current perspective on business operations

E-ISSN: XXXX-XXXX

ARTICLE

Business process transformation to maintain high performance: Driving an AI-based business value project

M. Elfan Kaukab [1], Ali Akbar Anggara [2]*, Ali Imron [3]

[1] Faculty of Economics and Business, Universitas Sains Al-Qur'an, Wonosobo, Indonesia; elvankaukab@yahoo.com
[2] Faculty of Economics and Business, Universitas Muhammadiyah Purwokerto, Purwokerto, Indonesia; aliakbarang@ump.ac.id
[3] Faculty of Creative Design and Digital Business, Institut Teknologi dan Sains Nahdlatul Ulama Pekalongan, Pekalongan, Indonesia; imron.ali-alta@gmail.com

* Correspondence: aliakbarang@ump.ac.id

Abstract

This study investigates the impact of Artificial Intelligence (AI) on firm performance, emphasizing the business value generated by AI-enabled transformation projects. Employing a four-step sequential approach, including (1) analysis of AI concepts and technologies, (2) in-depth review of cross-sector case studies, (3) data collection from AI solution providers' databases, and (4) literature review. This research draws on the theory of IT capabilities to examine AI's influence at organizational and process levels. The analysis is based on 500 case studies from sources including IBM, AWS, Cloudera, Nvidia, Conversica, and Universal Robots. Findings reveal that AI, encompassing technologies such as machine translation, chatbots, and self-learning algorithms, enhances business performance by optimizing processes, automating operations, improving information flows, and enabling predictive and interactive capabilities. However, performance gains are realized only when organizations leverage AI features to reconfigure and innovate their processes. AI adoption thus emerges not merely as a technological upgrade but as a driver of strategic transformation and competitive advantage. The study offers both theoretical and managerial contributions. Theoretically, it proposes a model for assessing AI's business value, addressing gaps in the literature. Managerially, it guides decision-makers in aligning data, talent, domain expertise, partnerships, and scalable infrastructure to maximize AI benefits. By viewing AI as an integrated set of IT configurations rather than a standalone tool, organizations can achieve higher performance, enhance investment returns, and strengthen competitive positioning. These insights position AI as a critical enabler for new business models and sustainable organizational growth.

Keywords: artificial intelligence, business process, business value, IT capabilities, firm performance

Academic Editor: Gara Huang

Received: August 01, 2025 | Revised: Agust 07, 2025 | Accepted: August 11, 2025 | Published: August 12, 2025

Citation: Kaukab, M.E., Anggara, A.A., & Imron, A. (2025). Business process transformation to maintain high performance: Driving an AI-based business value project. *Current Perspective on Business Operations,* 1(1), 1-20.

1. Introduction

Information technologies (ITs) are now a fundamental component of modern professional practices, reshaping and, in many cases, disrupting essential processes and operations across sectors (Devaraj & Kohli, 2003; Nwamen, 2006). When embedded within a business ecosystem, IT influences how organizations engage with customers, potential clients, and strategic partners (Lauterbach, 2019; Nwamen, 2006), while also driving the evolution of internal workflows and operational structures. Within this technological landscape, Artificial Intelligence (AI) has emerged as a particularly transformative force, achieving rapid progress unmatched by most other innovations in recent decades (Blanchet, 2016; Lee et al., 2018; Wiljer & Hakim, 2019). AI is broadly described as a suite of concepts, methods, and tools designed to create systems capable of emulating intelligent behavior with limited human input (Benko & Lányi, 2009; Haenlein & Kaplan, 2019; McCorduck et al., 1977).

Industry projections reflect AI's accelerating importance in business transformation. By 2019, AI technologies were integrated into approximately 40% of digital transformation projects, and it was anticipated that 75% of enterprise applications would incorporate AI functionalities by 2021 (Crews, 2019). Organizations are turning to AI to enhance efficiency, stimulate innovation, and develop new services (CIGREF, 2016, 2018; Crews, 2019). Global technology leaders such as the U.S.-based GAFAM and China's BATX have committed substantial resources to advanced AI domains, particularly machine learning and deep learning (Lee et al., 2018; PwC, 2019; Vochozka et al., 2018). The explosive growth of AI, propelled by the digitization of industries and the widespread generation of data from connected devices (Dopico et al., 2016; Sheth, 2016), underscores its potential as a driver of future competitive advantage (PwC, 2018, 2019; Tractica, 2018).

Although AI does not replicate the full complexity of human cognition, it demonstrates exceptional performance in specialized tasks, yielding significant organizational benefits (Blanchet, 2016; Lee et al., 2018; Wiljer & Hakim, 2019). This research seeks to address a critical gap by evaluating how AI capabilities contribute to improvements in both organizational and process-level performance. Drawing on prior academic work and an analysis of 500 case studies from AI vendors and industry publications, the study assesses the business value of AI-enabled transformation initiatives. The paper proceeds by outlining the material and method (Section 2), findings (Section 3), discussion (Section 4), and final conclusions, study limitations and implications (Section 5).

2. Materials and Methods

2.1. Evolution of AI

The origins of Artificial Intelligence (AI) trace back to the early days of computer science when pioneers such as Alan Turing explored the concept of machine intelligence. His influential works including Intelligent Machinery (1948) and Computing Machinery and Intelligence (1950), laid the groundwork for decades of subsequent AI research (Turing, 2009). AI, in its broadest sense, refers to the deployment of technological systems designed to replicate human cognitive functions in order to achieve specific goals autonomously, while adapting to contextual constraints (Benko & Lányi, 2009; Haenlein & Kaplan, 2019; McCorduck et al., 1977). Over time, multiple landmark studies and innovations have shaped the evolution of AI, as summarized in Table 1.

Table 1. Artificial Intelligence Evolution

Date	Authors' contribution to the development of AI
1940–1956	Norbert Wiener pioneered the field of cybernetics, exploring how the human mind functions and proposing it could be represented as a *"black box"* in which behavior is regulated by feedback loops. His work suggested that the brain's billions of cells could be expressed through mathematical models,

Date	Authors' contribution to the development of AI
	an idea later advanced by Donald Hebb, who contributed to the development of formal neurons with adaptive learning abilities (Brown & Milner, 2003). In 1943, Warren McCulloch and Walter Pitts introduced the first mathematical representation of a biological neuron, applying a physiological framework to AI research (Benko & Lányi, 2009; Haenlein & Kaplan, 2019; McCorduck et al., 1977). Herbert Simon, in 1947, put forward the concept of "bounded rationality," while in 1945, Allen Newell explored heuristic problem-solving, an empirical approach whose validity is context-dependent. Their combined contributions highlighted the reciprocal influence between AI and computer science: computing advancements enabled AI experiments, while AI challenges stimulated the creation of new computing tools (Benko & Lányi, 2009; Haenlein & Kaplan, 2019; McCorduck et al., 1977). Between 1937 and 1948, Claude Shannon linked Boolean algebra with electrical circuitry, laying the foundation for digital electronics and information theory (Verdu, 1998). Nathaniel Rochester developed the first symbolic assembler language and was instrumental in AI projects such as LISP, the Geometry Theorem Prover, and symbolic assembly (Gelernter et al., 1958; Rochester et al., 1956). In 1949, Hebb formulated the learning rule for artificial neurons, enabling memory functions to operate as feedback processes in neural networks and forging a connection between cognition and language (Benko & Lányi, 2009; Haenlein & Kaplan, 2019; McCorduck et al., 1977). John McCarthy applied logic to the creation of thinking machines (Kline, 2010; McCarthy, 1989), while Marvin Minsky proposed a schematic model for artificial neural networks (Minsky, 2007; Minsky & Papert, 1972). By 1954, researchers at Georgetown University produced a language translation program capable of processing several dozen basic sentences using a 250-word vocabulary and six grammar rules, executed on an IBM 701 (Hutchins, 2004). Contributions from John von Neumann on computer architecture and Alan Turing on computable functions further advanced AI theory (Benko & Lányi, 2009; Godfrey & Hendry, 1993; Haenlein & Kaplan, 2019; McCorduck et al., 1977). In 1956, Newell, Simon, and Shaw developed the Information Processing Language (IPL), which used list structures to simulate associative memory (Benko & Lányi, 2009; Haenlein & Kaplan, 2019; McCorduck et al., 1977). Other notable advancements included Ray Solomonoff's work in machine learning and algorithmic probability (Solomonoff, 1997) and Oliver Selfridge's early research in expert systems and pattern recognition (Husbands et al., 2008). Although AI ideas had appeared in popular culture for years, the field's formal inception is widely attributed to the 1956 Dartmouth Conference led by McCarthy (McCarthy et al., 2006). This period marked the beginning of AI's "golden age," characterized by strong public investment in research (Buchanan, 2005). Development of MYCIN, the first expert system for diagnosing bacterial infections and recommending antibiotics (Shortliffe et al., 1975).
1974–1980	During this period, the field of AI faced what became known as its first "winter." Ambitious goals collided with insufficient resources, leading to stalled progress and reduced enthusiasm in research (Benko & Lányi, 2009; Godfrey & Hendry, 1993; Haenlein & Kaplan, 2019; McCorduck et al., 1977).
1980–1987	AI research regained momentum with the emergence of more capable intelligent systems. Notably, Kai-Fu Lee and Sanjoy Mahajan created BILL, a Bayesian learning program designed to play the board game Othello, reflecting the era's renewed optimism and technical progress (Benko & Lányi, 2009; Godfrey & Hendry, 1993; Haenlein & Kaplan, 2019; McCorduck et al., 1977).

Date	Authors' contribution to the development of AI
1987–1993	The collapse of the specialized hardware industry triggered AI's second "winter," characterized by funding cutbacks and slowed development (Benko & Lányi, 2009; Haenlein & Kaplan, 2019; McCorduck et al., 1977; Wamba et al., 2017).
1993–2011	AI shifted towards a data-driven paradigm, fueled by growing computing capabilities (Buchanan, 2005). A landmark event occurred in 1997 when IBM's DeepBlue chess system defeated world champion Garry Kasparov (Campbell et al., 2002). The combination of greater data availability, improved connectivity, and more powerful devices accelerated advancements, contributing to a surge in AI-related patent filings after 2012 (Shoham, 2018).

2.2. AI and Business

Since 2010, AI has entered a renewed phase of rapid growth, driven by advancements in computing power and unprecedented access to vast datasets (CIGREF, 2018; PwC, 2019). This resurgence can be attributed to three key developments: (1) the creation of highly sophisticated algorithmic models, (2) the widespread availability of affordable graphics processing units capable of executing massive computations within milliseconds, and (3) the emergence of extensive, accurately annotated datasets enabling advanced learning in intelligent systems (Jain et al., 2004; Khashman, 2009; PwC, 2019).

Core AI technologies including machine learning, deep learning, chatbots, neural networks, and virtual assistants are reshaping corporate processes and organizational structures (CIGREF, 2018; Kuzey et al., 2014; PwC, 2019). They have altered how firms manage information, interact with their environment, and deliver value. However, capitalizing on these opportunities requires not only technological investment but also cultural, strategic, and skills-based transformation (Di Francescomarino & Maggi, 2020; Lee et al., 2018; Sikdar, 2018). An example is IBM's Watson platform, which can process natural language queries to support diverse domains such as marketing, management, legal services, and healthcare (Kohn et al., 2014). Watson Health, in particular, enables physicians to integrate patient records with up-to-date medical data, enhancing diagnostic precision and care personalization (Kohn et al., 2014).

AI's conceptual foundations date back to the 1960s, but its major breakthroughs have emerged in the 2000s with the rise of machine learning and, more recently, deep learning, which uses multi-layered neural networks (Buchanan, 2005; PwC, 2019; Yoav Shoham, 2018). These models learn patterns by processing millions of examples, ranging from medical diagnoses and energy reserve predictions to pricing forecasts (PwC, 2019; Zemouri et al., 2019). When combined with big data, such systems can perform complex operations faster and more accurately than humans.

The applications are broad: autonomous vehicles in transport (Falcone et al., 2007), disease detection in healthcare (Jiang et al., 2017; Koh & Tan, 2011), conversational agents for customer service (Rubin et al., 2010), natural language processing for email automation (Gabrilovich & Markovitch, 2009), facial recognition in security, and data-driven urban planning for smart cities (Srivastava et al., 2017). AI's integration spans the entire value chain from R&D, maintenance, operations, and logistics to sales, marketing, demand forecasting, and after-sales services (Kuzey et al., 2014; PwC, 2019). As a strategic growth driver, AI offers organizations several advantages:

- Enhancing operational efficiency, optimizing supply chains, improving customer experience, and refining product/service features, including recommendation systems (Kuzey et al., 2014; PwC, 2019).

- Facilitating rapid adaptation to market changes, enabling the creation of new business models, and improving forecasting and planning capabilities (Kuzey et al., 2014; PwC, 2019).
- Detecting fraud, automating cybersecurity threat analysis, streamlining IT processes, and optimizing sales workflows (CIGREF, 2018; PwC, 2019).
- Supporting medical diagnostics and treatment planning, predicting disease progression, recommending personalized therapies, and aiding in epidemic prevention and pharmaceutical safety (Jiang et al., 2017; Johnson et al., 2018).
- Automating quality control, asset management, and logistics across industries (Di Francescomarino & Maggi, 2020; Rubin et al., 2010; Sikdar, 2018).

Market forecasts reinforce AI's economic significance. According to Tractica (2018), global AI revenues are projected to approach $90 billion by 2025, up from $7 billion in 2018, with North America, Europe, and Asia–Pacific as primary beneficiaries. Three areas are expected to dominate revenue generation: (1) moving object detection and avoidance, (2) static image recognition and classification, and (3) medical data processing. Together, these domains could generate nearly €21 billion in revenue between 2016 and 2025.

2.3. IT Capabilities

In an increasingly globalized and competitive market, innovation, quality, and rising customer expectations have pushed organizations to embed information technology (IT) into their management strategies (Bolwijn et al., 2018; Rachinger et al., 2019). Historically, automation began with assembly lines replacing manual labor; today, technological advances enable machines to handle more complex, value-adding tasks (Dopico et al., 2016; Lee et al., 2018). Modern organizations face the challenge of innovating in rapidly changing markets where information is a critical strategic asset (Kuusisto, 2017). IT reshapes business processes, demanding changes in culture, mindset, and skills to fully leverage its potential (Devaraj & Kohli, 2003; Turulja & Bajgoric, 2018). AI, as part of the IT ecosystem, enhances performance, strengthens customer and partner relationships, and optimizes operations (Kelly et al., 2019).

The "economy of power" paradigm suggests that market positioning depends on resources that both secure and enhance competitive advantage (Liu et al., 2015). This raises two central questions: how IT capabilities improve organizational performance, and how they generate business value in transformation projects (Abijith & Wamba, 2012). Research since the 1980s shows mixed evidence, some finding no significant effect (Koski, 1999), others reporting positive impacts (Devaraj & Kohli, 2003).

Six main approaches link IT to performance:

- Economic theory – measuring IT's economic contribution (Lehr & Lichtenberg, 1999).
- Social psychology – assessing effects on individuals and groups (Davis, 1989).
- Competitive analysis – evaluating industry and market impacts.
- Strategic alignment – aligning IT with organizational strategy (Henderson & Venkatraman, 1999).
- Process-based – viewing IT as value-creation processes.
- Resource-based – leveraging unique, valuable resources for competitive advantage (Barney et al., 2001).

From a resource-based view, IT capabilities combine tangible assets, intangible assets, and human expertise to create value. These can be assessed through three dimensions: (1) IT management capabilities, (2) IT staff expertise, and (3) IT infrastructure flexibility (Abijith & Wamba, 2012; Kim et al., 2011).

2.4. Hypothesis Development

Our research model was developed in two stages: first, reviewing literature on IT's role in enhancing performance at both organizational and process levels (e.g., Abijith &

Wamba, 2012; Kim et al., 2011; Mooney et al., 1996), and second, analyzing mini-case studies to assess the business value of AI-enabled transformation. Six hypotheses emerged, linking AI capabilities to performance improvement (Figure 1).

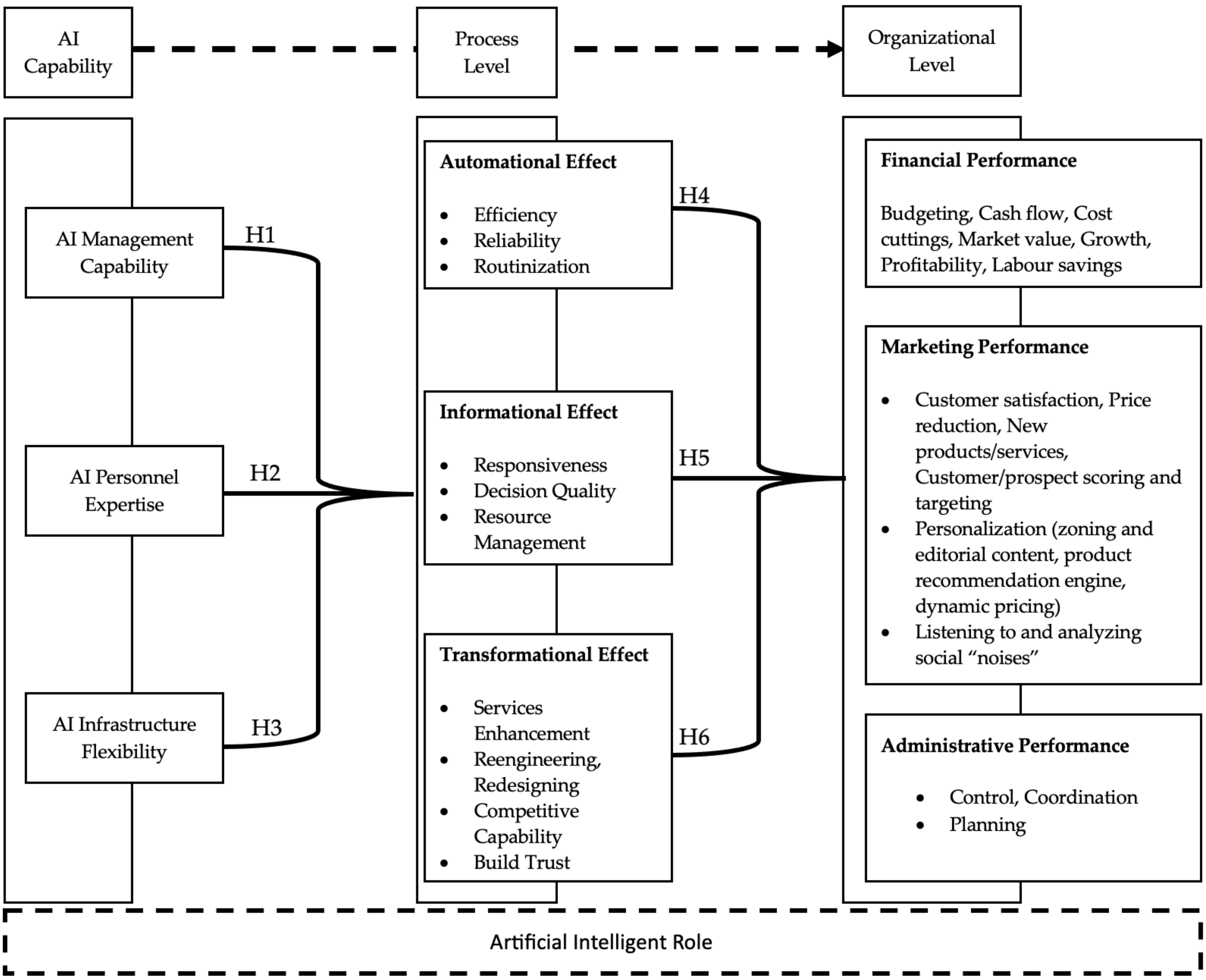

Figure 1. Proposed Research Model

AI capabilities refer to an organization's capacity to combine its organizational, human, and AI-specific resources to generate and capture business value (Abijith & Wamba, 2012; Kim et al., 2011; Liu et al., 2013). Resources within a firm may be organizational, human, material, or intangible (Kim et al., 2011; Liu et al., 2013). Drawing from prior studies, this research focuses on three main AI resource dimensions. AI Management Capability (AIMC) is the organizations and its employees' ability to oversee and model intelligent behaviors in technological systems to enhance long-term value and sustainability. This capability supports strategic planning, strengthens intra- and inter-organizational relationships, guides investment decisions, and facilitates coordination and control (Ha & Jeong, 2010; Hamet & Tremblay, 2017; Kim et al., 2011). Kim et al. (2011) further emphasizes that effective control, driven by staff expertise can improve infrastructure flexibility.

Hyphotesis 1: AI management capability contributes to enhance overall AI capabilities, which in turn enhance AI's impact at the process level.

AI Personal Expertise (AIPE) refers to the specialized skills and knowledge of organizational staff in AI technologies, business operations, and interpersonal competencies required to model or apply intelligent behavior in technological systems (Ha & Jeong, 2010; Hamet & Tremblay, 2017; Jiang et al., 2017; Kim et al., 2011). For IT teams, a balanced mix of technical awareness, ownership, integration, and management abilities which combined with knowledge of core IT components. It is essential for optimizing AI resource utilization. The ability to align AI initiatives with organizational strategy is a key driver of business value creation, and this alignment strengthens when staff possess the right skill set. When employees understand how strategic goals integrate with AI and IT capabilities, their expertise becomes a valuable intangible asset (Abijith & Wamba, 2012; Kim et al., 2011; Liu et al., 2013). Organizations with highly skilled AI professionals are better positioned to adapt to dynamic environments, align AI with strategic objectives, and develop efficient, reliable intelligent systems.

Hyphotesis 2: AI personal expertise contributes to enhance AI capabilities, which in turn enhance AI's impact at the process level.

AI Infrastructure Flexibility (AIIF) encompasses the full range of technological resources including software, hardware, data, systems, networks, and telecommunications which needed to operate AI solutions effectively (Kim et al., 2011; Liu et al., 2013; Wamba et al., 2017). Flexible infrastructure enables organizations to quickly adjust system components and adapt to shifts in market conditions, strategic partnerships, acquisitions, or global collaborations (Abijith & Wamba, 2012; Bhatt et al., 2010; Fink & Neumann, 2009). Successful AI deployment depends on aligning several critical factors: high-quality data, combined IT–AI talent, domain expertise, effective decision-making, external collaborations, and scalable infrastructure. While the first four elements serve as the "fuel," scalable infrastructure acts as the "engine" that powers AI operations. Robust and adaptable infrastructure allows efficient use of IT resources and supports organizational restructuring when integrating AI technologies. Advanced capabilities such as self-configuration, self-healing, and self-optimization which help prevent operational issues, drive innovation in business processes, and improve resource utilization (Kim et al., 2011; Liu et al., 2013; Wamba et al., 2017).

Hyphotesis 3: AI infrastructure flexibility contributes to enhance AI capabilities, which in turn enhance AI's impact at the process level.

The automation effect refers to AI's ability to replace or significantly reduce manual processes through standardized, repeatable instructions. This shift increases operational efficiency, enhances process reliability, and reduces labor costs by automating previously paper-based or human-intensive tasks (Abijith & Wamba, 2012; Kim et al., 2011; Liu et al., 2013).

Hyphotesis 4: The automation effect contributes at the process level, which is positively associated with the influence of AI at the organizational level.

The informational effect describes AI's capacity to gather, store, process, and share data within and across organizations. By converting high-quality data into timely, accurate, and relevant insights, AI enables faster and better decision-making, strengthens resource control, enhances coordination, and improves responsiveness among staff. These capabilities contribute to both financial stability and operational efficiency (Abijith & Wamba, 2012; Kim et al., 2011; Liu et al., 2013; Mooney et al., 1996).

Hyphotesis 5: The informational effect contributes at at the process level, which is positively associated with the influence of AI at the organizational level.

The transformational effect reflects AI's role in driving innovation and reengineering organizational processes. By enabling service enhancement, redesigning workflows, and building competitive capabilities, AI fosters strategic change and strengthens customer relationships. These innovations help organizations adapt to dynamic markets and create new products or services, positioning AI as a catalyst for long-term business transformation (Abijith & Wamba, 2012; Kim et al., 2011; Mooney et al., 1996).

Hyphotesis 6: The transformational effect contributes at the process level, which is positively associated with the influence of AI at the organizational level.

2.5. Methods

This study followed a three-phase process, as illustrated in Figure 2. The first phase was conceptual, focusing on selecting the target case studies for analysis. The second, a refinement and development stage, involved validating the accuracy and reliability of the case study data. The final assessment phase evaluated these cases to extract both practical insights and theoretical contributions to the IT capability framework.

An archival data analysis approach was employed, leveraging secondary data from documented case studies. In the current digital era, such data are widely accessible, cost-efficient, and suitable for in-depth analysis. This method is particularly appealing given that valuable, high-cost primary data often remain underutilized. Similar approaches have been used in prior research, such as Abijith and Wamba (2012) in examining the "Business Value of RFID-Enabled Healthcare Transformation Projects," and Faure et al. (2018), who analyzed 13 case studies to explore the impact of various agricultural research models in developing countries.

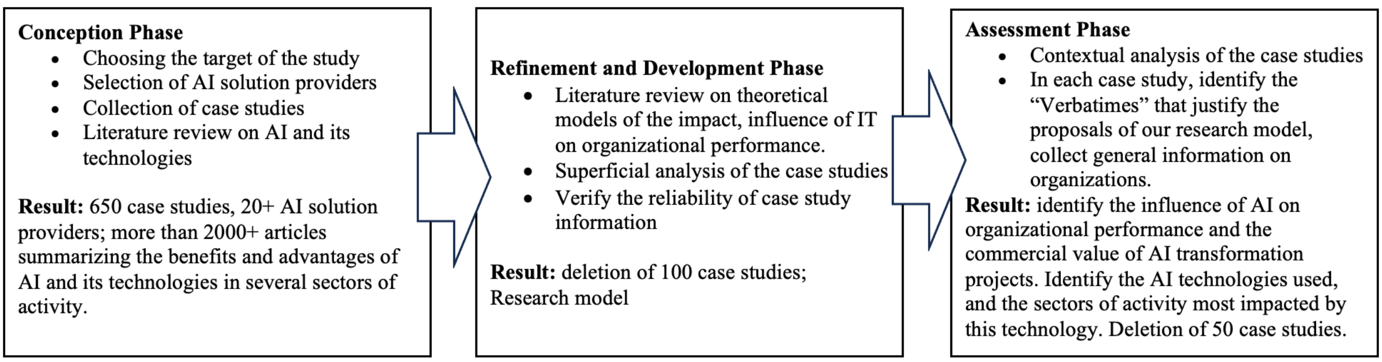

Figure 2. Research Model Development

3. Results

An in-depth review of the case studies confirms that artificial intelligence (AI) and its related technologies provide diverse opportunities, advantages, and services aimed at enhancing organizational performance. As outlined in Table 2, AI adoption delivers value across multiple business areas by transforming processes into intelligent, optimized, self-adjusting, and automated systems, replacing many resource-intensive, paper-based, and manual operations.

Table 2. AI-value Based Transformation Project

Industry	Common Benefits of AI-Enabled Organizational Transformation Projects
Agriculture, Food and Beverage	Optimizing supply chain, improving yield prediction, automating quality control, enhancing food safety monitoring

Industry	**Common Benefits of AI-Enabled Organizational Transformation Projects**
Banking and Financial Services	Fraud detection, risk assessment, customer behavior analysis, personalized financial services
Construction and Real Estate	Project planning automation, resource optimization, predictive maintenance of equipment, real-time site monitoring
Education	Personalized learning paths, intelligent tutoring systems, automated grading, enhanced learning analytics
Energy and Utilities	Predictive maintenance of infrastructure, demand forecasting, energy efficiency optimization, smart grid management
Healthcare	Disease diagnosis assistance, medical imaging analysis, patient care improvement, treatment personalization
Information Technology and Telecommunications	Automated network management, cybersecurity enhancement, AI-driven software testing, predictive analytics for customer retention
Manufacturing	Process automation, defect detection, production scheduling optimization, predictive equipment maintenance
Marketing, Advertising and Retail	Personalized marketing, product recommendation systems, demand forecasting, customer sentiment analysis
Transportation and Logistics	Route optimization, predictive maintenance of vehicles, real-time tracking, automated scheduling

AI's benefits span the entire organizational value chain, including R&D, maintenance, operations, marketing, sales, production planning, demand forecasting, and service delivery. Notable outcomes include:

- Improved operational efficiency, maintenance, and supply chain management.
- Enhanced customer experience and product/service quality through automation and recommendation systems.
- Greater adaptability to market changes and support for new business models.
- Better forecasting and planning to match supply with demand.
- Fraud detection in banking and other sectors.
- Automated threat monitoring and information system security.
- Advanced diagnostics, treatment, and patient care in healthcare.

From 500 examined cases (Table 3), 40.6% used integrated "pure" AI, involving multiple technologies for analytics, task automation, decision support, or digital transformation. Machine Learning was present in 31.2% of cases, valued for reducing human intervention and improving system accuracy over time. Around 18.6% implemented personal, virtual, or robotic assistants in production processes. Neural networks, while known for complexity, appeared less frequently, often developed in-house. Cognitive security AI represented only 1.2% of cases mainly IBM projects, due to its need for extensive complementary resources, diverse AI forms, and vast structured/unstructured data sources.

Table 3. Industry and Using AI by Type

No.	Industry (number of cases / percentage)	Types of AI (number of cases / percentage)
1	IT/telecom/computer services (74 / 14.80%); Health (42 / 8.40%)	AI strong or weak (206 / 41.2%)
2	Bank / financial markets / financial services (39 / 7.80%)	Machine learning (157 / 31.4%)
3	Business services / professional services (38 / 7.60%)	Deep learning (13 / 2.6%)
4	Trade / Distribution (37 / 7.40%); Automobile (36 / 7.20%); Machinery and equipment (27 / 5.40%)	Cognitive (65 / 13%)
5	Audiovisual, Show (24 / 4.80%); Electronics (20 / 4.00%); Other (19 / 3.80%); Metallurgy / Metalworking (19 / 3.80%)	Cognitive cyber security (6 / 1.2%)
6	Insurance (13 / 2.60%); Research (11 / 2.20%); Plastic / Rubber (11 / 2.20%)	Natural language processing / Understanding (69 / 13.8%)
7	Logistics and transport (10 / 2.00%); Education (10 / 2.00%)	Robotic personal assistant (93 / 18.6%)
8	Pharmaceutical industry (6 / 1.20%); Aircraft, rail and shipbuilding (4 / 0.80%)	Pattern / visual recognition (10 / 2%)
9	Petroleum industry (3 / 0.60%); E-commerce (2 / 0.4%); Aerospace and defense (3 / 0.60%)	Chatbots (38 / 7.6%)
10	Textile / clothing / headwear (3 / 0.60%); Army, security (3 / 0.60%); Social (2 / 0.40%); Construction / building materials (2 / 0.40%)	Neural networks (4 / 0.8%)
11	Art, design (2 / 0.40%); Studies and advice (1 / 0.20%); Hotels, restaurants and catering (1 / 0.20%)	Virtual companion / virtual assistant (39 / 7.8%)
12	Tourism, Leisure activities (1 / 0.20%); Government (9 / 1.80%); Agri-food industry (9 / 1.80%); Agriculture (9 / 1.80%); Energy (6 / 1.20%); Communication – marketing – advertising (4 / 0.80%)	Real-time emotion analytics (5 / 1%)
13		Real-time universal translation (6 / 1.2%)
14		Next GEN cloud robotics (3 / 0.6%)
15		Autonomous surgical robotics (3 / 0.6%)
16		Virtual reality (12 / 2.4%)

The case studies also highlight AI's transformative potential across industries. In technology sectors (IT, telecom, electronics), AI strengthens cybersecurity, enhances software development/testing, and supports Big Data-driven business intelligence. In healthcare and finance, AI powers computer vision, natural language processing, chatbots, and deep learning to secure sensitive data and improve services. Manufacturing and construction leverage AI for budgeting, planning, inventory control, resource optimization, and real-time asset tracking. In transport and logistics, AI aids predictive maintenance and customer engagement. Commerce, marketing, and retail benefit from virtual assistants, emotional agents, and chatbots for personalized customer interactions. Fashion industries apply AI to anticipate trends and tailor shopping experiences, while education uses AI to deliver adaptive, personalized learning paths.

The exploration of the link between IT and organizational performance continues to be relevant, though its focus has evolved over time. With the rapid advancements brought by artificial intelligence (AI), contemporary research often integrates multiple theories and models to examine how AI influences organizational outcomes and to determine the business value of AI-driven transformation initiatives. From the literature review, several theoretical underpinnings were identified as suitable for this study: the Paradox of Productivity (Kijek & Kijek, 2019; Polak, 2017; Triplett, 1999), the Process-Oriented Perspective (Mooney et al., 1996), the Resource-Based View (Barney et al., 2001; Grant, 1991), and the Dynamic Capabilities framework (Kim et al., 2011). Insights from these theories were further enriched through a preliminary analysis of the selected case studies to construct a solid conceptual research model.

To ensure the reliability and credibility of the secondary data in the mini-case studies, each was assessed for verifiable details, including: (1) the organization's contact information, (2) the roles, responsibilities, and positions of individuals involved, and (3) excerpts from interviews with these actors. For certain cases, we visited the official websites of the organizations to evaluate the extent of collaboration with their AI solution providers, and in some instances, we contacted organization members directly via the email addresses listed in the reports. Only case studies with a clearly defined or well-examined issue were included in the final sample. Each was evaluated based on its context, the challenges addressed, the stakeholders engaged in the transformation process, the results achieved, and its relevance to the research problem. Guiding questions included: Are the cases comparable? Are the research questions meaningful? Is the data presented in raw form or pre-analyzed?

The final sample comprised case studies covering diverse AI applications, such as: "*AI-powered customer query resolution in seconds; intelligent workflows enhancing insurance customer experiences; real-time, behavior-responsive smart marketing; predictive maintenance for machinery and equipment; image and video recognition in security applications; personalized financial planning; fraud detection and anti–money laundering systems; automation of banking and insurance transactions; customized design and manufacturing; automated inventory and delivery systems; media archiving and retrieval; creative content generation in music, marketing, and film; tailored marketing and advertising; optimization of supply chains and production systems; on-demand manufacturing; self-driving trucks and autonomous delivery; traffic and congestion management; improved safety measures; data-driven diagnostic support; pandemic detection; and advanced imaging diagnostics in radiology and pathology.*"

Table 4. Hypotesis Summary

No	Hypothesis	Results	Number of Case Studies
H1	AI management capabilities have a significant positive effect on AI capabilities, which are positively associated with the impact of AI at the process level	Supported	425
H2	AI personal expertise has a significant positive effect on AI capabilities, which are positively associated with the influence of AI at the process level	Supported	173
H3	AI infrastructure flexibility has a significant positive effect on AI capabilities, which are positively associated with the influence of AI at the process level	Supported	179
H4	The automational effect has a significant positive impact at the process level, which is positively associated with the influence of AI at the organizational level	Supported	397

No	Hypothesis	Results	Number of Case Studies
H5	The informational effect has a significant positive impact at the process level, which is positively associated with the influence of AI at the organizational level	Supported	455
H6	The transformational effect has a significant positive impact at the process level, which is positively associated with the influence of AI at the organizational level	Supported	426

4. Discussion

4.1. AI Capabilities

Findings from the case study analysis indicate that the effective integration of artificial intelligence (AI) in organizations relies on three core components: (1) scalable, high-speed computing infrastructure; (2) advanced algorithms such as machine learning, deep learning, and neural networks; and (3) extensive, high-quality datasets. Together, these elements form the foundation of AI capabilities, encompassing AI Management Capabilities (AIMC), AI Personal Expertise (AIPE), and AI Infrastructure Flexibility (AIIF).

The case evidence shows that organizations typically maintain direct control over AIMC, while AIPE and AIIF are often heavily dependent on external providers. In certain cases, organizational managers had only a limited understanding of AI's strategic value, relying on vendors such as IBM or Cloudera to supply both technical expertise and adaptable infrastructure for efficient data processing and value creation.

Notably, many organizations already possessed some form of IT resources, yet these were often underdeveloped, inefficient, or unsuitable for optimal AI deployment. By combining available resources with automated, intelligent processes supported by robust planning, coordination, and process control. Organizations were able to enhance decision-making quality and streamline workflows.

Regarding AIPE, two distinct scenarios emerged:

- On-site collaboration with AI providers – Direct vendor involvement facilitated needs assessment, algorithmic process modeling, and system deployment. This close partnership enabled organizations to reshape strategies, enhance competitiveness, and upgrade products and services.
- AI-as-a-Service (AIaaS) or Infrastructure-as-a-Service (AI IaaS) – In such arrangements, organizational staff typically did not gain significant exposure to provider expertise. Their involvement was limited to defining requirements, specifying data inputs, and using the final solution, with minimal skill transfer.

Overall, these three capabilities can significantly influence organizational processes, driving high performance and maximizing the business value derived from AI transformation initiatives.

4.2. Process Level

Case studies revealed that AI adoption at the process level is typically aimed at addressing a specific operational challenge, whether through automation, improved information flows, or transformational change. A deeper examination identified several recurring objectives:

- Re-engineering and redesigning organizational structures to enhance customer relationships.
- Automating core processes and procedures.
- Leveraging diverse internal and external data sources.
- Improving the collection, storage, processing, and dissemination of information within and across organizational boundaries.
- Restructuring processes to reduce costs, improve integration, and strengthen business intelligence.
- Enhancing process efficiency.
- Facilitating the acquisition and assimilation of knowledge from both internal and external sources.
- Configuring or reconfiguring resources to align with strategic goals.

The informational effects of AI improve administrative performance by enabling faster access to accurate data, enhancing decision quality, and boosting responsiveness in resource management. The automation effects observed in reduced redundancy, minimized human error, and increased real-time resource visibility, contribute directly to efficiency, reliability, and consistency in operational processes, thereby strengthening both administrative and marketing outcomes. As a disruptive technology, AI also generates transformational effects by enabling the creation of innovative products, services, and production processes that address evolving consumer needs. Examples from the case studies include process re-engineering to enhance customer value, decentralizing operational decision-making, raising customer satisfaction levels, and improving product and service quality. While earlier research often emphasized financial performance as the primary measure of AI's impact, our findings expand the perspective to include administrative and marketing performance. This broader view underscores AI's direct and indirect contributions to organizational outcomes and its role in delivering tangible business value through transformation projects.

5. Conclusions

5.1. Conclusion

The significance of AI has grown increasingly evident as the scope of digital transformation becomes clearer. Organizations are now recognizing the immense value embedded in the data they possess and the necessity of tools to fully leverage it. The advancement of AI is driven by two converging forces: the digitization of the economy coupled with the automation of existing processes, and the disruption brought by new service models that capitalize on data utilization.

In this research, which examined the impact of AI on organizational performance, a qualitative method was employed through the analysis of 500 case studies. This approach was chosen due to its ability to draw meaningful insights from secondary data, enabling a deeper understanding of each case, the extraction of organization-specific details, and the identification of the business value derived from AI transformation initiatives. It also allowed us to reveal AI's influence on both organizational and process-level performance. The findings from this qualitative assessment are summarized in the number of case studies supporting each proposition, as shown in Table 4.

Despite its potential, AI adoption remains a subject of mixed perspectives. While many see it as a groundbreaking technological advance with vast potential for organizational growth, its practical applications still face unresolved hurdles. A key concern is the absence of comprehensive regulations to govern AI operations and ensure ethical compliance (Dignum, 2018; Hooker & Kim Tae, 2019; PwC, 2018). Various bodies, including IEEE and CERNA, have begun formulating guidelines and issuing recommendations for researchers and developers to create intelligent yet ethical AI systems (Davis, 2005; Hooker & Kim Tae, 2019; Schweitzer & Puig-Verges, 2018).

The moral implications of AI are also drawing attention, especially in systems relying on deep learning and artificial neural networks, which are often criticized for their "black box" nature, offering little to no transparency on the reasoning behind algorithmic outputs. This raises an important trust issue: how can we rely on AI-generated decisions if their underlying logic remains beyond our understanding?

5.2. Limitation

This study has not limitation free. The information collected is based on secondary rather than primary sources, meaning that data are not captured in real time. In some cases, datasets may be incomplete or contain gaps. While the case studies provided substantial insight, there is the potential for bias such as overstated claims or restrictions on publicly shared information. To enhance accuracy and depth, we recommend using multiple data collection methods, including interviews, surveys, secondary data analysis, and direct observation. Such triangulation would enable cross-validation and yield richer, more comprehensive findings.

A future replication of this study that incorporates fieldwork, observations, and interviews with relevant organizations could offer additional perspectives and deepen the understanding of AI's influence on organizational performance. Furthermore, as this research is cross-sectional, it offers only a snapshot of the relationship between AI and organizational capacity at a single point in time. It does not account for how these relationships may evolve over extended periods.

A longitudinal approach could track how AI capabilities develop, identify which elements have the greatest impact on long-term performance, and assess productivity trends over time. One notable limitation of many reviewed studies is the lack of detailed data on the costs and timelines associated with AI-driven transformation projects. Evaluating these factors could equip organizations with clearer economic justifications for such investments, as well as practical guidance on resource allocation. Knowing project durations, for instance, would enable the creation of a detailed task schedule that accounts for dependencies and sequencing, thereby improving planning for future AI initiatives.

5.3. Implication

Every organization requires a clear operational strategy to achieve its goals, which can only be met when leaders mobilize adequate human, technological, and financial resources. The integration of Artificial Intelligence can address numerous organizational challenges by improving both process-level outcomes (automation, information flow, and transformation) and overall performance metrics (financial, marketing, and administrative results).

This study not only addresses the central question "Can AI create tangible benefits for my organization, and in what ways can it innovate?" but also offers practical guidance for overcoming internal challenges. To fully leverage AI, organizations should cultivate three critical capabilities:

- Mutualization – the capacity to adapt existing services for use across multiple contexts,
- Scalability – the ability to handle increasing volumes without compromising system architecture, and
- Resilience – the capability to maintain operations in the face of disruptions.

Analysis of the case studies suggests that AI adoption is best managed as a project-based initiative, requiring several preparatory and ongoing actions:

- Prepare and train leaders, employees, and stakeholders to understand the specific demands of AI-driven transformation,
- Ensure the quality and sustainability of jobs in human–machine collaboration contexts,
- Establish internal and external "control towers" to address ethical issues in data and algorithms,
- Recruit and retain AI-specific talent while anticipating shifts in skills, roles, and professional identities,
- Adapt training programs to meet higher volumes and evolving content,
- Adjust governance structures to balance centralized and decentralized decision-making,
- Support new AI-enabled workflows with cross-functional collaboration and transparency, while redefining managerial roles.

Unlike many prior studies that focus on a single AI technology in one sector such as healthcare, automotive, or finance. This research simultaneously examines the use of multiple AI technologies across a wide range of industries. This holistic perspective reflects the reality that most organizations benefit from a combination of AI solutions rather than a single technology. For solution providers, the findings underscore the importance of offering integrated AI systems that combine various technologies. For managers, they highlight the advantages of exploring multi-technology AI strategies to maximize performance gains. Ultimately, the study emphasizes the multifaceted nature of AI, framing it not as a singular innovation but as an adaptable suite of technological configurations applied across diverse business domains.

This research makes several contributions to the study of AI capabilities (AICAP) and their relationship with organizational performance. First, it is among the earliest works to assess the direct impact of AICAP on firm outcomes, thereby reinforcing the importance of investing in AI-related expertise and infrastructure flexibility. Such investments can significantly enhance the business value of AI transformation projects. Second, it expands the growing body of literature on the organizational benefits of AI, offering a foundation for future research into AI-enabled service innovations and cross-industry applications.

Acknowledgments: The authors would like to express their sincere gratitude to all individuals and institutions that provided administrative and technical support throughout this research. Special thanks are extended to Universitas Muhammadiyah Purwokerto for their valuable assistance and contributions.

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

References

Abijith, A., & Wamba, S. F. (2012). Business value of RFID-enabled healthcare transformation projects. *Business Process Management Journal*, *19*(1), 31. https://doi.org/10.1108/14637151311294895

Barney, J., Wright, M., & Ketchen, D. J. (2001). The resource-based view of the firm: Ten years after 1991. *Journal of Management, 27*(6), 625–641. https://doi.org/10.1016/S0149-2063(01)00114-3

Benko, A., & Lányi, C. S. (2009). History of artificial intelligence. In *Encyclopedia of Information Science and Technology* (2nd ed., pp. 1759–1762). IGI Global.

Benner, M. J. (2009). Dynamic or static capabilities? Process management practices and response to technological change. *Journal of Product Innovation Management, 26*(5), 473–486.

Bhatt, G., Emdad, A., Roberts, N., & Grover, V. (2010). Building and leveraging information in dynamic environments: The role of IT infrastructure flexibility as enabler of organizational responsiveness and competitive advantage. *Information & Management, 47*(7), 341–349. https://doi.org/10.1016/j.im.2010.08.001

Blanchet, M. J. O. T. (2016). Industrie 4.0 nouvelle donne industrielle, nouveau modèle économique. *Revue Européenne de Géopolitique, 1*, 62–85.

Bolwijn, R., Casella, B., & Zhan, J. (2018). International production and the digital economy. In R. van Tulder, A. Verbeke, & L. Piscitello (Eds.), *International business in the information and digital age* (Vol. 13, pp. 39–64). Emerald Publishing.

Brown, R. E., & Milner, P. M. (2003). The legacy of Donald O. Hebb: More than the Hebb synapse. *Nature Reviews Neuroscience, 4*(12), 1013–1019.

Buchanan, B. G. (2005). A (very) brief history of artificial intelligence. *AI Magazine, 26*(4), 53–53.

Campbell, M., Hoane, A. J., Jr., & Hsu, F. H. (2002). Deep Blue. *Artificial Intelligence, 134*(1–2), 57–83.

Chaumon, M.-E. B., Cuvillier, B., Sarnin, P., & Vacherand-Revel, J. (2018). Usage des TIC et évolutions des pratiques socioprofessionnelles des cadres: Quels repères pour le métier et quelles incidences sur la santé? *Pratiques Psychologiques, 24*(4), 349–373.

CIGREF. (2016). Gouvernance de l'intelligence artificielle dans les grandes entreprises: Enjeux managériaux, juridiques et éthiques. https://www.cigref.fr/wp/wp-content/uploads/2016/09/Gouvernance-IA-CIGREF-LEXING-2016.pdf

CIGREF. (2018). Intelligence artificielle et capital humain, quels défis pour les entreprises? https://www.cigref.fr/wp/wp-content/uploads/2018/10/Cigref-Intelligence-Artificielle-en-entreprise-Strategies-gouvernances-challenges-Data-Intelligence-2018.pdf

Crews, C. J. (2019). What machine learning can learn from foresight: A human-centered approach. *Research-Technology Management, 62*(1), 30–33.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340.

Davis, J. B. (2005). Neoclassicism, artificial intelligence, and the marginalization of ethics. *International Journal of Social Economics, 32*(7), 590–601. https://doi.org/10.1108/03068290510601126

DeLone, W. H., & McLean, E. R. (1992). Information systems success: The quest for the dependent variable. *Information Systems Research, 3*(1), 60–95.

DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: A ten-year update. *Journal of Management Information Systems, 19*(4), 9–30.

Devaraj, S., & Kohli, R. (2003). Performance impacts of information technology: Is actual usage the missing link? *Management Science, 49*(3), 273–289.

Di Francescomarino, C., & Maggi, F. M. (2020). Preface to the special issue on artificial intelligence for business process management 2018. *Journal on Data Semantics.* https://doi.org/10.1007/s13740-020-00111-w

Dignum, V. (2018). Ethics in artificial intelligence: Introduction to the special issue. *Ethics and Information Technology, 20*(1), 1–3. https://doi.org/10.1007/s10676-018-9450-z

Dopico, M., Gomez, A., De la Fuente, D., García, N., Rosillo, R., & Puche, J. (2016). A vision of Industry 4.0 from an artificial intelligence point of view. In *Proceedings on the International Conference on Artificial Intelligence (ICAI)*. The Steering Committee of the World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp).

Falcone, P., Borrelli, F., Asgari, J., Tseng, H. E., & Hrovat, D. (2007). Predictive active steering control for autonomous vehicle systems. *IEEE Transactions on Control Systems Technology, 15*(3), 566–580.

Farhanghi, A. A., Abbaspour, A., & Ghassemi, R. A. (2013). The effect of information technology on organizational structure and firm performance: An analysis of consultant engineers firms (CEF) in Iran. *Procedia - Social and Behavioral Sciences, 81*, 644–649. https://doi.org/10.1016/j.sbspro.2013.06.490

Faure, G., Barret, D., Blundo-Canto, G., Dabat, M.-H., Devaux-Spatarakis, A., Le Guerroué, J. L., Marquié, C., Mathé, S., Temple, L., Toillier, A., Triomphe, B., & Hainzelin, E. (2018). How different agricultural research models contribute to impacts: Evidence from 13 case studies in developing countries. *Agricultural Systems, 165*, 128–136. https://doi.org/10.1016/j.agsy.2018.06.002

Fink, L., & Neumann, S. (2009). Exploring the perceived business value of the flexibility enabled by information technology infrastructure. *Information & Management, 46*(2), 90–99. https://doi.org/10.1016/j.im.2008.11.007

Gabrilovich, E., & Markovitch, S. (2009). Wikipedia-based semantic interpretation for natural language processing. *Journal of Artificial Intelligence Research, 34*, 443–498.

Gelernter, H. L., & Rochester, N. J. (1958). Intelligent behavior in problem-solving machines. *IBM Journal of Research and Development, 2*(4), 336–345.

Godfrey, M. D., & Hendry, D. F. (1993). The computer as von Neumann planned it. *IEEE Annals of the History of Computing, 15*(1), 11–21.

Grant, R. M. (1991). The resource-based theory of competitive advantage: Implications for strategy formulation. *California Management Review, 33*(3), 114–135.

Ha, B. M., & Jeong, S. R. (2010). Analysis of the relationship between corporate IT capability and corporate performance through Korea IT success cases: An empirical approach. *Asia Pacific Journal of Information, 20*(3), 91–114.

Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California Management Review, 61*(4), 5–14.

Hamet, P., & Tremblay, J. (2017). Artificial intelligence in medicine. *Metabolism, 69*, S36–S40.

Henderson, J. C., & Venkatraman, H. (1999). Strategic alignment: Leveraging information technology for transforming organizations. *IBM Systems Journal, 38*(2–3), 472–484.

Hooker, J., & Kim, T. W. (2019). Ethical implications of the fourth industrial revolution for business and society. *Business Ethics, 3*, 35–63.

Husbands, P., Holland, O., & Wheeler, M. (2008). An interview with Oliver Selfridge. In *The mechanical mind in history* (pp. 399–412). Springer. https://doi.org/10.1007/978-3-540-30194-3_12

Hutchins, W. J. (2004). The Georgetown-IBM experiment demonstrated in January 1954. In *Proceedings of the Conference of the Association for Machine Translation in the Americas*. Springer.

Jain, A. K., Ross, A., & Prabhakar, S. (2004). An introduction to biometric recognition. *IEEE Transactions on Circuits and Systems for Video Technology, 14*(1), 4–20.

Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., Wang, Y., Dong, Q., Shen, H., & Wang, Y. (2017). Artificial intelligence in healthcare: Past, present and future. *Stroke and Vascular Neurology, 2*(4), 230–243.

Johnson, K. W., Soto, J. T., Glicksberg, B. S., Shameer, K., Miotto, R., Ali, M., Ashley, E., & Dudley, J. T. (2018). Artificial intelligence in cardiology. *Journal of the American College of Cardiology, 71*(23), 2668–2679. https://doi.org/10.1016/j.jacc.2018.03.521

Kelly, C. J., Karthikesalingam, A., Suleyman, M., Corrado, G., & King, D. (2019). Key challenges for delivering clinical impact with artificial intelligence. *BMC Medicine, 17*(1), 195. https://doi.org/10.1186/s12916-019-1426-2

Khashman, A. (2009). Application of an emotional neural network to facial recognition. *Neural Computing and Applications, 18*(4), 309–320.

Kijek, T., & Kijek, A. (2019). Is innovation the key to solving the productivity paradox? *Journal of Innovation and Knowledge, 4*(4), 219–225. https://doi.org/10.1016/j.jik.2017.12.010

Kim, G., Shin, B., Kim, K. K., & Lee, H. G. (2011). IT capabilities, process-oriented dynamic capabilities, and firm financial performance. *Journal of the Association for Information Systems, 12*(7), 487.

Kline, R. J. (2010). Cybernetics, automata studies, and the Dartmouth conference on artificial intelligence. *IEEE Annals of the History of Computing, 33*(4), 5–16.

Koh, H. C., & Tan, G. (2011). Data mining applications in healthcare. *Journal of Healthcare Information Management*, *19*(2), 65.

Kohn, M. S., Sun, J., Knoop, S., Shabo, A., Carmeli, B., Sow, D., Syed-Mahmood, T., & Rapp, W. (2014). IBM's health analytics and clinical decision support. *Yearbook of Medical Informatics, 23*(1), 154–162.

Koski, H. (1999). The implications of network use, production network externalities and public networking programmes for firm's productivity. *Research Policy, 28*(4), 423–439.

Kuusisto, M. (2017). Organizational effects of digitalization: A literature review. *International Journal of Organization Theory and Behavior, 20*(3), 341–362. https://doi.org/10.1108/IJOTB-20-03-2017-B003

Kuzey, C., Uyar, A., & Delen, D. (2014). The impact of multinationality on firm value: A comparative analysis of machine learning techniques. *Decision Support Systems, 59*, 127–142. https://doi.org/10.1016/j.dss.2013.11.001

Lauterbach, A. (2019). Artificial intelligence and policy: Quo vadis? *Digital Policy, Regulation and Governance, 21*(3), 238–263. https://doi.org/10.1108/DPRG-09-2018-0054

Lebas, M. J. (1995). Performance measurement and performance management. *International Journal of Production Economics, 41*(1–3), 23–35.

Lee, J., Davari, H., Singh, J., & Pandhare, V. (2018). Industrial artificial intelligence for Industry 4.0-based manufacturing systems. *Manufacturing Letters, 18*, 20–23.

Lehr, B., & Lichtenberg, F. R. (1999). Information technology and its impact on productivity: Firm-level evidence from government and private data sources, 1977–1993. *The Canadian Journal of Economics, 32*(2), 335–362.

Lichtenberg, F. R. (1995). The output contributions of computer equipment and personnel: A firm-level analysis. *Economics of Innovation and New Technology, 3*(3–4), 201–218.

Liu, H., Ke, W., Wei, K. K., & Hua, Z. (2013). The impact of IT capabilities on firm performance: The mediating roles of absorptive capacity and supply chain agility. *Decision Support Systems, 54*(3), 1452–1462.

Liu, H., Huang, Q., Wei, S., & Huang, L. (2015). The impacts of IT capability on internet-enabled supply and demand process integration, and firm performance in manufacturing and services. *The International Journal of Logistics Management, 26*(1), 172–194. https://doi.org/10.1108/IJLM-11-2013-0132

McCarthy, J. (1989). Artificial intelligence, logic and formalizing common sense. In *Philosophical Logic and Artificial Intelligence* (pp. 161–190). Springer.

McCarthy, J., Minsky, M. L., Rochester, N., & Shannon, C. E. (2006). A proposal for the Dartmouth summer research project on artificial intelligence (1955). *AI Magazine, 27*(4), 12–12.

McCorduck, P., Minsky, M., Selfridge, O. G., & Simon, H. A. (1977). History of artificial intelligence. In *Proceedings of the International Joint Conferences on Artificial Intelligence (IJCAI)* (pp. 951–954).

Meyer, B. (2015). Case studies. In *Researching Translation and Interpreting* (pp. 195–202). Routledge.

Minsky, M. (2007). *The emotion machine: Commonsense thinking, artificial intelligence, and the future of the human mind*. Simon and Schuster.

Minsky, M., & Papert, S. A. (1972). *Artificial intelligence progress report*. M.I.T., Project MAC.

Mooney, J. G., Gurbaxani, V., & Kraemer, K. L. (1996). A process-oriented framework for assessing the business value of information technology. *ACM SIGMIS Database: The DATABASE for Advances in Information Systems, 27*(2), 68–81.

Nwamen, F. J. (2006). Impact des technologies de l'information et de la communication sur la performance commerciale des entreprises. *La Revue des Sciences de Gestion, 2*, 111–121.

Polak, P. (2017). The productivity paradox: A meta-analysis. *Information Economics and Policy, 38*, 38–54. https://doi.org/10.1016/j.infoecopol.2016.11.003

Ponelis, S. R. (2015). Using interpretive qualitative case studies for exploratory research in doctoral studies: A case of information systems research in small and medium enterprises. *International Journal of Doctoral Studies, 10*, 535–550.

PwC. (2018). L'intelligence artificielle: Quelle place pour la morale? https://www.pwc.fr/fr/decryptages/transformation/ia-quelle-place-pour-la-morale.html

PwC. (2019). Sizing the prize: Exploiting the AI revolution. What's the real value of AI for your business and how can you capitalise? https://www.pwc.com/gx/en/issues/data-and-analytics/publications/artificial-intelligence-study.html

Queiroz Maciel, M., Pereira, S. C. F., Telles, R., & Machado, M. C. (2019). Industry 4.0 and digital supply chain capabilities: A framework for understanding digitalisation challenges and opportunities. *Benchmarking: An International Journal*. Advance online publication. https://doi.org/10.1108/BIJ-12-2018-0435

Rachinger, M., Rauter, R., Müller, C., Vorraber, W., & Schirgi, E. (2019). Digitalization and its influence on business model innovation. *Journal of Manufacturing Technology Management, 30*(8), 1143–1160. https://doi.org/10.1108/JMTM-01-2018-0020

Ridder, H. G. (2017). The theory contribution of case study research designs. *Business Research, 10*(2), 281–305. https://doi.org/10.1007/s40685-017-0045-z

Rochester, N., Holland, J., Haibt, L., & Duda, W. (1956). Tests on a cell assembly theory of the action of the brain, using a large digital computer. *IRE Transactions on Information Theory, 2*(3), 80–93.

Rubin, V. L., Chen, Y., & Thorimbert, L. M. (2010). Artificially intelligent conversational agents in libraries. *Library Hi Tech, 28*(4), 496–522. https://doi.org/10.1108/07378831011096196

Ruiz-Mercader, J., Meroño-Cerdan, A. L., & Sabater-Sánchez, R. (2006). Information technology and learning: Their relationship and impact on organisational performance in small businesses. *International Journal of Information Management, 26*(1), 16–29. https://doi.org/10.1016/j.ijinfomgt.2005.10.003

Santos, J. B., & Brito, L. A. (2012). Toward a subjective measurement model for firm performance. *BAR - Brazilian Administration Review, 9*(SPE), 95–117.

Schweitzer, M. G., & Puig-Verges, N. (2018). La robotique développementale et l'intelligence artificielle conduiront-elles à l'émergence de nouvelles valeurs pour l'homme? *Annales Médico-psychologiques, Revue Psychiatrique, 176*(3), 291–295. https://doi.org/10.1016/j.amp.2018.01.008

Sheth, A. (2016). Internet of things to smart IoT through semantic, cognitive, and perceptual computing. *IEEE Intelligent Systems, 31*(2), 108–112. https://doi.org/10.1109/MIS.2016.34

Shortliffe, E. H., Davis, R., Axline, S. G., Buchanan, B. G., Green, C. C., & Cohen, S. N. (1975). Computer-based consultations in clinical therapeutics: Explanation and rule acquisition capabilities of the MYCIN system. *Computers and Biomedical Research, 8*(4), 303–320.

Sikdar, S. (2018). Artificial intelligence, its impact on innovation, and the Google effect. *Clean Technologies and Environmental Policy, 20*(1), 1–2. https://doi.org/10.1007/s10098-017-1478-y

Solomonoff, R. J. (1997). The discovery of algorithmic probability. *Journal of Computer and System Sciences, 55*(1), 73–88.

Srivastava, S., Bisht, A., & Narayan, N. (2017). Safety and security in smart cities using artificial intelligence—A review. In *Proceedings of the 2017 7th International Conference on Cloud Computing, Data Science and Engineering—Confluence* (pp. 727–732). IEEE.

Stank, T., Esper, T., Goldsby, T. J., Zinn, W., & Autry, C. (2019). Toward a digitally dominant paradigm for twenty-first century supply chain scholarship. *International Journal of Physical Distribution and Logistics Management, 49*(10), 956–971. https://doi.org/10.1108/IJPDLM-03-2019-0076

Tractica. (2018). Artificial intelligence market forecasts. https://www.tractica.com/research/artificial-intelligence-market-forecasts/

Triplett, J. E. (1999). The Solow productivity paradox: What do computers do to productivity? *The Canadian Journal of Economics, 32*(2), 309–334.

Turing, A. M. (2009). Computing machinery and intelligence. In *Parsing the Turing test* (pp. 23–65). Springer.

Turulja, L., & Bajgoric, N. (2018). Information technology, knowledge management and human resource management: Investigating mutual interactions towards better organizational performance. *VINE Journal of Information and Knowledge Management Systems, 48*(2), 255–276. https://doi.org/10.1108/VJIKMS-06-2017-0035

Verdú, S. (1998). Fifty years of Shannon theory. *IEEE Transactions on Information Theory, 44*(6), 2057–2078.

Vochozka, M., Kliestik, T., Kliestikova, J., & Sion, G. (2018). Participating in a highly automated society: How artificial intelligence disrupts the job market. *Economics, Management, and Financial Markets, 13*(4), 57–62.

Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research, 70*, 356–365. https://doi.org/10.1016/j.jbusres.2016.08.009

Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic Management Journal, 5*(2), 171–180.

Wiljer, D., & Hakim, Z. (2019). Developing an artificial intelligence–enabled health care practice: Rewiring health care professions for better care. *Journal of Medical Imaging and Radiation Sciences, 50*(4 Suppl 2), S8–S14. https://doi.org/10.1016/j.jmir.2019.09.010

Shoham, Y., Perrault, R., Brynjolfsson, E., Clark, J., Manyika, J., Niebles, J. C., Lyons, T., Etchemendy, J., Grosz, B., & Bauer, Z. (2018). *Artificial intelligence index 2018 annual report*. https://creativecommons.org/licenses/by-nd/4.0/legalcode

Zemouri, R., Devalland, C., Valmary-Degano, S., & Zerhouni, N. (2019). Intelligence artificielle: Quel avenir en anatomie pathologique? *Annales de Pathologie*. https://doi.org/10.1016/j.annpat.2019.01.004

Zhong, Y. (2008). Structuralism? Functionalism? Behaviorism? Or mechanism? Looking for a better approach to AI. *International Journal of Intelligent Computing and Cybernetics, 1*(3), 325–336. https://doi.org/10.1108/17563780810893437

Zmud, R. W. (1979). Individual differences and MIS success: A review of the empirical literature. *Management Science, 25*(10), 966–979.