implications

The results highlight five distinct AI-enabled capabilities for driving organisational impact: (1) Robust data acquisition and pre-processing (accurate decision-making relies heavily on high-quality data, i.e. leads to more accurate insights, better predictions, and informed strategic decisions); (2) Insight extraction and interpretation through AI-enabled predictive modelling (predictive modelling guides strategy, resources, and sales for enhanced competitiveness and profitability); (3) Facilitating AI-enhanced human-computer interaction and collaboration (AI-driven interaction enhances customer satisfaction and loyalty while boosting internal efficiency, innovation, and product or service quality); (4) Augmenting or automating decision-making processes through AI-enabled systems (AI-driven decision automation minimises errors, speeds up processes, and optimises operations, resources, costs, and market competitiveness in line with objectives); and (5) Seamless integration of AI technologies with existing IT resources and devices (ensuring the seamless utilisation and optimisation of AI capabilities within the current organisational framework, enhancing productivity and competitiveness).These AI capabilities enhance decision-making, cost-effectiveness, productivity, customer satisfaction, and competitive edge, ultimately bolstering operational performance and market sustainability.

Based on the findings, managers should: harness AI to boost operational efficiency and quality, acknowledging its indirect impact on organisational performance (OP); prioritise optimising process execution by leveraging AI's speed, scalability, granularity and accuracy (tasks can be performed faster and on a bigger scale while maintaining high precision) to streamline operations, reduce error, and achieve smoother workflows for increased productivity and effectiveness; and emphasise enhancing Decision-Making Performance (DMP) to extract AI business value via improved Business Process Performance (BPP). This strategic use of AI directly enhances decision-making, leading to the faster extraction and propagation of knowledge, ultimately impacting OP.

Regarding the automation or augmentation dilemma, current automation practices chiefly revolve around supporting and supervising decision-making across structured and unstructured processes. The results show that BPA has no significant direct effect on BPP for more complex tasks in terms of efficiency of execution or scalability. However, it has an expected significant direct impact on DMP. In summary, automate routine, well-structured tasks and augment complex, ambiguous ones.Adopting AI is noticeably beneficial for enhancing human–machine collaboration and adding business value by improving decision-making processes. Managers should therefore foster collaboration between human expertise and AI capabilities. This implies recognising machines as a distinct category of organisational agents rather than mere artefacts.

The study explored AI adoption from a knowledge perspective by integrating the Organisational Learning (OL) mediator. The findings confirm that leveraging AI enhances knowledge capabilities and significantly impacts DMP, BPP (via knowledge-intensive processes) and Business Process Innovation (BPI). AI-enabled knowledge capabilities and insights help organisations make informed decisions promptly, positively impacting their strategies and operations. Moreover, they facilitate innovative approaches and methods within business processes. This was confirmed by observing that OL partly mediates the direct impact of AI adoption on Incremental and Radical BPI, i.e. transformational effects.

Transformational effects of adopting AI are established with mediation by incremental process improvements significantly impacting DMP, while radical process improvements directly affect BPP. Managers should recognise the transformational effects and strategically plan the adoption of AI to maximise its impact on decision-making and overall business process performance. The findings align with existing research on process innovation (Cao and Jiang, 2022), suggesting that incremental improvements are mostly related to AI-assisted decision-making and contribute steadily to enhancing efficiency. However, radical improvements, the redesigning or creating of new processes with AI, provide significant leaps in performance. Organisations should thus prioritise AI knowledge and skill development for employees to drive incremental and radical improvements using AI tools effectively. An optimal blend of both is crucial for sustained progress. This suggests that AI is a distinct technology which can simultaneously enable and drive the exploitation and exploration of process innovation – striking a balance, leading to a more versatile and innovative approach to business processes and strategies. Hence, it can help managers achieve the illusive ambidextrous organisation (through the AI adoption process) that outperforms other organisational types (O'Reilly and Tushman, 2011) regarding adaptability, efficiency and market responsiveness to gain competitive advantage.

In summary, the presented findings highlight the need for managers to adopt a structured approach to the organisation-wide deployment of AI for all end-to-end organisational processes. This underscores the importance of prioritising AI knowledge and skill development for employees. Managers should consider the five proposed AI-enabled capabilities as key application domains and view process automation, innovation and organisational learning as the key BPM capabilities for generating business value from AI before any measurable organisational performance gains can be expected.

6. Conclusions

AI research and development has been ongoing since the 1960s. It has re-emerged on the stage as a vital technology playing a central role in realising organisations' performance and competitive advantages (Davenport and Ronanki, 2018). This study was principally motivated by managers' and academics' renewed interest in the business value held by AI.

AI capabilities may be expected to positively leverage decision-making processes and process transformation activities, establishing business value by pursuing business goals with critical BPM activities, including by improving decision-making, overcoming inertia, and implementing innovation and change.

The study's empirical results validate the proposed serial multiple-mediation model, allowing the conclusion that BPM capabilities, i.e. process automation–augmentation, organisational learning, and incremental and radical process improvements, are important predictors for boosting DMP and BPP.

A noteworthy finding of this study is that AI's knowledge-related and transformational characteristics facilitate the efficient exploration and exploitation of information and knowledge. This permits organisations to compete in mature markets while simultaneously innovating new products and services for emerging markets – an ability known as organisational ambidexterity. In light of the ongoing digital transformation of organisations, AI is a wide-reaching and promising capability that must be constantly explored by the IS community.

The study is not without limitations. A cross-sectional survey was used to validate the proposed research model. Self-report bias and endogeneity issues are typical limitations of such a research design (Jordan and Troth, 2020). A longitudinal approach may be considered for future studies to ascertain differences before and after AI is adopted. In contrast, although a case study research design would resolve endogeneity issues, it would not add to the generalisability of the findings. Further, several moderators presenting complementary organisational resources (e.g. culture, digital maturity, BPM maturity) could be included to identify behaviour in more complex relationships.

References

Abbad, M., Jaber, F., AlQeisi, K. and Eletter, S. (2021), "Artificial intelligence, big data, and value Co-creation: a conceptual model", *The Fourth Industrial Revolution: Implementation of Artificial Intelligence for Growing Business Success*, pp. 475-483, doi: 10.1007/978-3-030-62796-6_28.

Agrawal, A., Gans, J. and Goldfarb, A. (2017), *What to Expect from Artificial Intelligence*, MIT Sloan Management Review, Cambridge, MA.

Ahmad, T. and Van Looy, A. (2020), "Business process management and digital innovations: a systematic literature review", *Sustainability*, Vol. 12 No. 17, 6827, doi: 10.3390/su12176827.

Akter, S., Michael, K., Uddin, M.R., McCarthy, G. and Rahman, M. (2022), "Transforming business using digital innovations: the application of AI, blockchain, cloud and data analytics", *Annals of Operations Research*, Vol. 308 Nos 1-2, pp. 1-33, doi: 10.1007/s10479-020-03620-w.

Aljumah, A.I., Nuseir, M.T. and Alam, M.M. (2021), "Organizational performance and capabilities to analyze big data: do the ambidexterity and business value of big data analytics matter?", *Business Process Management Journal*, Vol. 27 No. 4, pp. 1088-1107, doi: 10.1108/bpmj-07-2020-0335.

Almuslamani, H.A.I. (2022), "Developing artificial intelligence via organizational learning capability to improve innovation performance: a case study of aluminium Bahrain (Alba)", *2022 ASU International Conference in Emerging Technologies for Sustainability and Intelligent Systems (ICETSIS)*, pp. 46-52.

Ansari, W.A., Diya, P., Patil, S. and Patil, S. (2019), "A review on robotic process automation-the future of business organizations", *SSRN 3372171*.

Armstrong, J.S. and Overton, T.S. (1977), "Estimating nonresponse bias in mail surveys", *Journal of Marketing Research*, Vol. 14 No. 3, pp. 396-402, doi: 10.2307/3150783.

Ashaari, M.A., Singh, K.S.D., Abbasi, G.A., Amran, A. and Liebana-Cabanillas, F.J. (2021), "Big data analytics capability for improved performance of higher education institutions in the Era of IR 4.0: a multi-analytical SEM & ANN perspective", *Technological Forecasting and Social Change*, Vol. 173, 121119, doi: 10.1016/j.techfore.2021.121119.

Aydiner, A.S., Tatoglu, E., Bayraktar, E. and Zaim, S. (2019a), "Information system capabilities and firm performance: opening the black box through decision-making performance and business-process performance", *International Journal of Information Management*, Vol. 47, pp. 168-182, doi: 10.1016/j.ijinfomgt.2018.12.015.

Aydiner, A.S., Tatoglu, E., Bayraktar, E., Zaim, S. and Delen, D. (2019b), "Business analytics and firm performance: the mediating role of business process performance", *Journal of Business Research*, Vol. 96, pp. 228-237, doi: 10.1016/j.jbusres.2018.11.028.

Bag, S., Gupta, S., Kumar, A. and Sivarajah, U. (2021), "An integrated artificial intelligence framework for knowledge creation and B2B marketing rational decision making for improving firm performance", *Industrial Marketing Management*, Vol. 92, pp. 178-189, doi: 10.1016/j.indmarman.2020.12.001.

Banasiewicz, A.D. (2019), *Organizational Learning in the Age of Data*, Springer Nature, Cham, doi: 10.1007/978-3-030-74866-1.

Benner, M.J. and Tushman, M.L. (2015), "Reflections on the 2013 Decade Award—"Exploitation, exploration, and process management: the productivity dilemma revisited" ten years later", *Academy of Management Review*, Vol. 40 No. 4, pp. 497-514, doi: 10.5465/amr.2015.0042.

Berruti, F., Nixon, G., Taglioni, G. and Whiteman, R. (2017), "Intelligent process automation: the engine at the core of the next-generation operating model", *Digital McKinsey*, p. 9.

Bohanec, M., Robnik-Šikonja, M. and Borštnar, M.K. (2017), "Organizational learning supported by machine learning models coupled with general explanation methods: a Case of B2B sales forecasting", *Organizacija*, Vol. 50 No. 3, pp. 217-233, doi: 10.1515/orga-2017-0020.

Brace, I. (2018), *Questionnaire Design: How to Plan, Structure and Write Survey Material for Effective Market Research*, Kogan Page, London.

Cao, R. and Jiang, R. (2022), "Resolving strategic dilemmas in ambidextrous organizations: an integrated second-order factor model perspective", *Frontiers in Psychology*, Vol. 13, p. 655, doi: 10.3389/fpsyg.2022.797645.

Chen, D., Esperança, J.P. and Wang, S. (2022), "The impact of artificial intelligence on firm performance: an application of the resource-based view to e-commerce firms", *Frontiers in Psychology*, Vol. 13, 884830, doi: 10.3389/fpsyg.2022.884830.

Collier, J.E. (2020), *Applied Structural Equation Modeling Using AMOS: Basic to Advanced Techniques*, Routledge Taylor & Francis Group, New York, doi: 10.4324/9781003018414.

Daugherty, P.R. and Wilson, H.J. (2018), *Human+ Machine: Reimagining Work in the Age of AI*, Harvard Business Press, Boston, MA.

Davenport, T.H. and Ronanki, R. (2018), "Artificial intelligence for the real world", *Harvard Business Review*, Vol. 96 No. 1, pp. 108-116.

De Haes, S., Van Grembergen, W., Joshi, A. and Huygh, T. (2020), "COBIT as a framework for enterprise governance of IT", *Enterprise Governance of Information Technology*, pp. 125-162.

Di Ciccio, C., Marrella, A. and Russo, A. (2015), "Knowledge-intensive processes: characteristics, requirements and analysis of contemporary approaches", *Journal on Data Semantics*, Vol. 4 No. 1, pp. 29-57, doi: 10.1007/s13740-014-0038-4.

DiBella, A.J., Nevis, E.C. and Gould, J.M. (1996), "Understanding organizational learning capability", *Journal of Management Studies*, Vol. 33 No. 3, pp. 361-379, doi: 10.1111/j.1467-6486.1996.tb00806.x.

Duan, Y., Edwards, J.S. and Dwivedi, Y.K. (2019), "Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda", *International Journal of Information Management*, Vol. 48, pp. 63-71, doi: 10.1016/j.ijinfomgt.2019.01.021.

Dumas, M., La Rosa, M., Mendling, J. and Reijers, H.A. (2013), *Fundamentals of Business Process Management*, Springer, Berlin.

Dwarkanhalli, H., Ananthanarayanan, M. and Mazumder, A. (2018), *How Cognitive Computing Unlocks Business Process Management's Performance-Enhancing Virtues*, Cognizant, London.

Eisenhardt, K.M. and Martin, J.A. (2000), "Dynamic capabilities: what are they?", *Strategic Management Journal*, Vol. 21 No. 10-11, pp. 1105-1121, doi: 10.1002/1097-0266(200010/11)21:10/113.0.co;2-e.

Enholm, I.M., Papagiannidis, E., Mikalef, P. and Krogstie, J. (2021), "Artificial intelligence and business value: a literature review", *Information Systems Frontiers*, Vol. 24 No. 5, pp. 1-26, doi: 10.1007/s10796-021-10186-w.

Eurostat (2020), "Artificial intelligence by NACE Rev.2 activity [dataset]", doi: 10.2908/ISOC_EB_AIN2, available at: https://ec.europa.eu/eurostat/databrowser/view/isoc_eb_ain2/default/table?lang=en&category=isoc.isoc_e.isoc_eb (accessed 16 October 2022).

Fornell, C. and Larcker, D.F. (1981), "Evaluating structural equation models with unobservable variables and measurement error", *Journal of Marketing Research*, Vol. 18 No. 1, pp. 39-50, doi: 10.2307/3151312.

Fredrickson, J.W. and Mitchell, T.R. (1984), "Strategic decision processes: comprehensiveness and performance in an industry with an unstable environment", *Academy of Management Journal*, Vol. 27 No. 2, pp. 399-423, doi: 10.5465/255932.

García-Morales, V.J., Jiménez-Barrionuevo, M.M. and Gutiérrez-Gutiérrez, L. (2012), "Transformational leadership influence on organizational performance through organizational learning and innovation", *Journal of Business Research*, Vol. 65 No. 7, pp. 1040-1050, doi: 10.1016/j.jbusres.2011.03.005.

Gaskin, J. (2021), "Confirmatory factor analysis", available at: http://statwiki.gaskination.com/index.php?title=CFA (accessed 21 September 2022).

Ghattas, J., Soffer, P. and Peleg, M. (2014), "Improving business process decision making based on past experience", *Decision Support Systems*, Vol. 59, pp. 93-107, doi: 10.1016/j.dss.2013.10.009.

Grewal, D., Hulland, J., Kopalle, P.K. and Karahanna, E. (2020), "The future of technology and marketing: A multidisciplinary perspective", *Journal of the Academy of Marketing Science*, Vol. 48, pp. 1-8.

Grønsund, T. and Aanestad, M. (2020), "Augmenting the algorithm: emerging human-in-the-loop work configurations", *The Journal of Strategic Information Systems*, Vol. 29 No. 2, 101614, doi: 10.1016/j.jsis.2020.101614.

Haarhaus, T. and Liening, A. (2020), "Building dynamic capabilities to cope with environmental uncertainty: the role of strategic foresight", *Technological Forecasting and Social Change*, Vol. 155, 120033, doi: 10.1016/j.techfore.2020.120033.

Haefner, N., Wincent, J., Parida, V. and Gassmann, O. (2021), "Artificial intelligence and innovation management: a review, framework, and research agenda✰", *Technological Forecasting and Social Change*, Vol. 162, 120392, doi: 10.1016/j.techfore.2020.120392.

Hair, J.F., Black, W.C., Babin, B.J. and Anderson, R.E. (2013), *Multivariate Data Analysis*, Pearson new international edition, Pearson Education, London.

Hancock, G.R. and Mueller, R.O. (2001), "Rethinking construct reliability within latent variable systems", *Structural Equation Modeling: Present and Future*, Vol. 195, p. 216.

Helbin, T. and Van Looy, A. (2021), "Is business process management (BPM) ready for ambidexterity? Conceptualization, implementation guidelines and research agenda", *Sustainability*, Vol. 13 No. 4, 1906, doi: 10.3390/su13041906.

Henseler, J., Ringle, C.M. and Sarstedt, M. (2015), "A new criterion for assessing discriminant validity in variance-based structural equation modeling", *Journal of the Academy of Marketing Science*, Vol. 43 No. 1, pp. 115-135, doi: 10.1007/s11747-014-0403-8.

Hernaus, T., Bosilj Vuksic, V. and Indihar Štemberger, M. (2016), "How to go from strategy to results? Institutionalising BPM governance within organisations", *Business Process Management Journal*, Vol. 22 No. 1, pp. 173-195, doi: 10.1108/bpmj-03-2015-0031.

Hong, W., Chan, F.K., Thong, J.Y., Chasalow, L.C. and Dhillon, G. (2014), "A framework and guidelines for context-specific theorizing in information systems research", *Information Systems Research*, Vol. 25 No. 1, pp. 111-136, doi: 10.1287/isre.2013.0501.

Jarrahi, M.H., Kenyon, S., Brown, A., Donahue, C. and Wicher, C. (2022), "Artificial intelligence: a strategy to harness its power through organizational learning", *Journal of Business Strategy*, Vol. 44 No. 3, pp. 126-135, doi: 10.1108/jbs-11-2021-0182.

Jarvis, C.B., MacKenzie, S.B. and Podsakoff, P.M. (2003), "A critical review of construct indicators and measurement model misspecification in marketing and consumer research", *Journal of Consumer Research*, Vol. 30 No. 2, pp. 199-218, doi: 10.1086/376806.

Johnson, P.C., Laurell, C., Ots, M. and Sandström, C. (2022), "Digital innovation and the effects of artificial intelligence on firms' research and development–Automation or augmentation, exploration or exploitation?", *Technological Forecasting and Social Change*, Vol. 179, 121636, doi: 10.1016/j.techfore.2022.121636.

Jordan, P.J. and Troth, A.C. (2020), "Common method bias in applied settings: the dilemma of researching in organizations", *Australian Journal of Management*, Vol. 45 No. 1, pp. 3-14, doi: 10.1177/0312896219871976.

Karan, E., Safa, M. and Suh, M.J. (2021), "Use of artificial intelligence in a regulated design environment – a beam design example", *Lecture Notes in Civil Engineering*, pp. 16-25, doi: 10.1007/978-3-030-51295-8_2.

Katila, R. and Ahuja, G. (2002), "Something old, something new: a longitudinal study of search behavior and new product introduction", *Academy of Management Journal*, Vol. 45 No. 6, pp. 1183-1194, doi: 10.5465/3069433.

Keding, C. (2021), "Understanding the interplay of artificial intelligence and strategic management: four decades of research in review", *Management Review Quarterly*, Vol. 71 No. 1, pp. 91-134, doi: 10.1007/s11301-020-00181-x.

Kerpedzhiev, G.D., König, U.M., Röglinger, M. and Rosemann, M. (2020), "An exploration into future business process management capabilities in view of digitalization", *Business and Information Systems Engineering*, Vol. 63 No. 2, pp. 83-96, doi: 10.1007/s12599-020-00637-0.

Kim, T., Park, Y. and Kim, W. (2022), "The impact of artificial intelligence on firm performance", *2022 Portland International Conference on Management of Engineering and Technology (PICMET)*, pp. 1-10.

Krakowski, S., Luger, J. and Raisch, S. (2023), "Artificial intelligence and the changing sources of competitive advantage", *Strategic Management Journal*, Vol. 44 No. 6, pp. 1425-1452, doi: 10.1002/smj.3387.

Linton, N.M., Kobayashi, T., Yang, Y., Hayashi, K., Akhmetzhanov, A.R., Jung, S.-M., Yuan, B., Kinoshita, R. and Nishiura, H. (2020), "Incubation period and other epidemiological characteristics of 2019 novel coronavirus infections with right truncation: a statistical analysis of publicly available case data", *Journal of Clinical Medicine*, Vol. 9 No. 2, p. 538, doi: 10.3390/jcm9020538.

Lui, A.K., Lee, M. and Ngai, E.W. (2022), "Impact of artificial intelligence investment on firm value", *Annals of Operations Research*, Vol. 308 No. 1, pp. 373-388, doi: 10.1007/s10479-020-03862-8.

MacKenzie, S.B., Podsakoff, P.M. and Podsakoff, N.P. (2011), "Construct measurement and validation procedures in MIS and behavioral research: integrating new and existing techniques", *MIS Quarterly*, Vol. 35 No. 2, pp. 293-334, doi: 10.2307/23044045.

March, J.G. (1991), "Exploration and exploitation in organizational learning", *Organization Science*, Vol. 2 No. 1, pp. 71-87, doi: 10.1287/orsc.2.1.71.

May, A., Sagodi, A., Dremel, C. and van Giffen, B. (2020), "Realizing digital innovation from artificial intelligence", *International Conference on Information Systems 2020 Proceedings*, Hyderabad, India, Vol. 6.

Mele, C., Spena, T.R. and Peschiera, S. (2018), "Value creation and cognitive technologies: opportunities and challenges", *Journal of Creating Value*, Vol. 4 No. 2, pp. 182-195, doi: 10.1177/2394964318809152.

Melville, N., Kraemer, K. and Gurbaxani, V. (2004), "Review: information technology and organizational performance: an integrative model of IT business value", *MIS Quarterly*, Vol. 28 No. 2, pp. 283-322, doi: 10.2307/25148636.

Mikalef, P. and Gupta, M. (2021), "Artificial intelligence capability: conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance", *Information and Management*, Vol. 58 No. 3, 103434, doi: 10.1016/j.im.2021.103434.

Mishra, A.N. and Pani, A.K. (2020), "Business value appropriation roadmap for artificial intelligence", *VINE Journal of Information and Knowledge Management Systems*, Vol. 51 No. 3, pp. 353-368, doi: 10.1108/vjikms-07-2019-0107.

Mishra, S.K. and Pati, S.S. (2020), "A solar-hydro based frequency regulation in two-area power system incorporating unified power flow control", in *Smart Intelligent Computing and Applications: Proceedings of the Third International Conference on Smart Computing and Informatics*, Vol. 1, Springer, pp. 485-493.

Mishra, S., Ewing, M.T. and Cooper, H.B. (2022), "Artificial intelligence focus and firm performance", *Journal of the Academy of Marketing Science*, Vol. 50 No. 6, pp. 1-22, doi: 10.1007/s11747-022-00876-5.

Moshagen, M. and Erdfelder, E. (2016), "A new strategy for testing structural equation models", *Structural Equation Modeling: A Multidisciplinary Journal*, Vol. 23 No. 1, pp. 54-60, doi: 10.1080/10705511.2014.950896.

Ng, S.C., Rungtusanatham, J.M., Zhao, X. and Lee, T. (2015), "Examining process management via the lens of exploitation and exploration: reconceptualization and scale development", *International Journal of Production Economics*, Vol. 163, pp. 1-15, doi: 10.1016/j.ijpe.2015.01.021.

Ng, K.K., Chen, C.-H., Lee, C.K., Jiao, J.R. and Yang, Z.-X. (2021), "A systematic literature review on intelligent automation: aligning concepts from theory, practice, and future perspectives", *Advanced Engineering Informatics*, Vol. 47, 101246, doi: 10.1016/j.aei.2021.101246.

Nielsen, B.B. and Raswant, A. (2018), "The selection, use, and reporting of control variables in international business research: a review and recommendations", *Journal of World Business*, Vol. 53 No. 6, pp. 958-968, doi: 10.1016/j.jwb.2018.05.003.

Norman, D.A. and Verganti, R. (2014), "Incremental and radical innovation: design research vs technology and meaning change", *Design Issues*, Vol. 30 No. 1, pp. 78-96, doi: 10.1162/desi_a_00250.

OECD (2019), *Artificial Intelligence in Society*, OECD Publishing, Paris, doi: 10.1787/eedfee77-en.

O'Reilly, I.I.I.C.A. and Tushman, M.L. (2011), "Organizational ambidexterity in action: how managers explore and exploit", *California Management Review*, Vol. 53 No. 4, pp. 5-22, doi: 10.1525/cmr.2011.53.4.5.

Parasuraman, R., Sheridan, T.B. and Wickens, C.D. (2000), "A model for types and levels of human interaction with automation", *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, Vol. 30 No. 3, pp. 286-297, doi: 10.1109/3468.844354.

Patas, J., Bartenschlager, J. and Goeken, M. (2012), "Resource-based view in empirical it business value research–an evidence-based literature review", *2012 45th Hawaii International Conference on System Sciences*, pp. 5062-5071.

Podsakoff, P.M., MacKenzie, S.B. and Podsakoff, N.P. (2016), "Recommendations for creating better concept definitions in the organizational, behavioral, and social sciences", *Organizational Research Methods*, Vol. 19 No. 2, pp. 159-203, doi: 10.1177/1094428115624965.

Posen, H.E., Keil, T., Kim, S. and Meissner, F.D. (2018), "Renewing research on problemistic search—a review and research agenda", *Academy of Management Annals*, Vol. 12 No. 1, pp. 208-251, doi: 10.5465/annals.2016.0018.

Raghu, T. and Vinze, A. (2007), "A business process context for Knowledge Management", *Decision Support Systems*, Vol. 43 No. 3, pp. 1062-1079, doi: 10.1016/j.dss.2005.05.031.

Rahman, M.S., Hossain, M.A. and Fattah, F.A.M.A. (2021), "Does marketing analytics capability boost firms' competitive marketing performance in data-rich business environment?", *Journal of Enterprise Information Management*, Vol. 35 No. 2, pp. 455-480, doi: 10.1108/jeim-05-2020-0185.

Raisch, S. and Krakowski, S. (2021), "Artificial intelligence and management: the automation–augmentation paradox", *Academy of Management Review*, Vol. 46 No. 1, pp. 192-210, doi: 10.5465/amr.2018.0072.

Rammer, C., Fernández, G.P. and Czarnitzki, D. (2022), "Artificial intelligence and industrial innovation: evidence from German firm-level data", *Research Policy*, Vol. 51 No. 7, 104555, doi: 10.1016/j.respol.2022.104555.

Robert Baum, J. and Wally, S. (2003), "Strategic decision speed and firm performance", *Strategic Management Journal*, Vol. 24 No. 11, pp. 1107-1129, doi: 10.1002/smj.343.

Rocha, G.S., Lacerda, D.P., Veit, D.R., Rodrigues, L.H. and Dresch, A. (2017), "In the process babel: definitions, concepts, and tools in a disordered field", *Knowledge and Process Management*, Vol. 24 No. 3, pp. 196-203, doi: 10.1002/kpm.1543.

Roeglinger, M., Seyfried, J., Stelzl, S. and Muehlen, M.Z. (2018), "Cognitive computing: what's in for business process management? An exploration of use case ideas", in *Business Process Management Workshops: BPM 2017 International Workshops, Barcelona*, Springer International, pp. 419-428.

Rosemann, M., De Bruin, T. and Hueffner, T. (2004), "A model for business process management maturity", *ACIS 2004 Proceedings*, p. 6.

Rouse, W.B. and Spohrer, J.C. (2018), "Automating versus augmenting intelligence", *Journal of Enterprise Transformation*, Vol. 8 Nos 1-2, pp. 1-21, doi: 10.1080/19488289.2018.1424059.

Rowe, F., Besson, P. and Hemon, A. (2017), "Socio-technical inertia, dynamic capabilities and environmental uncertainty: senior management views and implications for organizational transformation", *Proceedings of the 25th European Conference on Information Systems (ECIS)*, Guimarães, Portugal.

Russel, S. and Norvig, P. (2016), *Artificial Intelligence: A Modern Approach, Global Edition*, 3rd ed., Pearson Education, London.

Santhanam, R. and Hartono, E. (2003), "Issues in linking information technology capability to firm performance", *MIS Quarterly*, Vol. 27 No. 1, pp. 125-153, doi: 10.2307/30036521.

Saunila, M., Ukko, J., Rantala, T., Nasiri, M. and Rantanen, H. (2020), "Preceding operational capabilities as antecedents for productivity and innovation performance", *Journal of Business Economics*, Vol. 90 No. 4, pp. 537-561, doi: 10.1007/s11573-019-00963-0.

Schryen, G. (2013), "Revisiting IS business value research: what we already know, what we still need to know, and how we can get there", *European Journal of Information Systems*, Vol. 22 No. 2, pp. 139-169, doi: 10.1057/ejis.2012.45.

Senge, P. (1998), *The Fifth Discipline Fieldbook: Strategies and Tools for Building a Learning Organisation*, Bantam Doubleday Dell Publishing Group, New York, NY.

Sindhgatta, R., ter Hofstede, A.H.M. and Ghose, A. (2020), "Resource-based adaptive robotic process automation: formal/technical paper", in Dustdar, S., Yu, E., Pant, V., Salinesi, C. and Rieu, D. (Eds), *32nd International Conference on Advanced Information Systems Engineering, CAiSE 2020*, Springer, pp. 451-466.

Steininger, D.M., Mikalef, P., Pateli, A. and Ortiz-de-Guinea, A. (2022), "Dynamic capabilities in information systems research: a critical review, synthesis of current knowledge, and recommendations for future research", *Journal of the Association for Information Systems*, Vol. 23 No. 2, pp. 447-490, doi: 10.17705/1jais.00736.

Szelagowski, M. and Lupeikiene, A. (2020), "Business process management systems: evolution and development trends", *Informatica*, Vol. 31 No. 3, pp. 579-595, doi: 10.15388/20-infor429.

Tallon, P.P., Kraemer, K.L. and Gurbaxani, V. (2000), "Executives' perceptions of the business value of information technology: a process-oriented approach", *Journal of Management Information Systems*, Vol. 16 No. 4, pp. 145-173, doi: 10.1080/07421222.2000.11518269.

Templeton, G.F., Lewis, B.R. and Snyder, C.A. (2002), "Development of a measure for the organizational learning construct", *Journal of Management Information Systems*, Vol. 19 No. 2, pp. 175-218, doi: 10.1080/07421222.2002.11045727.

Trocin, C., Hovland, I.V., Mikalef, P. and Dremel, C. (2021), "How Artificial Intelligence affords digital innovation: a cross-case analysis of Scandinavian companies", *Technological Forecasting and Social Change*, Vol. 173, 121081, doi: 10.1016/j.techfore.2021.121081.

Vagia, M., Transeth, A.A. and Fjerdingen, S.A. (2016), "A literature review on the levels of automation during the years. What are the different taxonomies that have been proposed?", *Applied Ergonomics*, Vol. 53, pp. 190-202, doi: 10.1016/j.apergo.2015.09.013.

Vukšić, V.B., Bach, M.P., Grublješič, T., Jaklič, J. and Stjepić, A.-M. (2017), "The role of alignment for the impact of business intelligence maturity on business process performance in Croatian and Slovenian companies", in *2017 40th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO)*, pp. 1355-1360.

Wamba, S.F. (2022), "Impact of artificial intelligence assimilation on firm performance: the mediating effects of organizational agility and customer agility", *International Journal of Information Management*, Vol. 67, 102544, doi: 10.1016/j.ijinfomgt.2022.102544.

Wamba, S.F., Dubey, R., Gunasekaran, A. and Akter, S. (2020), "The performance effects of big data analytics and supply chain ambidexterity: the moderating effect of environmental dynamism", *International Journal of Production Economics*, Vol. 222, 107498, doi: 10.1016/j.ijpe.2019.09.019.

Wamba-Taguimdje, S.-L., Wamba, S.F., Kamdjoug, J.R.K. and Wanko, C.E.T. (2020a), "Impact of artificial intelligence on firm performance: exploring the mediating effect of process-oriented dynamic capabilities", *Digital Business Transformation*, pp. 3-18, doi: 10.1007/978-3-030-47355-6_1.

Wamba-Taguimdje, S.-L., Wamba, S.F., Kamdjoug, J.R.K. and Wanko, C.E.T. (2020b), "Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects", *Business Process Management Journal*, Vol. 26 No. 7, pp. 1893-1924, doi: 10.1108/bpmj-10-2019-0411.

Wang, Y.L. and Ellinger, A.D. (2011), "Organizational learning: perception of external environment and innovation performance", *International Journal of Manpower*, Vol. 32 Nos 5/6, pp. 512-536, doi: 10.1108/01437721111158189.

Wang, N., Liang, H., Zhong, W., Xue, Y. and Xiao, J. (2012), "Resource structuring or capability building? An empirical study of the business value of information technology", *Journal of Management Information Systems*, Vol. 29 No. 2, pp. 325-367, doi: 10.2753/mis0742-1222290211.

Wijnhoven, F. (2022), "Organizational learning for intelligence amplification adoption: lessons from a clinical decision support system adoption project", *Information Systems Frontiers*, Vol. 24 No. 3, pp. 731-744, doi: 10.1007/s10796-021-10206-9.

Wiklund, J. and Shepherd, D.A. (2008), "Portfolio entrepreneurship: habitual and novice founders, new entry, and mode of organizing", *Entrepreneurship Theory and Practice*, Vol. 32 No. 4, pp. 701-725, doi: 10.1111/j.1540-6520.2008.00249.x.

Williams, C. and Mitchell, W. (2004), "Focusing firm evolution: the impact of information infrastructure on market entry by US telecommunications companies, 1984-1998", *Management Science*, Vol. 50 No. 11, pp. 1561-1575, doi: 10.1287/mnsc.1040.0223.

Wu, S.J., Melnyk, S.A. and Swink, M. (2012), "An empirical investigation of the combinatorial nature of operational practices and operational capabilities: compensatory or additive?", *International Journal of Operations and Production Management*, Vol. 32 No. 2, pp. 121-155, doi: 10.1108/01443571211208605.

Zasada, A. (2019), "How cognitive processes make us smarter", in Di Francescomarino, C., Dijkman, R. and Zdun, U. (Eds), *Business Process Management Workshops*, Cham, pp. 45-55.

Zebec, A. and Štemberger, M.I. (2020), "Conceptualizing a capability-based view of artificial intelligence adoption in a BPM context", *International Conference on Business Process Management*, pp. 194-205.

Further reading

Bawack, R.E., Fosso Wamba, S. and Carillo, K. (2019), "Artificial intelligence in practice: implications for IS research", *Americas Conference on Information Systems (AMCIS) 2019*, Cancun, Mexico.

Dunston, P.S. and Wang, X. (2005), "Mixed reality-based visualization interfaces for architecture, engineering, and construction industry", *Journal of Construction Engineering and Management*, Vol. 131 No. 12, pp. 1301-1309, doi: 10.1061/(asce)0733-9364(2005)131:12(1301).

Farshid, M., Paschen, J., Eriksson, T. and Kietzmann, J. (2018), "Go boldly!: explore augmented reality (AR), virtual reality (VR), and mixed reality (MR) for business", *Business Horizons*, Vol. 61 No. 5, pp. 657-663, doi: 10.1016/j.bushor.2018.05.009.

Heimbach, I., Kostyra, D.S. and Hinz, O. (2015), "Marketing automation", *Business and Information Systems Engineering*, Vol. 57 No. 2, pp. 129-133, doi: 10.1007/s12599-015-0370-8.

Kelly, J.E. (2015), "Computing, cognition and the future of knowing", *Whitepaper, IBM Research*, Vol. 2.

Kuhn, M. and Johnson, K. (2013), *Applied Predictive Modeling*, Springer, New York, NY, doi: 10.1007/978-1-4614-6849-3.

Phillips-Wren, G. (2012), "Ai tools in decision making support systems: a review", *International Journal on Artificial Intelligence Tools*, Vol. 21 No. 02, 1240005, doi: 10.1142/s0218213012400052.

Prieto, B. (2019), "Impacts of artificial intelligence on management of large complex projects", *PM World Journal*, Vol. 8 No. 5, pp. 1-20.

Schatsky, D., Muraskin, C. and Gurumurthy, R. (2014), "Demystifying artificial intelligence: what business leaders need to know about cognitive technologies", in *A Deloitte Series on Cognitive Technologies*.

Suvetha, M., Swathi, S., Rani, M., Vinoth, S. and Suriya, R. (2018), "A study on artificial intelligence", *Bonfring International Journal of Industrial Engineering and Management Science*, Vol. 9 No. 1, p. 6.

Tavana, M., Szabat, K. and Puranam, K. (2016), *Organizational Productivity and Performance Measurements Using Predictive Modeling and Analytics*, Business Science Reference (an imprint of IGI Global), Hershey, PA.

Taylor, J. (2011), *Decision Management Systems: A Practical Guide to Using Business Rules and Predictive Analytics*, Pearson Education, Boston, MA.

van der Aalst, W.M.P., Becker, J., Bichler, M., Buhl, H.U., Dibbern, J., Frank, U., Hasenkamp, U., Heinzl, A., Hinz, O., Hui, K.-L., Jarke, M., Karagiannis, D., Kliewer, N., König, W., Mendling, J., Mertens, P., Rossi, M., Voss, S., Weinhardt, C., Winter, R. and Zdravkovic, J. (2018), "Views on the past, present, and future of business and information systems engineering", *Business and Information Systems Engineering*, Vol. 60 No. 6, pp. 443-477, doi: 10.1007/s12599-018-0561-1.

About the authors

Aleš Zebec, Managing Partner and CIO at BuyITC, holds an MSc in Economics (University of Ljubljana), a BSc in Computer Science and Informatics Engineering, and is a PhD candidate. He has 25 years of experience in Information Systems Development and has successfully managed over 80 projects in application development, web development, IS development, and mobile business software solutions. As a member of the Business Intelligent Systems Research Group (BIS), his research interests include economics, business process management, mobile and web technologies, information systems integration in organisations, project management, databases, business intelligence, artificial intelligence, software architecture, and mobile and web-based solutions. Aleš Zebec is the corresponding author and can be contacted at: ales.zebec@ef.uni-lj.si

Mojca Indihar Štemberger is Full Professor, Vice-Dean for Academic Affairs and Chair of study programme Business Informatics at School of Economics and Business, University of Ljubljana. Her main research areas are business process management, digital transformation and information systems management. She published in the International Journal of Information Management, Information Technology and People, International Journal of Production Economics, Simulation, Supply Chain Management, Business Process Management Journal and other international journals. She is also Senior PC Member of BPM conference and Reviewer for several international journals and conferences.