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AS MUDANÇAS DE PROCESSOS DE NEGÓCIOS NA IMPLEMENTAÇÃO DE INTELIGÊNCIA ARTIFICIAL

BUSINESS PROCESSES CHANGES ON THE IMPLEMENTATION OF ARTIFICIAL INTELLIGENCE

OSCAR DO AMARAL ADORNO

Orientador: Prof. Dr. Paulo Tromboni de Souza Nascimento

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Dissertação apresentada ao Programa de Pós-Graduação em Administração do Departamento de Administração da Faculdade de Economia, Administração e Contabilidade da Universidade de São Paulo, como requisito parcial para a obtenção do título de Mestre em Ciências.

Orientador : Prof. Dr. Paulo Tromboni de Souza Nascimento

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“Imagination will often carry us to worlds that never were. But without it we go nowhere.”

Carl Sagan, Cosmos (1980) Ch 1.

RESUMO

Adorno, O. A. (2020). *As Mudanças de Processos de Negócios na implementação de Inteligência Artificial*. Dissertação de Mestrado. Faculdade de Administração, Economia e Contabilidade da Universidade de São Paulo, São Paulo, SP, Brasil.

O processo de transformação digital é um fenômeno que afetará todas as organizações. Nas empresas que já iniciaram a transformação digital começam a aparecer soluções de Inteligência Artificial (IA). Quais os desafios e mudanças de processos se vislumbram ou já estão em andamento em empresas brasileiras nesse campo? Projetos dessa natureza promovem novos desafios e geram mudanças organizacionais nos processos de negócio, operacionais e administrativos. As iniciativas de IA apresentarão um impacto competitivo nas organizações líderes em transformação digital. Nosso objetivo foi a identificação de mudanças, potenciais efeitos e impactos das tecnologias de IA nos processos de negócios, dinâmica das transformações, estruturas organizacionais e administração. Esta pesquisa qualitativa examinou casos de cinco grandes empresas: quatro subsidiárias multinacionais sediadas no Brasil e uma empresa brasileira. Seus setores são de telecomunicações e tecnologia, serviços profissionais, serviços de logística, produtos químicos e serviços financeiros. As empresas estão engajadas em uma transformação digital de longo prazo e na implantação da IA. Diferentes empresas têm estruturas organizacionais distintas para gerenciamento de portfólio e implementação de projetos de IA. Seus desafios e mudanças foram identificados por meio da análise de conteúdo com protocolo de entrevista semiestruturada. Foram coletados dados publicamente disponíveis e dados fornecidos pelas empresas. Os principais desafios relatados foram priorização e seleção de projetos de IA, falta de pessoas com as competências necessárias, problemas relacionados a gestão da mudança, resistência cultural e integração com processos e sistemas existentes. Os processos de negócios mais afetados abrangem os serviços de atendimento tanto externo (clientes) como interno (funcionários) e processos de atividades internas (análise de documentos, saúde, fiscal e cadastro de fornecedores). O avanço do trabalho profissional e acadêmico nesse campo tem grande relevância neste momento, pois profissionais e acadêmicos estão começando a compreender o potencial transformador das tecnologias de IA em nossa sociedade.

Palavras-chave: Transformação digital, processos de negócio, inteligência artificial, implementação

ABSTRACT

Adorno, O. A. (2020*). Business Process Changes on the Implementation of Artificial Intelligence*. Dissertação de Mestrado. Faculdade de Administração, Economia e Contabilidade da Universidade de São Paulo, São Paulo, SP, Brasil.

The process of digital transformation will affect all organizations. In businesses that have already started this process, artificial intelligence (AI) solutions have begun to appear. What are the current or incoming challenges and business process changes for Brazilian companies on this journey? Projects on digital transformation pose new challenges and cause organizational changes in business, operational and administrative processes. AI initiatives will have a competitive impact on organizations leading digital transformation. Our objective was to identify changes, potential effects, and impacts of AI technologies on business processes, transformation dynamics, organizational structures, and management. This qualitative research examined the cases of five large companies: four multinational subsidiaries based in Brazil and one Brazilian company. Their industries were telecom & technology, professional services, logistics services, chemistry, and financial services. These companies have been engaged in a long-term digital transformation and AI implementation. Different companies have distinct organizational structures for portfolio management and project implementation. Their challenges and changes were identified through content analysis with a semi-structured interview protocol. Publicly available data and data provided by the companies were collected. The main reported challenges were prioritization and selection of AI projects, lack of people with the required abilities, change management issues, cultural resistance, and integration with existing processes and systems. The most affected business processes were assistance services: external (customers) and internal relationships (employees) and process of internal activities (document analysis, health, and fiscal and supplier registration). Improving professional and academic work in this field has great relevance at this moment, as professionals and scholars have begun to understand the transformative potential of AI technologies in our society.

Keywords: Digital transformation, business processes, artificial intelligence, implementation

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SUMMARY

1 INTRODUCTION

In the past years, the terms “Industry 4.0” and “Fourth Industrial Revolution” have conquered the position of most discussed subjects in magazines, fairs, and conferences related to manufacturing and business operations. Due to their great impacts around the world, these topics were on the agenda of the 2016 Davos World Economic Forum, in articles in the international press, and in reports from major consulting companies, such as Boston Consulting Group and McKinsey & Company, and from major global technology suppliers, such as General Electric, SAP, Oracle, and Siemens.

The title *Industrie 4.0* was created in Germany in 2011. It named a program to fortify the German industry, the *Plattform Industrie 4.0*, designed to face rising foreign competitive threats, mainly from Eastern countries (Plattform Industrie 4.0, 2019; Vogel-Heuser & Hess, 2016). The program succeeded in allocating large investments to new information and communication technologies applied to manufacturing, which aimed to impact the productivity, quality, flexibility, and sustainability of supply chains (Kang et al., 2016). Moreover, the fourth industrial revolution enabled the rise of “smart factories” and a world where virtual and physical manufacturing systems globally cooperate with each other in a flexible way (Schwab, 2017).

In terms of data-related technologies, the main areas of Industry 4.0 are (i) Cyber Physical Systems (CPS), (ii) Industrial Internet of Things (IIoT), (iii) Cloud Solutions & Decentralized Services, and (iv) Big Data & Stream Processing (Nabati E.G., 2017; Tao et al., 2018). In terms of use cases, Industry 4.0 has the following three areas: (i) intelligent products (Porter, M. E.; Heppelmann, 2014), (ii) intelligent processes, and (iii) intelligent machines (Sahal et al., 2020). Concerning intelligent products, Industry 4.0 applications manage all necessary information about products and the production processes connected on them. Intelligent processes focus on the results and consequences of product creation, including asset information management (Wang et al., 2017). Intelligent machine scenarios focus on industrial machinery performance and applications that predict breakdowns, detect quality issues, and indicate the need for preemptive maintenance, for example.

Schwab (2017) stated that the fourth revolution promotes a staggering “confluence of emerging technology breakthroughs, covering a wide-ranging field such as Artificial Intelligence (AI), robotics, internet of thing (IoT), autonomous vehicles, 3D printing, nanotechnology, biotechnology, materials science, energy storage and quantum computing to name a few".

Muhuri et al. (2019) found that Germany and China were the most productive countries in Industry 4.0 while the South China University of Technology in China is the institute with the highest number of publications. The most common keywords were cyber–physical system, internet of things, smart manufacturing and simulation.

Haeffner & Panuwatwanich (2018) performed a study to understand the effects of Industry 4.0 on the manufacturing process and on the skills and knowledge required from the workforce over the next decades. They reviewed the literature and conducted semi-structured interviews with experts within Germany's manufacturing context. Based on their results, the manufacturing process will become more integrated, and robots and machines will increasingly support or even replace manual labor, enabling more autonomous, independent and dynamic manufacturing. For workforce implications, Haeffner & Panuwatwanich (2018) observed an increase in the required skills and knowledge.

Other countries have undertaken similar initiatives. Three initiatives in the United States had a great global impact: The Industrial Internet Consortium, promoter of the term IIoT, the Smart Manufacturing Leadership Coalition, with the term smart manufacturing, and the US Advanced Manufacturing Partnership (Executive Office of the President, 2012). Other important regional movements are *Nouvelle France Industrielle*, from France (Conseil National Del'industrie, 2014), European Factories of the Future Research Association, from the European Union, Smart Industry, from the Netherlands (European Commission, 2013), and Future of Manufacturing, from the United Kingdom (Foresight, 2013). In response, Eastern countries with important industrial economies also presented programs, such as China's Made in China 2025 (State Council of China, 2015), Innovation in Manufacturing 3.0 in South Korea (Kang et al., 2016), Research, Innovation and Enterprise in Singapore (National Research Foundation, 2016), and Robot Revolution Initiative Society 5.0 in Japan (New Robot Strategy, 2015).

In 2019, the Brazilian government—coordinated by the ministries of Science, Technology, Innovations, and Communications (MCTIC) and Economy (ME)—built an industry action plan for the period from 2019 to 2022 called *Indústria 4.0.* The government partnered with more than 30 government, private, and research institutions. The plan created the Brazilian Chamber of Industry 4.0 to increase the competitiveness and productivity of Brazilian companies through advanced manufacturing (Ministério da Economia, 2019). In that direction, MCTIC announced the creation of eight artificial intelligence (AI) laboratories in Brazil. One of the AI centers is InovaUSP – Innovation Center, located at the University of São Paulo, São Paulo, Brazil (Cruz, 2019).

Integrating and exploiting new digital technologies is one of the biggest challenges that companies currently face. No industry or organization is immune to the effects of digital transformation (DT). The market-changing potential of digital technologies is often wider than products, business processes, sales channels, or supply chains—entire business models have been reshaped and frequently overturned (Downes & Nunes, 2013).

Alongside the evolution of new, mobile, and internet-based technologies, there are financial crises and economic developments, which have supported the changing needs and behaviors of customers. However, these scenarios have put a heavy pressure on the world's and countries' economy, budget deficits, financial services, and businesses, especially on the profitability and revenue sides of financial sheets (Dirican, 2015).

New technologies oftentimes have a great potential to create value and are widely recognized as competitive weapons (G. P. Pisano & Hayes, 1995; Porter, 1985; Skinner, 1986). John Chambers, former CEO of Cisco, forecast, "at least 40% of all businesses will die in the next 10 years… if they do not figure out how to change their entire company to accommodate new technologies" (Ross, 2015).

AI has driven changes in business and organizational activities, as well as in underlying processes and skills (Van der Meulen, 2018). After the AI "winters" (1974-1980s and 1987-1993), during which AI development encountered substantive obstacles, an AI "summer" started: workplace professionals and work designers have joined the current so-called AI arms race by introducing a variety of AI-augmented tools and applications to work design experimentation, attributing specific types of intelligence to machines (Moore, 2019). AI is poised to transform every industry, just as electricity did 100 years ago (E Brynjolfsson & McAfee, 2017; Ng, 2019).

According to IDC (2020a), investments in cognitive and AI systems will reach $99.9 billion by 2023, more than 2.5 times the $37.5 billion spent in 2019. The Compound Annual Growth Rate (CAGR) for the 2018-2023 forecast will be 28.4%. Organizations worldwide have increased their investments in AI by 23% in 12 months, and they are expected to double it over the next two years (Vanson Bourne, 2019).

By 2025, AI-powered enterprises will see a 100% increase in knowledge worker productivity, resulting in shorter reaction times due to anticipated market and operational changes, greater product innovation success, and improved customer satisfaction (a 1.5 times higher Net Promoter Score [NPS] than competitors' due to the companies' capability to offer a wider variety of experiences) (Bailey et al., 2020). A survey with 2,360 corporations indicated that 58% of respondents reported that they were using AI in at least one function or business unit in 2019, an increase of 11% compared to 2018 (McKinsey & Company, 2019).

The rise of AI presents an opportunity in all industries to differentiate and defend businesses. But implementing a company-wide AI strategy is challenging, especially for legacy enterprises (Ng, 2019). According to Brynjolfsson & McAfee (2017), the bottleneck for AI is in management, implementation, and business imagination.

Companies across industries have increasingly relied on AI technologies to automate structured and repetitive work processes, gain insights through extensive analysis of large datasets, and engage with customers and employees in new ways (T. H. Davenport, 2018). As a result, AI may alter work and organization in significant ways, and scholars have recently debate to what extent this technology will substitute or complement humans in the workforce (Aleksander, 2017; Larson, 2010). Research is required to identify the effects of AI technologies on transforming expertise in organizations (Beane, 2019), offering novel forms of coordination and control (Faraj et al., 2018), developing organizational capabilities for leveraging AI (Tarafdar et al., 2019), changing the nature and the future of work (Ford, 2015; Schwartz et al., 2019), among other situations. There is still room to explore the conditions under which new human-machine configurations can or cannot be affected, such as amplifying human abilities, performing key processes autonomously, contributing to innovativeness, and affecting a both short-term and sustained competitive advantage (Benbya & Leidner, 2018; James Wilson & Daugherty, 2018; Yan et al., 2018).

According to Ransbotham et al. (2017), companies also face many managerial challenges regarding technology-driven transformations. These challenges include vision and leadership, openness and ability to change, long-term thinking, close alignment between business and technology strategy, and effective collaboration. When implementing AI, management challenges include the following (Ransbotham et al., 2017):

(i) Developing an intuitive understanding of AI. A basic understanding of how AI techniques work, how programs learn from data, and how AI can benefit a particular business.

(ii) Organizing for AI. Adopting AI broadly will likely place a premium on soft skills and organizational flexibility. There are different implementation models—such as centralized, distributed, and hybrid—but ultimately, a hybrid model emphasizing cross-functional collaboration may make more sense. "*We have to bring in people from different disciplines. And then, of course, we need the machine learning and AI people*" and "*Somebody who can lead that type of team holistically is very important*" said Wells Fargo's Executive vice president, corporate model risk, Agus Sudjianto. Organizational flexibility is a centerpiece in all AI models. In large companies, the culture change required to implement AI is daunting, according to executives.

(iii) Competitive landscape. How can humans and computers build on each other's strengths? Amy Hoe, Chief Technology and Operation Officer of the insurance company FWD Group, says that companies need privileged access to data (which many companies do not have, according to our findings). They need to put in place flexible organizational structures and learn how to make people and machines work effectively together. These requirements mean tough cultural changes for both the company and its employees. Davenport (2018) discussed that cognitive technologies are not implemented overnight. A set of barriers and challenges affect the broad implementation of AI solutions, such as process applications and organizational implications.

In this context, to engage in the DT journey and remain competitive in their industries, companies need to understand the business process changes cause by the implications of DT, especially AI implementations. It is essential to improve our understanding about the potential effects of AI technologies on organizations.

1.1 Research question

From the literature review and our case studies, we generated research questions to guide the study:

Research Question 1 (R1): What are the main impacts and changes in business processes caused by the adoption of AI solutions?

Thus, this study seeks to identify primarily the impact of AI implementation on business processes.

Additionally, this inquiry analyzes in more detail:

Research Question 2 (R2): *How was AI implemented in each company?*

Research Question 3 (R3): *What are the main implementation challenges?*

Research Question 4 (R4): *What are the main impacts on business?*

Research Question 5 (R5): *How does the integration of AI solutions interact with current business operations?*

1.2 Objectives

For this investigation, we outlined the following objectives:

- General objective: to assess the main changes in business processes in an AI implementation project.

Specific objectives:

- To identify the project roadmap for the DT journey;
- To analyze which AI initiatives and technologies have been or are being implemented;
- To assess the responsibilities of initiatives and changes in the organizational structure;
- To analyze the main implementation challenges in AI projects;
- To identify whether AI projects had the expected outcome and unintended consequences of AI implementation and benefits;
- To analyze the impacts on business, operational, and management processes;

- To analyze the integration of new digital technology with existing technology and data issues;
- To analyze similarities and differences between AI projects in companies from distinct industries;

Moreover, based on the literature and on practical cases, a complementary objective was to assist management leaders in understanding the challenges and impacts of an AI project in a DT background on the organization.

1.3 Motivation

In recent years, firms in almost all industries have conducted several initiatives to explore new digital technologies and exploit their benefits. In Brazil, for example, the Bradesco bank has partnered with IBM to develop BIA (*Bradesco Inteligência Artificial*, or Bradesco Artificial Intelligence). This project started with employees in branches using AI to answer common customer questions about the bank's products and services. Currently, BIA is trained in several products and services, answering an average of 300,000 questions per month, with an accuracy rate of 95% (Segura, 2018).

Dasa, a diagnostic medicine company, has created DasAInova, an internal advanced research laboratory structure, to study and develop solutions for AI. The company has developed algorithms to perform computational analyses of image examinations and alert specialists about which examination should be prioritized. The technology also allows verifications in the existing medical bibliography and cross-check information (DASA, 2020).

Sky—a satellite TV operator—uses AI to coordinate its telecommunication operation: the company has developed a control panel that catalogs and analyzes more than one million daily alerts of the system, about all types of problems that may affect the company's broadband operation. Moreover, Sky has a virtual agent with a technical diagnosis for customer service, which currently handles 25% of the 175 calls received per month, and an AI trading portal for collection and retention (Bluelab, 2020; Sandoval, n.d.; Segura, 2018).

These initiatives change key business operations and affect products, processes, organizational structures, and management concepts. Companies need to establish management practices to govern these complex transformations (T Hess et al., 2016; Matt et al., 2015).

Faced with the DT challenge and the need to remain competitive in their industries, business leaders must formulate and execute strategies that embrace the implications of DT and drive better operational performance. Unfortunately, many organizations have failed to keep pace with the new digital reality. Prominent examples include the bankruptcy of the movie-rental company Blockbuster and the sale of *The Washington Post* to Jeff Bezos, founder of Amazon—largely resulting from those firms' inability to rapidly develop and implement new digital-based business models (T Hess et al., 2016).

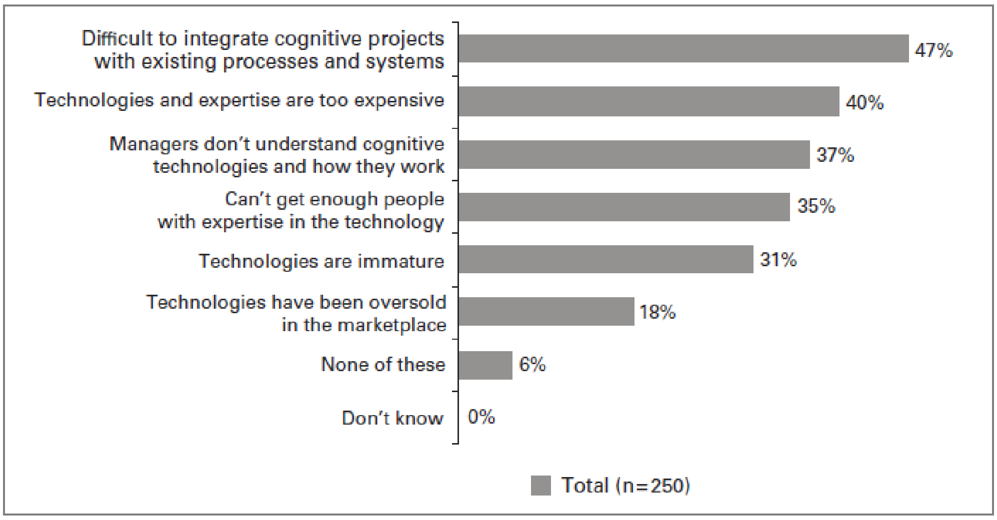
The AI movement is expected to transform jobs, processes, supply chains, business models, and social structures (Brynjolfsson & McAfee, 2017; Downes & Nunes, 2013).

Incumbent businesses also have some difficulties in integrating and implementing AI solutions. They typically have a set of legacy IT systems and well-developed business processes that drive and inform their activities (Davenport, 2018; Ng, 2019). Integrating AI-based decisions and actions into their businesses is a hard mission. If, for example, a company has developed a new set of sales propensity models to identify the most likely buyers of particular products and services, integrating the recommendations into customer relationship management systems and processes and into salespeople's behavior is a hard job. Big companies often also have bureaucratic planning processes and well-established capital allocation processes that do not change as often as they should. Nevertheless, they are generally more likely to implement AI than small- to mid-sized companies. Unfortunately for those smaller firms, AI is likely to help big companies get bigger (Davenport, 2018).

Davenport & Ronanki (2018) stated that before a business begins implementing an AI initiative, it must understand which technologies perform what types of tasks and the strengths and limitations of each. Rule-based expert systems and Robotic Process Automation (RPA), for example, are transparent in how they do their work, but neither is capable of learning or improving. Deep learning, in contrast, is great at learning from large volumes of labeled data, but it is almost impossible to understand how it creates its models. This "black box" issue can be problematic in highly regulated industries such as financial services, in which regulators insist on knowing why decisions are made in a certain way (Davenport, 2018).

Davenport et al. (2017), in a Deloitte's survey on cognitive awareness reported that senior executives faced challenges working with cognitive technologies. Forty-seven percent found it "difficult to integrate cognitive projects with existing processes and systems." In terms of other challenges, 40% felt that "technologies and expertise are too expensive," and 37% noted "managers do not understand cognitive technologies and how they work." Thirty-five percent of respondents reported being challenged because they could not "get enough people with expertise in the technology." Fewer people felt that "technologies are immature" (31%) or that "technologies have been oversold in the marketplace" (18%). The report stated that companies typically react to these feelings by postponing their implementations of technologies. Figure 1 shows the survey's results.

Figure 1. Challenges encountered with AI/cognitive technologies



Source: Davenport et al., 2017

Implementation can be a challenge with any technology but given the relative innovation of AI tools and the low levels of experience with them, this was expectedly the most-cited challenge. Integration into the business is also problematic for technologies in general, but particularly so for AI given its potential impact on knowledge workers' tasks and skills. The following year's survey by Deloitte—*State of AI in the Enterprise* (Loucks et al., 2018)—found that AI implementation by integration into roles and functions as well as measuring and proving the business value of AI solutions were top challenges of AI initiatives (Table 1).

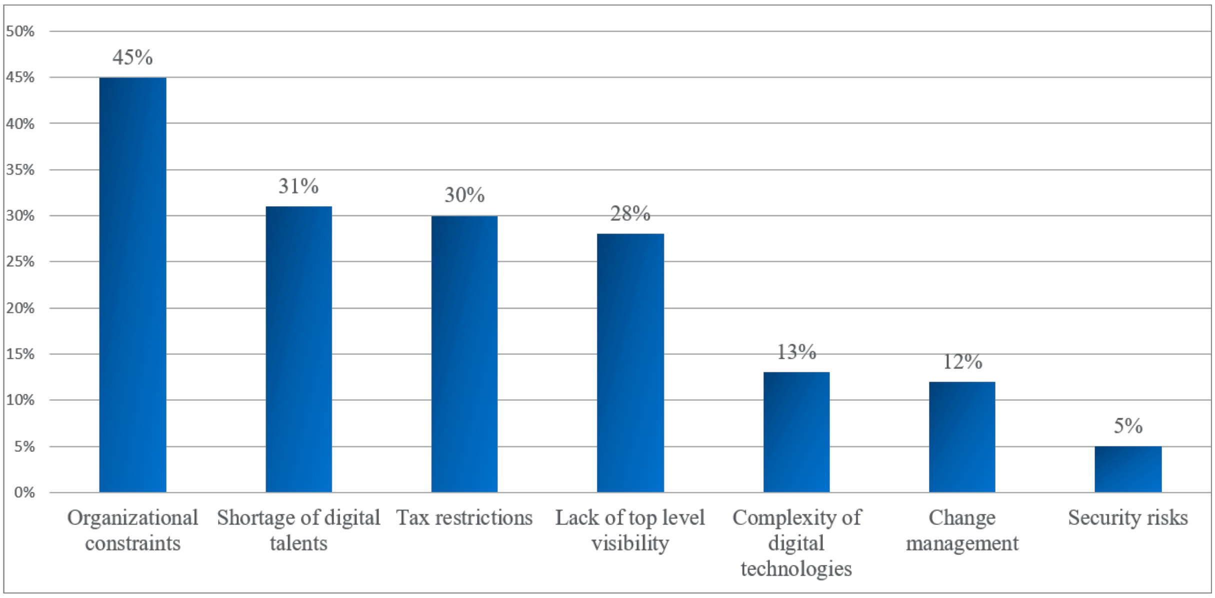
Table 1. Top challenges for AI initiatives

	Ranked 1	Ranked 2	Ranked 3	Ranked top three
Implementation challenges	13%	14%	12%	39%
Integrating AI into the company's roles and functions	14%	13%	12%	39%
Data issues (e.g., data privacy, accessing and integrating data)	16%	13%	10%	39%
Cost of AI technologies/ solution development	13%	12%	11%	36%
Lack of skills	11%	10%	10%	31%
Challenges in measuring and proving business value	10%	11%	9%	30%

Source: Loucks et al., 2018

Organizational challenges were the main barriers to the improvement of DT, according to McKinsey Digital Service's (2016) survey results, shown in Figure 2.

Figure 2. Challenges to the improvement of DT



Source: Adapted from McKinsey Digital Service, 2016

The results from the *Big Data and AI Executive Survey 2019*, from NewVantage Partners LLC (2019), reinforced the relevance of cultural and organizational issues for big data/AI initiatives. The same survey determined that 75% of companies cited fear of disruption from data-driven digital competitors as the top reason of their investment. Table 2 presents the biggest challenges to business adoption.

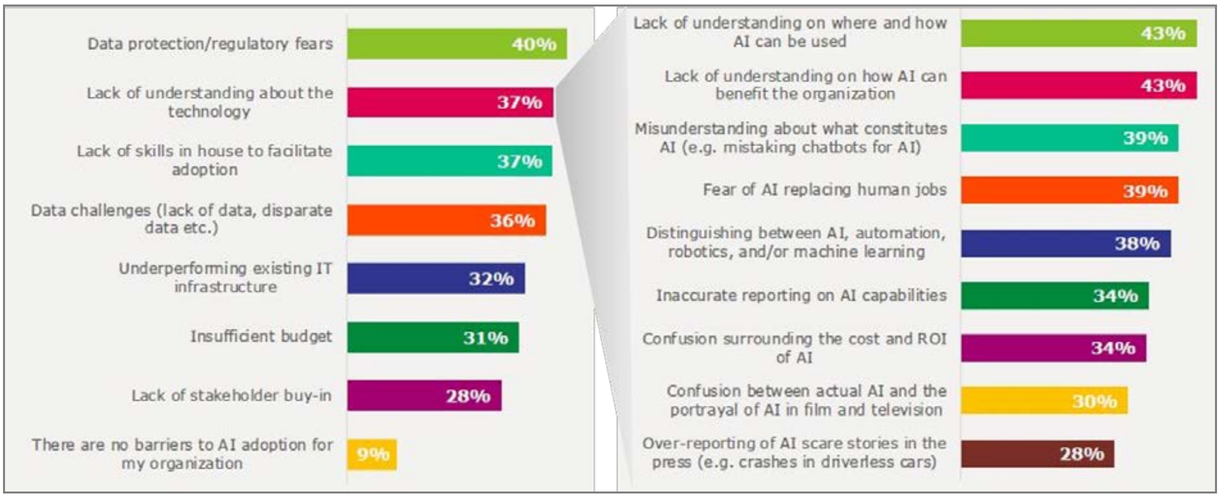
Table 2. Biggest challenges to improve DT

Biggest Challenge to Business Adoption	2018	2019
Lack of organizational alignment/agility	25.0%	40.3%
Cultural resistance	32.5%	23.6%
Understanding data as an asset	30.0%	13.9%
Executive leadership	7.5%	7.0%
Technology solutions	5.0%	5.0%

Source: NewVantage Partners – Big Data and AI Executive Survey, 2019

In spring 2019, the Vanson Bourne global survey commissioned by Avaya, with 2,800 IT and business decision-makers, showed that data protection/regulatory fears, lack of understanding about the technology, and lack of skills in house to facilitate adoption were the top three barriers to AI adoption (Vanson Bourne, 2019). The survey also asked what specifically hampered understanding about AI within organizations. Figure 3 presents the survey results.

Figure 3. Barriers to AI adoption



Source: Vanson Bourne (2019)

From the same survey, in Brazil, most respondents (71%) believed that their organizations wanted to adopt more AI but did not know how to do this, while 34% thought that their companies were unable to use AI effectively in any area. Many did not understand the technology (more than 26%) or lacked the necessary skills to facilitate adoption (22%).

Over half of technology executives in the 2019 Gartner CIO Survey said they intended to employ AI before the end of 2020 and the number of enterprises implementing AI grew 270% in the past four years (Gartner, 2019). If a company is moving too slowly, it could be thrown out of business by a competitor using AI.

Nevertheless, if a company moves too quickly, it can risk taking an approach it does not truly know how to manage (Merril, 2019).

Dwivedi et al. (2019) brought the collective insights from several leading experts to highlight significant opportunities, realistic assessment of impact, challenges, and a potential AI research agenda. Based on the literature, Dwivedi et al. (2019) reported AI challenges, presented in Table 3.

Table 3. AI challenges from the literature

AI Challenge	Details	References
Social challenges	Patient/clinician education; cultural barriers; human rights; country-specific disease profiles; unrealistic expectations toward AI technology; country-specific medical practices; and insufficient knowledge on values and advantages of AI technologies	Xu et al., 2019; Sun & Medaglia, 2019; Risse, 2019; DIN & DKE, 2018; Jonsson & Svensson, 2016; Makridakis, 2018; Wang, Törngren, & Onori, 2015a; Wang, Li, & Leung, 2015b; Wang & Wang, 2016
Economic challenges	Affordability of required computational expenses; high treatment costs for patients; high cost and reduced profits for hospitals; and ethical challenges including lack of trust toward AI-based decision making and unethical use of shared data.	Reza Tizhoosh & Pantanowitz, 2018; Sun & Medaglia, 2019; Bughin, Seong, Manyika, Chui, & Joshi, 2018
Data challenges	Lack of data to validate benefits of AI solutions; quantity and quality of input	Khanna et al., 2013; Xu et al., 2019; Reza Tizhoosh & Pantanowitz, 2018; Varga-

	data; transparency and reproducibility; dimensionality obstacles; insufficient size of available data pool; lack of data integration and continuity; lack of standards of data collection; format and quality; lack of data integration and continuity; and lack of standards for data collection.	Szemes, Jacobs & Schoepf, 2018; Sun & Medaglia, 2019
Organizational and managerial challenges	Realism of AI; better understanding of health systems' needs; organizational resistance to data sharing; lack of in-house AI talent; threat of replacement of human workforce; lack of strategy for AI development; and lack of interdisciplinary talents.	Reza Tizhoosh & Pantanowitz, 2018; Khanna et al., 2013; Sun & Medaglia, 2019
Technological and technology implementation challenges	Non-Boolean nature of diagnostic tasks; adversarial attacks; lack of transparency and interpretability; design of AI systems; AI safety; specialization and expertise; big data; architecture issues; and complexities in interpreting unstructured	Reza Tizhoosh & Pantanowitz, 2018; Cleophas & Cleophas, 2010; Kahn, 2017; Cheshire, 2017; Baldassarre, Santucci, Cartoni, & Caligiore, 2017; Edwards, 2018; Sun & Medaglia, 2019; Thrall et al., 2018; Nguyen & Shetty,

	data	2018; Thrall et al., 2018; Varga-Szemes et al., 2018; Mitchell, 2019
Political, legal, and policy challenges	Copyright issues; governance of autonomous intelligence systems; responsibility and accountability; privacy/safety; national security threats from foreign-owned companies collecting sensitive data; lack of rules of accountability in the use of AI; costly human resources still legally required to account for AI-based decisions; and lack of official industry standards of AI use and performance evaluation.	Gupta & Kumari, 2017; Zatarain, 2017; Wirtz, Weyerer & Geyer, 2019; Sun & Medaglia, 2019
Ethical challenges	Responsibility and explanation of decisions made by AI; processes relating to AI and human behavior; compatibility of machine versus human value judgement; moral dilemmas; and AI discrimination.	Sun & Medaglia, 2019; Duan et al., 2019; Gupta & Kumari ,2017; Bostrom & Yudkowsky, 2011

Source: Adapted from Dwivedi et al. (2020)

The digital age has deeply transformed types of business. From e-signature, e-invoice, and e-commerce to internet, mobile banking, and e-payments, the so-called “e-business” has created efficiency in corporate and individual levels. To minimize or optimize work, the reengineering of business processes caused a shift from the industrial age towards the digital age with the help of e-business environments (Dirican, 2015).

Considering that the challenges of AI implementation presented in the literature refer to issues of organizational and business processes, this study’s fundamental motivation was to understand these main business process changes and challenges related to the adoption of AI. We aimed to clarify the potential effects of AI technologies in organizations (such as business process management, transforming dynamics, patterns, and structure of organizations and management). We highlighted the main issues and changes in business process due to AI implementation. Moreover, we perform a content analysis through case studies, comparing different industries to find similarities and differences.

Advancing both practitioner and academic work in these fields is important at this particular moment in time, as practitioners and academics are beginning to understand the transformative potential of AI in society.

2 LITERATURE REVIEW

In this section, we reviewed the literature to establish operational definitions and explain the conceptual frameworks and propositions that guided the research stream. First, we offer an overview of DT and the implementation of AI solutions. Second, we discuss AI, AI capabilities, and the implementation of AI solutions in business. Third, we address business process management, operational process, and their interaction with DT and AI.

2.1 Digital Transformation and implementation of Artificial Intelligence solutions

DT has been essential in strategic research and leadership agendas, as well as for practitioners (Bharadwaj et al., 2013; Fitzgerald et al., 2014; Hess et al., 2016; Piccinini et al., 2015; Singh & Hess, 2017; Vial, 2019; Warner & Wäger, 2019; Westerman et al., 2012). DT comprehends profound changes taking place in society and industries using digital technologies (Agarwal et al., 2010; Majchrzak et al., 2016). Irniger (2017) defined DT as the process of devising new business applications that integrate all digitized data and digitalized applications.

At the organizational level, Hess et al. (2016) argued that firms must find ways to innovate with these technologies by devising “strategies that embrace the implications of DT and drive better operational performance.” This phenomenon is perhaps the most pervasive managerial challenge for incumbent firms of the last and coming decades (Nadkarni & Prügl, 2020).

When discussing the *Digital Advantage: How digital leaders outperform their peers in every industry* survey, conducted by Capgemini Consulting in partnership with the Massachusetts Institute of Technology (MIT) Digital Business Center, with 400 companies around the world over a two-year period, Westerman et al. (2012) presented that most organizations with a highly developed approach to the use of digital technologies achieved a 26% higher profitability than competitors, besides obtaining 9% more revenue and a market valuation 12% more expressive than that of rivals.

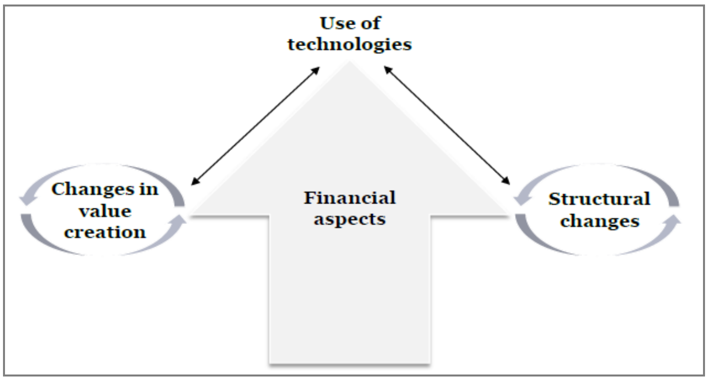
The literature has helped us understand specific aspects of DT. In line with previous findings on IT-enabled transformation, research has shown that technology itself is only part of the complex puzzle that must be solved for organizations to remain competitive in a digital world (Vial, 2019).

Notwithstanding these contributions, we currently lack a comprehensive understanding of this phenomenon (Gray & Rumpe, 2017; Gerald C Kane, 2017; Matt et al., 2015) as well as its implications at multiple levels of analysis.

DT is a complex issue that affects many or all segments within a company (Hess et al., 2016). Managers must simultaneously balance the exploration and exploitation of their firms’ resources to achieve organizational agility—a necessary condition for the successful transformation of their businesses (Clauss et al., 2020; Ransbotham et al., 2017).

Matt et al. (2015) proposed the DT framework illustrated in Figure 4, which identifies four key dimensions of DT.

Figure 4. The DT framework



Source: Matt et al. (2015)

1. The *use of technologies* reflects a firm's approach and capability to explore and exploit new digital technologies.

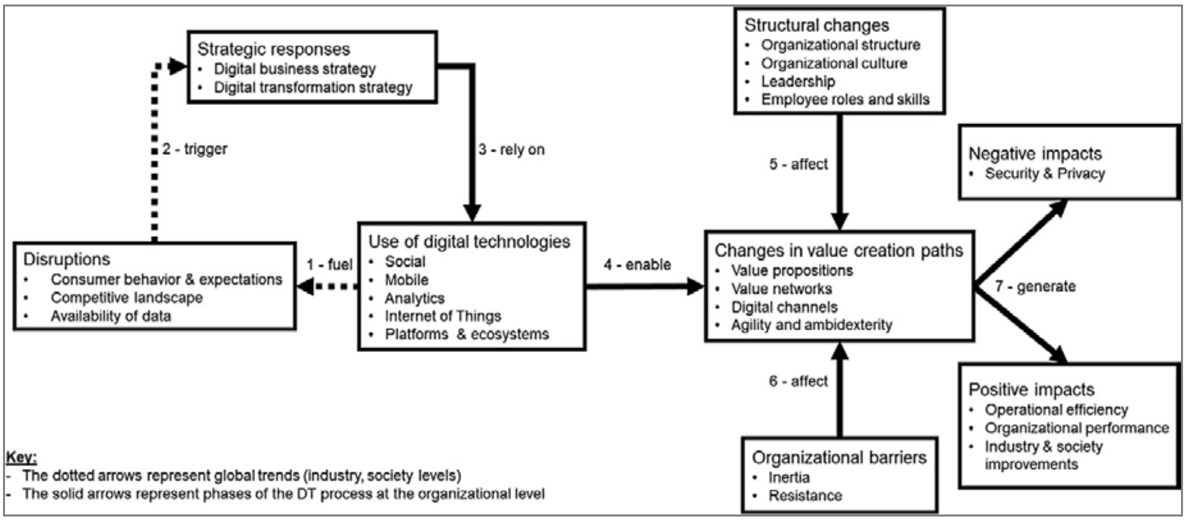
2. *Changes in value creation* reflect the influence of DT on a firm's value creation.

3. *Structural changes* refer to the modifications in organizational structures, processes, and skill sets necessary to cope with and exploit new technologies.

4. The *financial aspects* dimension relates both to a firm's need for action in response to a struggling core business and to its ability to finance a DT.

Vial (2019) reviewed the literature and proposed a DT framework in which digital technologies create disruptions, triggering strategic responses from organizations that seek to alter their value creation paths while managing the structural changes and organizational barriers that affect the positive and negative outcomes of this process. Figure 5 presents the building blocks for the DT process.

Figure 5. Building blocks of the DT process



Source: Vial (2019)

In the context of DT, we have key structural changes in the process of value creation (Vial, 2019):

- *Organizational structure*. Consistent with the idea that agility and ambidexterity are necessary capabilities to compete in a digital world, the literature has highlighted cross-functional collaboration as an important element of DT (Earley, 2014; Maedche, 2016; Selander & Jarvenpaa, 2016);

- *Organizational culture*. The disruption spurred by DT also requires changes in the culture of the focal organization (Hartl & Hess, 2017). In incumbent firms, for instance, there is evidence that the traditional separation between IT and business functions is so ingrained into the fabric of the organization that it becomes part of the organization’s values (Haffke et al., 2017);

- *Leadership*. In the context of DT, organizational leaders must ensure that their organizations develop a digital mindset while responding to the disruptions associated with digital technologies (Benlian & Haffke, 2016; Hansen et al., 2011);

- *Employee roles and skills.* In the context of DT, changes to an organization’s structure and culture lead employees to assume roles traditionally outside of their functions. Specifically, DT fosters situations in which non-IT employees take the lead on technology-intensive projects (Karimi & Walter, 2015; Yeow et al., 2018). The skills required for future workers who will form the digital workforce (Colbert et al., 2016) are also becoming increasingly relevant (Watson, 2017).

Vial (2019) reported two main barriers to changing value creation:

- *Inertia*. One of the most significant barriers to DT is inertia (35 sources). Inertia is relevant where existing resources and capabilities can hamper disruption (Islam et al., 2017; Svahn et al., 2017), highlighting path dependence as a constraining force for innovation through digital technologies (Srivastava & Shainesh, 2015; Wenzel et al., 2015);

- *Resistance*. Another barrier to DT is employees' potential resistance when disruptive technologies are introduced into the organization (Fitzgerald et al., 2014; Kane, 2016; Lucas & Goh, 2009; Singh & Hess, 2017). Resistance raises important questions regarding the ways and the pace at which technologies are introduced into an organization. Fitzgerald et al. (2014) highlighted "innovation fatigue" as one of the causes of resistance.

Vial (2019) also described the impacts of DT at the organizational level:

- *Operational efficiency*. Operational efficiency—which includes automation (Andriole, 2017), the improvement of business processes (G Gust et al., 2017), and savings (Pagani, 2013)—is a benefit of DT;

- *Operational performance*. DT brings innovativeness (Svahn et al., 2017), financial performance (Karimi & Walter, 2015), firm growth (Tumbas et al., 2015), reputation (Kane, 2016; Yang et al., 2012), as well as competitive advantage (Neumeier et al., 2017);

- *Positive impacts*. Digital technologies can greatly improve individuals' quality of life (Agarwal et al., 2010; Pramanik et al., 2016);

- *Undesirable outcomes*. Notwithstanding these positive outcomes, the literature has also reflected on potential issues associated with the pervasive use of digital technologies, primarily in terms of security and privacy (Carmon et al., 2019; Newell & Marabelli, 2015; Piccinini et al., 2015).

In th DT background journey, project implementations with AI solutions begin to emerge in business lately.

The implementation of AI solutions follows the same pattern of other digital technologies. Tech firms adopt technologies early on for obvious reasons. Startups build their businesses around new technologies. Large enterprises are typically next in line; they have the technological sophistication to make informed investments in new technologies and can hire people to build and implement new solutions (Davenport, 2018).

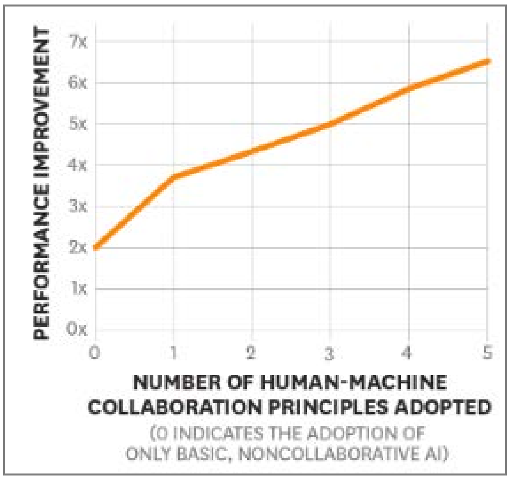
When AI technologies are effectively integrated into workflows, they can directly influence how organizations accomplish tasks, make decisions, create engaging interactions, and generate stronger business outcomes. Nevertheless, cognitive technologies are still maturing. The vendor landscape is fragmented; there is still a shortage of talent. Many initiatives have only focused on internal functions within companies, instead of developing new products or improving customer interactions. Integration with existing systems has remained a principal challenge (Davenport et al., 2017).

Companies benefit from optimizing collaboration between humans and AI. Five principles can improve that relationship, according to James Wilson & Daugherty (2018):

1. Reimagine business processes;
2. Embrace experimentation/employee involvement;
3. Actively direct AI strategy;
4. Responsibly collect data;
5. Redesign work to incorporate AI and cultivate related employee skills.

A survey of 1,075 companies in 12 industries found that the more they adopted these principles, the better their AI initiatives performed in terms of speed, cost savings, revenues, or other operational measures (James Wilson & Daugherty, 2018). Figure 6 represents the value of collaboration between humans and AI, and Table 4 presents the types of collaboration found in the survey.

Figure 6. Value of collaboration



Source: James Wilson & Daugherty (2019)

Table 4. Types of AI collaboration

Element	Business Process	Company or Organization	Type of collaboration
Flexibility	Auto manufacturing	Mercedes-Benz	Assembly robots work safely alongside humans to customize cars in real time.
	Product design	Autodesk	Software suggests new product design concepts as a designer changes parameter such as materials, cost, and performance requirements.
	Software development	Gigster	AI helps analyze any type of software project, no matter the size or complexity, enabling humans to quickly estimate the work required, organize experts, and adapt workflows in real time.
Speed	Fraud detection	HSBC	AI screens credit- and debit-card transactions to instantly approve legitimate ones while flagging questionable ones for human evaluation.
	Cancer treatment	Roche	AI aggregates patient data from disparate IT systems, speeding collaboration among specialists.
	Public safety	Singapore government	Video analytics during public events predicts crowd behavior, helping responders address security incidents rapidly.

Scale	Recruiting	Unilever	Automated applicant screening dramatically expands the pool of qualified candidates for hiring managers to evaluate.
	Customer service	Virgin Trains	Bot responds to basic customer requests, doubling the volume handled and freeing humans to address more complex issues.
	Casino management	GGH Morowitz	Computer-vision system helps humans continuously monitor every gaming table in a casino.
Decision making	Equipment maintenance	General Electric	“Digital twins” and Predix diagnostic application provide techs with tailored recommendations for machine maintenance.
	Financial services	Morgan Stanley	Robo-advisers offer clients a range of investment options based on real-time market information.
	Disease prediction	Icahn School of Medicine at Mount Sinai	Deep Patient system helps doctors predict patients’ risk of specific diseases, allowing preventive intervention.
Personalization	Guest experience	Carnival Corporation	Wearable AI device streamlines the logistics of cruise-ship activities and anticipates guest preferences, facilitating tailored staff support.
	Healthcare	Pfizer	Wearable sensors for Parkinson’s patients track symptoms 24/7, allowing customized treatment.
	Fashion retail	Stitch Fix	AI analyzes customer data to advise human stylists, who give customers individualized clothing and styling recommendations.

Source: Adapted from James Wilson & Daugherty (2018)

From Figure 6 and Table 4 it was possible to observe the adoption of AI in different business processes and industries as well as the improvement in performance as the collaboration of human-machines increases, representing a competitive advantage for companies that have implemented AI solutions.

2.2 Artificial Intelligence

AI is based on several areas of knowledge, such as philosophy, mathematics, economics, neuroscience, psychology, computer engineering, control theory, cybernetics and linguistics (Russel & Norvig, 2020).

Russel & Norvig (2020) classified the definitions of AI into four categories:

(1) thinking humanly—“*[the automation of] activities that we associate with human thinking, activities such as decision-making, problem solving, learning . . .”* (Bellman, 1978);

(2) acting humanly—“*the art of creating machines that perform functions that require intelligence when performed by people*” (Kurzweil, 1992);

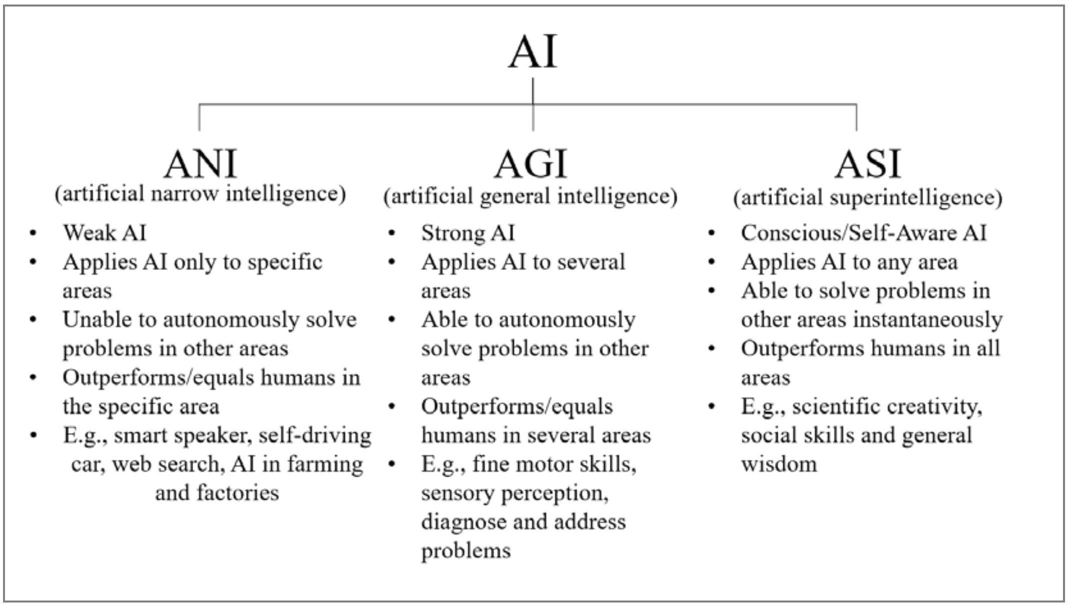
(3) thinking rationally—“*the study of the computations that make it possible to perceive, reason, and act*” (Winston, 1992);

(4) acting rationally—“*Computational Intelligence is the study of the design of intelligent agents”* (Poole et al., 1998).

AI covers a wide range of computing capabilities that enable machines to infer solutions, suggest or take actions, and create outputs based on rules and outcomes rather than on pre-specified commands and lines of computer code establishing the actions to be taken at every step to resolve a problem (Roberts et al., 2017). Kaplan & Haenlein (2019) defined AI as a system’s ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation. Poole & Mackworth (2010) defined AI as “computational agents that act intelligently” and perceive their environments to take actions that maximize chances of success.

Regarding terminology, weak AI, applied AI, or narrow AI (artificial narrow intelligence—ANI) refer to systems that simulate human intelligence for specific tasks to produce commercially viable smart programs or machines (Paschen et al., 2020). The assertion that those machines are *thinking* (not just simulating thinking) is called the strong AI hypothesis (Russel & Norvig, 2020) or artificial general intelligence (AGI), which aims to develop machine intelligence capable of undertaking any task, much like a human (Paschen et al., 2020). A third stream is artificial superintelligence (ASI), in which AI will far exceed human knowledge and capabilities (Cellan-Jones, 2014). Our investigation focuses on weak AI. Figure 7 represents the main AI terminology.

Figure 7. AI Terminology



Source: Adapted from Ng (2019b), Cellan-Jones (2014) and Kaplan & Haenlin (2019)

In relation to AI history, Warren McCulloch & Walter Pitts did the first AI work in 1943. They used knowledge derived from philosophy, functions of neurons in the brain, a formal analysis of Russell's and Whitehead's propositional logic, and Turing's theory of computing. Then, they proposed a model of artificial neurons in which they showed, for example, that any computable function could be computed by the same network of connected neurons, and that logical connectives (and, or, not, etc.) could be implemented by simple network structures. The hypothesis was that these networks, when properly defined, could also be learned (Russel & Norvig, 2020).

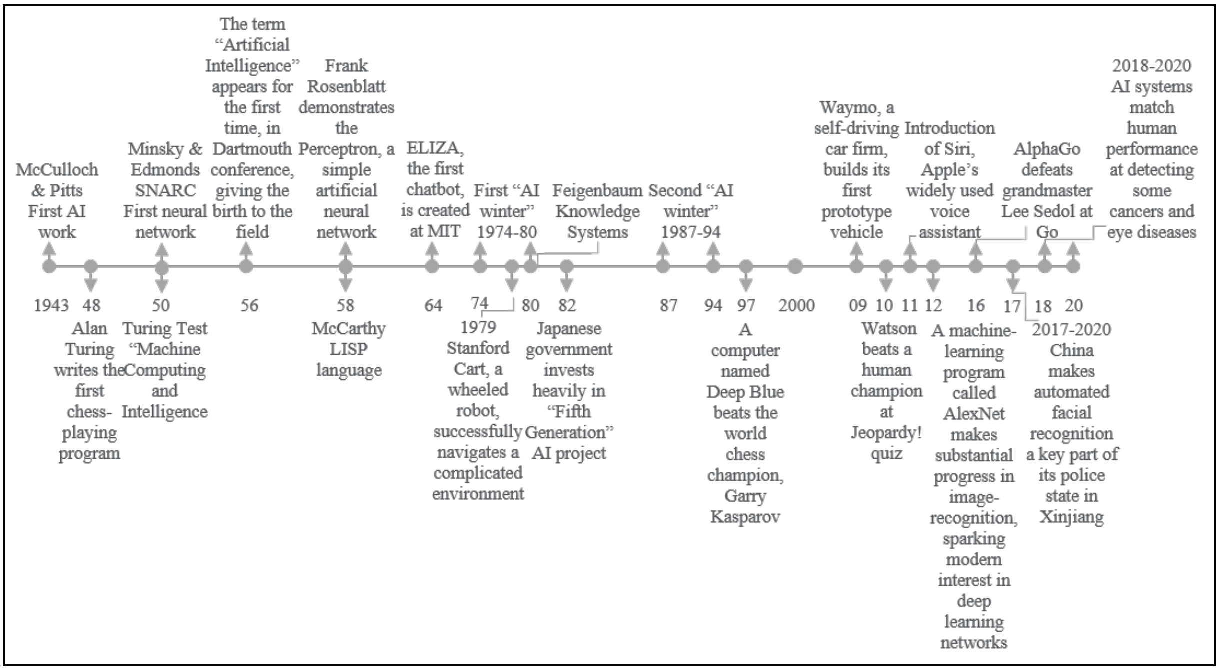
Afterwards, in Princeton, Marvin Minsky and Dean Edmonds constructed the first neural network computer in 1951, SNARC. Nevertheless, it was Alan Turing who first articulated a complete AI view in *Machine Computing and Intelligence,* written in 1950. He introduced the Turing Test, machine learning, genetic algorithms, and learning enhancement. The formulation of this test propelled the beginning of research in AI. In broad terms, the Turing Test ascertained the ability of a machine to be human: based on the results, the question was whether this imitation could be so perfect that a human judge would be confused in deciding whether tasks were performed by a human or by a machine. This made Alan Turing one of the fathers of computer science: his concept of a Computer Logic Machine later became known as the Turing Machine (Russel & Norvig, 2020).

In 1956, John McCarthy proposed a conference in Dartmouth, in which Claude Shannon, Marvin Minsky, Hebert Simon, Allen Newell, Trenchard More, Arthur Samuel, Ray Solomonoff, and Oliver Selfridge participated. These researchers were interested in automata theory, neural nets, and the study of intelligence. This was the first official usage of McCarthy's term "artificial intelligence."

Afterward, other programs were also critical in the development of AI, such as the General Problem Solver (GPS). This program was initially designed to mimic human problem-solving protocols, but the order in which the program considered goals and actions turned out to be similar to that of humans in relation to the same problems. Thus, GPS can be considered the first program to incorporate the proposal of "human thinking." The success of such programs led Newell and Simon (1976) to formulate another hypothesis: that intelligent systems, either human or machines, must operate by manipulating symbolic data structures. Later, in 1958 at MIT, John McCarthy defined the Lisp language, which became the dominant language for AI programming, and created the Advice Taker, a hypothetical program that can be considered the first complete AI system (Russel & Norvig, 2020).

Figure 8 shows the main AI selected events (The Economist, 2020; Kaplan. 2016).

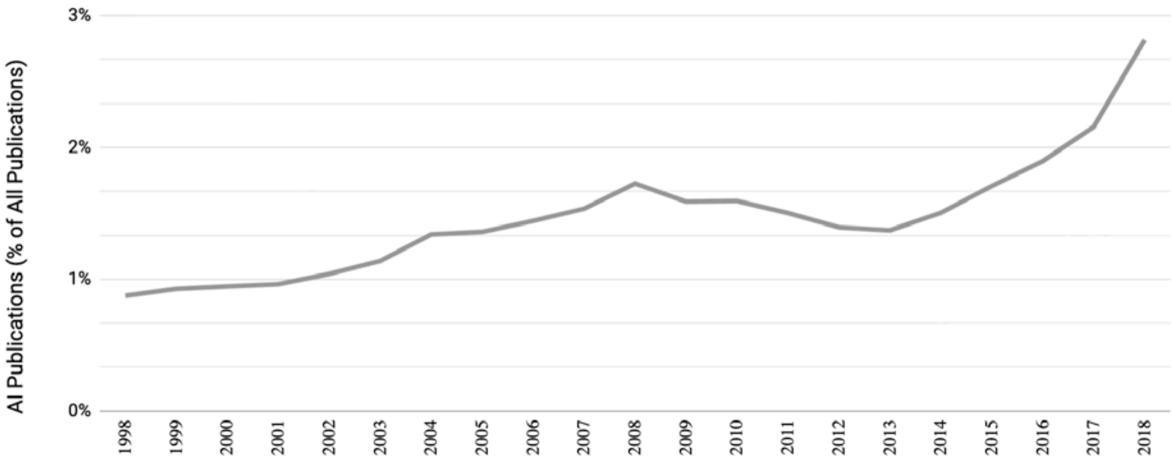
Figure 8. AI Timeline



Source: Adapted from The Economist (2020) and Kaplan (2016)

In relation to AI publications, it is possible to notice an interest increase on the topic. The graph on Figure 9 shows the percentage of peer-reviewed AI publications (conferences, journals, reviews, and articles) in 1998–2018 from Elsevier's Scopus database. In the late 1990s, AI papers accounted for less than 1% of articles and around 3% of conference publications. By 2018, the share of published AI papers in total papers tripled, accounting for 3% of peer-reviewed journal publications and 9% of published conference papers (Perrault et al., 2019).

Figure 9. AI papers in all publications



Source: Perrault et al. (2019)

Brynjolfsson & McAfee (2017) deemed AI the most important general-purpose technology of our era. According to Teece (2018), AI may be called an enabling technology. The impact of these innovations on business and the economy will be reflected not only in their direct contributions but also in their ability to enable and inspire complementary innovations. New products and processes are being enabled by better vision systems, speech recognition, intelligent problem solving, and many other machine learning capabilities.

Table 5 describes AI technologies and functionalities based on Davenport (2018) and Davenport et al. (2017). Davenport & Ronanki (2018) classified three types of AI from the perspective of business capabilities: automating business processes, gaining insight through data analysis, and engaging with customers and employees. The literature has generally classified different types of AI related to the presence of three skills or types of competencies: cognitive intelligence (e.g., competencies related to pattern recognition and systematic thinking), emotional intelligence (e.g., adaptability, selfconfidence, emotional self-awareness, achievement orientation), and social intelligence (e.g., empathy, teamwork, inspirational leadership). Kaplan & Haenlein (2019) classified AI systems in three groups: analytical AI (cognitive intelligence), human-inspired AI (cognitive and emotional intelligence), and humanized AI (cognitive, emotional and social intelligence).

Table 5. AI technologies and functionalities

Technology	Brief description	Application examples
Statistical machine learning	Automates the process of training and fitting models to data	Highly granular marketing analyses on big data
Neural networks	Uses artificial "neurons" to weight inputs and relate them to outputs	Credit fraud identification, weather forecast
Deep learning	Uses neural networks with many layers of variables or features	Image and voice recognition, extraction of meaning from text
Natural language processing (NLP)/generation	Analyzes and "understands" human speech and text	Speech recognition, chatbots, intelligent agents
Rule-based expert systems	Uses a set of logical rules derived from human experts	Insurance underwriting, credit approval
Physical robots	Automates a physical activity	Factory and warehouse tasks
Robotic process automation (RPA)	Automates structured digital tasks and interfaces with systems	Credit card replacement, validation of online credentials, ability to open e-mail attachments, complete e-forms, record and e-key data

Source: Adapted from Davenport (2018) and Davenport et al. (2017)

AI currently encompasses a huge variety of subfields, ranging from general (learning and perception) to specific, such as playing chess, proving mathematical theorems, writing poetry, driving a car on a crowded street, and diagnosing diseases. Relevant to any intellectual task, AI is truly a universal field (Russel & Norvig, 2020). Table 6 presents some examples of AI applications in the literature.

Table 6. Examples of AI applications in the literature

AI Application	Sources

Robotic vehicles	Thrun et al. (2007)
Speech recognition	Seneff (2004)
Autonomous planning and scheduling	Ai-Chang et al. (2004) ; Cesta et al. (2007); Jónsson et al. (2000)
Game playing	Goodman & Keene, (1997)
Spam fighting	Goodman & Heckerman (2004); Sahami et al. (1998)
Education	Chaudhri et al. (2013)
Logistics planning	Cross & Walker (1994)
Robotics	Foran (2015)
Manufacturing	Kusiak (1987; Lee (2002); Jain & Mosier (1992); Kumar (2017); Li et al. (2017); Zhong et al. (2017)
Marketing and Sales	Antonio (2018); Davenport et al. (2020); Loring, (2018)
Construction	Parveen (2018)
Healthcare	Dreyer & Allen (2018); Goldfarb et al. (2020); Kahn (2017); Khanna et al. (2013)
Machine translation	Brants et al., (2007)

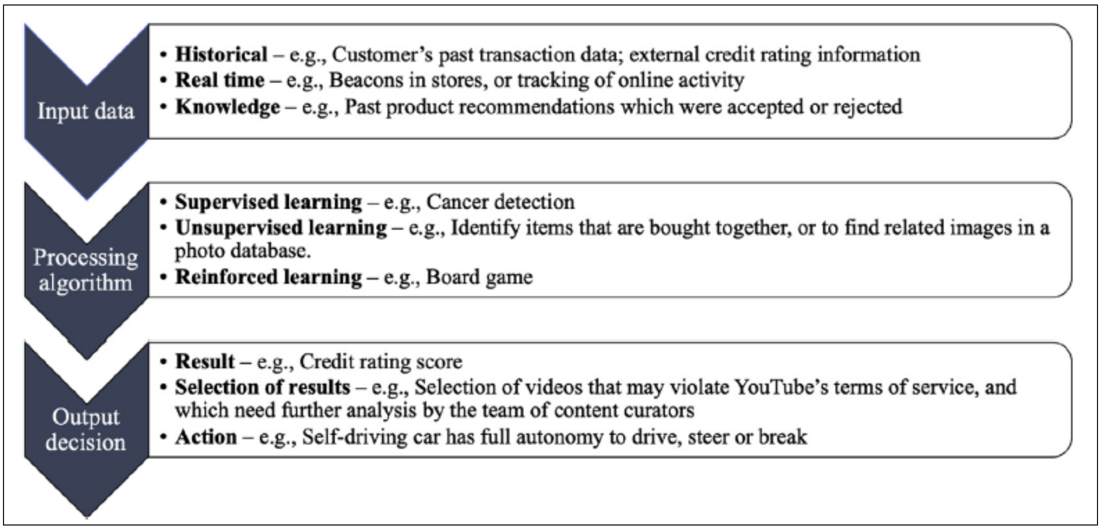
Source: Adapted from Russel & Norvig (2016) and Dwivedi (2020)

Figure 10 (Canhoto & Clear, 2020) presents three key components of AI solutions. The first is input data. AI can handle large volumes of data, making it increasingly important in the dawning age of big data (Kietzmann et al., 2018). Additionally, AI is increasingly able to use unstructured inputs, such as images, speech, or conversations, besides structured inputs like transaction data (Paschen et al., 2020). Many companies use historical data and real-time data (e.g., with physical sensors or by tracking online activity) in their AI applications. Ackoff (1989) supported a similar input-process-output interaction method: inputs are raw data from human or physical sources; process is the value-creating manipulation of this data; and outputs consist of meaningful information feedback to the environment.

The second key AI component is the processing algorithm: the machine learning algorithm is the computational procedure that processes data inputs (Skiena, 2010). There are three types of machine learning algorithms: supervised, unsupervised, and reinforcement. In supervised machine learning, human experts give the computer training data sets with both the inputs and the correct outputs so the algorithm can learn the patterns and develop rules to be applied to future instances of the same problem. In unsupervised learning, the computer is given a training data set with inputs but no labels. The algorithm's task is to find the best way of clustering the data points and establishing how they may be related. In reinforcement learning, the algorithm is given a training data set plus a goal; it then must find the best combination of actions to achieve the objective (Canhoto & Clear, 2020).

The third key AI component is the output decision resulting from the machine learning process. AI could produce a single result, such as a deception score (Elkins et al., 2013). Otherwise, the system may produce a selection of results for further action by human analysis. A third result could be an autonomous action based on the results of machine´s analysis; for instance, a self-driving car can drive (Goodall, 2016).

Figure 10. Key components of an AI Solution



Source: Canhoto & Clear (2020)

Paschen et al. (2020) summarized the six building blocks of AI: structured data (internal and external), unstructured data (text, audio, and video files), preprocesses (natural language understanding and computer vision), main processes (problem solving, reasoning, and machine learning), a knowledge base (data storage), and value-added information outputs (natural language generation, image generation, and robotics). Paschen et al. (2020) developed an AI typology (Figure 11) to help organizations find creative solutions to business problems and exploit opportunities:

- *Competence-enhancing process innovations* enabled by AI are order-of-magnitude improvements to internal processes that increase efficiencies.

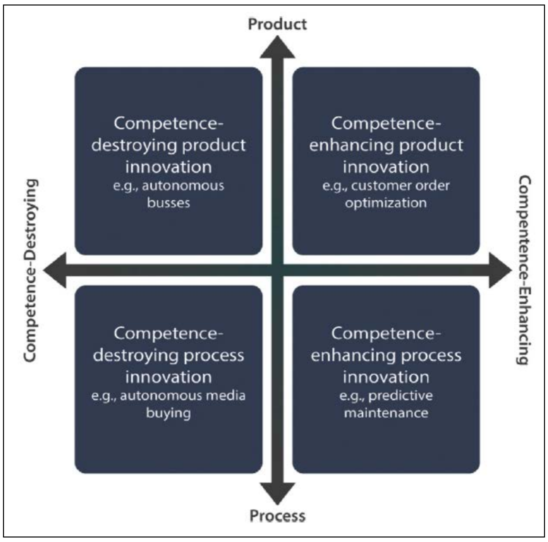
These advances build on existing knowledge and skills and provide the core for later improvements of internal processes;

- *Competence-enhancing product innovations* yield better product performance for customers by improving existing competencies in an industry. Such innovations replace older technologies but do not obviate the skills required to master them;

- *Competence-destroying product innovations* enabled by AI either create a new class of offerings or replace an existing good or service;

- *Competence-destroying process innovations* represent a fundamentally new way of producing a given offering, rendering existing knowledge and skills in an obsolete organization or industry.

Figure 11. A typology of AI-enabled innovations and their effects on competencies



Source: Paschen et al. (2020)

2.3 AI and capabilities

Davenport (2018) described three types of AI capabilities to support essential business activities and processes:

- *Process automation*: automating structured and repetitive work processes, often via robotics or RPA;

- *Cognitive insight*: gaining insight through extensive analysis of structured data, most often using machine learning;

- *Cognitive engagement*: engaging with customers and employees, using natural language processing chatbots, intelligent agents, and machine learning.

Davenport (2018) claimed that some early projects have already failed or encountered substantial difficulties because neither the technologies nor the organizations using them were quite ready. Just as the smartest investors “get rich slow,” companies need to become more cognitive slowly over time. The businesses and organizations that succeed with AI will be those that invest steadily, rise above the hype, make a good match between their business problems and the capabilities of AI, and take the long view.

Regarding the division of labor between humans and machines, the spectrum of AI—besides automation of repetitive manual and cognitive tasks by machines—consists of three general areas (Davenport, 2018; PricewaterhouseCoopers, 2018; Rao, 2017):

• *Assisted intelligence*: it improves what people and organizations are doing today;

• *Augmented intelligence*: currently in development, it allows people to do things that they would otherwise not be able to do;

• *Autonomous intelligence*: developed for the future, it creates machines that act independently.

Mason (2017) exhibited three main capabilities of AI and machine learning data: (1) understanding the business (analytics or business intelligence): to ask questions and analyze information to make better decisions; (2) product data science: to build algorithms and systems—which may use machine learning and AI—that actually improve the product (i.e., spam filters, recommendation systems, search algorithms, and data visualization); and (3) Research & Development (R&D) capability: to use data to launch new products and open new businesses and new revenue opportunities.

New AI capabilities that can recognize context, concepts, and meaning have opened surprising new pathways for collaboration between knowledge workers and machines. Experts can provide more of their own input to train, control quality, and fine-tune AI outcomes. Machines can augment the expertise of their human collaborators and sometimes help create new experts. These systems, in more closely mimicking human intelligence, are proving to be more robust than big data-driven systems. For instance, deep learning and machine learning need many data to train and build systems from bottom up. In the future, top-down systems will require far less data for their construction and training, enabling machines to capture and embody workers' specialized knowledge. Nevertheless, to take full advantage of the possibilities of this smarter AI, companies will need to redesign knowledge-work processes and jobs (James Wilson & Daugherty, 2018).

Building organizational AI capabilities requires a fundamental reengineering of existing business processes. AI, like other forms of IT, requires a lot of preexisting investment in various other assets, such as technical expertise, business processes, data, and culture, to be productive and provide value in a new context. Therefore, AI requires management to grow with the new capabilities of the organization (Rock, 2020), and these efforts include hiring or training technical talent (Scur et al., 2019).

Managing AI risks requires designing an effective management and reporting structure (Helper et al., 2019). Organizational design choices play an important role in this context. For instance, are AI engineers developing products for internal clients, or are they part of those client teams? Some companies prefer a hub-and-spoke model, where a core analytics team supports many different internal client groups, while others embed data scientists in each of those groups. The same organizational models can be applied to AI. When AI developers are not embedded in internal client groups, some of those clients may be worried about AI replacing them or challenging their position in the company (Rock, 2020). They might stand in the way of implementing a new process if they perceive it as a threat (Goldfarb et al., 2020). Effective communication and education about AI are therefore paramount. AI is only (very) useful for a subset of the tasks that people do in the workforce (Brynjolfsson et al., 2018; Felten et al., 2018; Webb, 2019).

Brock & von Wangenheim (2019) investigated case studies and the results of two global surveys among senior managers from different industries. The authors showed that AI is typically implemented and used with other advanced digital technologies in firms' DT projects. DT projects that deployed AI mostly supported firms' existing businesses. These digital transformations skills comprised four, interrelated organizational capabilities according to Brock & von Wangenheim's study (2019):

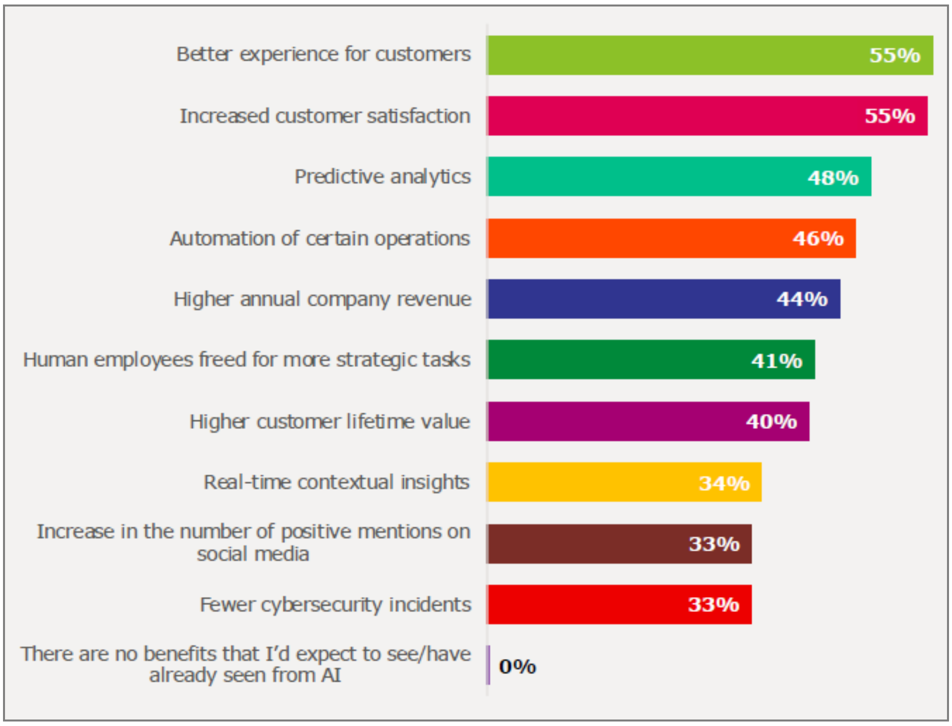
- Strategic capabilities: digital strategy and digital business development skills;
- Technology capabilities: skills in new digital technologies such as AI or Internet of Things (IoT);

• Data capabilities: data science skills;

• Security capabilities: cybersecurity skills.

The Vanson Bourne (2019) survey showed that 25% of companies fully implemented the AI strategy. In Brazil, this rate is slightly higher, 28%. More than a half (51%) of Brazilian companies wants to expand the number of areas where technology is applied. About the benefits of an AI strategy, better experience for customers (55%), increased customer satisfaction (55%), and predictive analytics (48%) were the top three gains mentioned. Figure 12 shows the results.

Figure 12. Benefits of an AI strategy

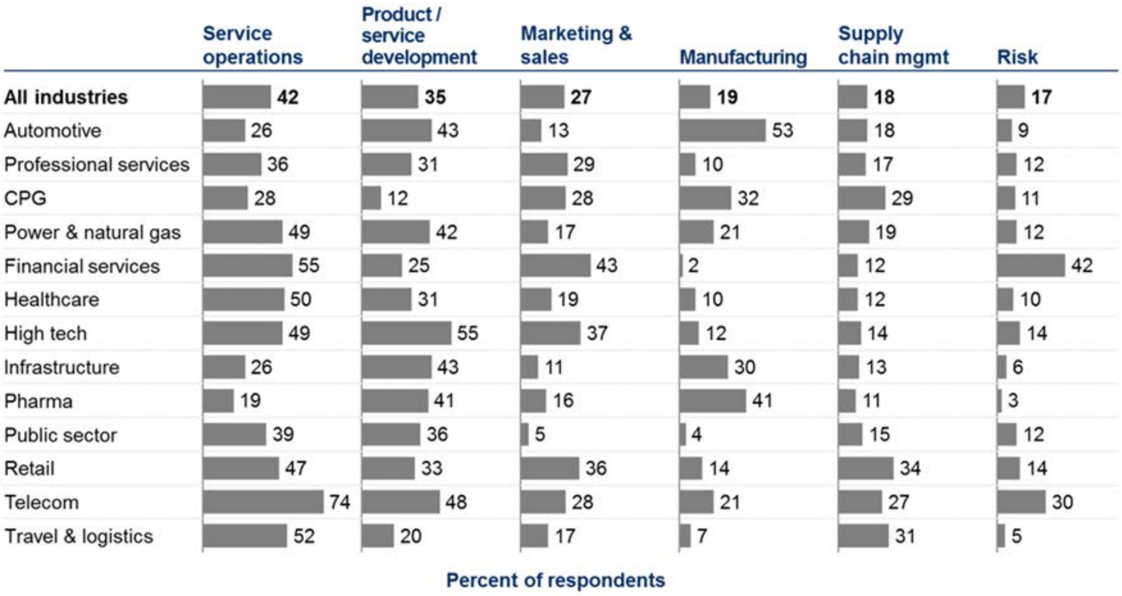


Source: Vanson Bourne (2019)

About organizations' success in measuring their AI strategy, the survey identified the following indicators: customer satisfaction scores (62%), efficiency/productivity gains (60%), financial results (profit, revenue, etc.) (50%), employee satisfaction scores (46%), fewer operational errors (46%), and quicker cybersecurity incident resolution (41%) (Vanson Bourne, 2019).

The McKinsey & Company (2019) survey revealed that AI adoption per industry provides mostly value in business functions (Figure 13). For instance, the automotive industry is most likely to adopt AI in manufacturing, and those working in financial services are more likely to adopt AI in risk functions.

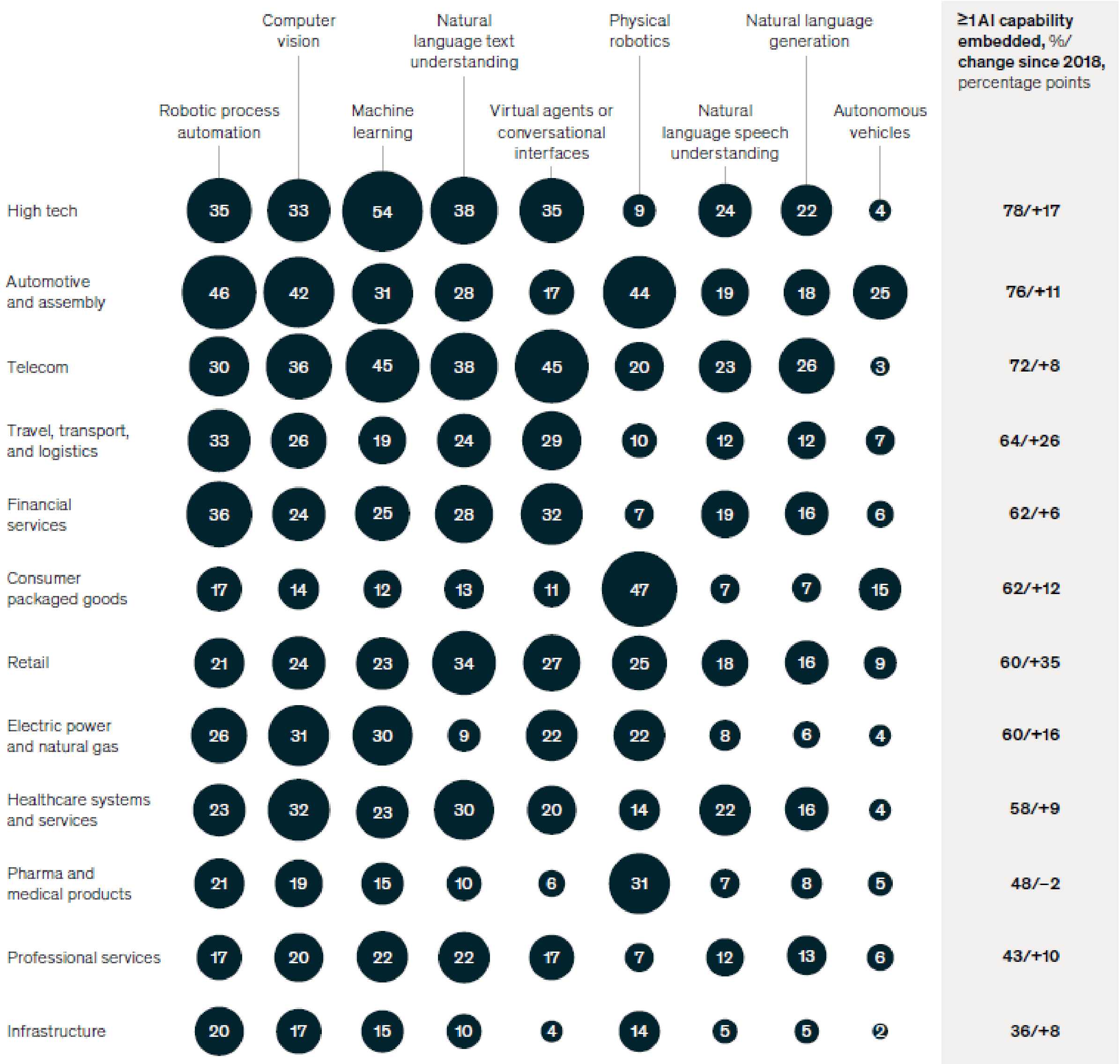
Figure 13. AI adoption per industry and function



Source: McKinsey & Company (2019)

The same survey presented that AI capabilities differ meaningfully between industries. For instance, natural language capabilities are adopted most often in industries with large volumes of customer or operational data in text form, including high tech, telecom, retail, financial services, and healthcare. By contrast, physical robotics is frequently adopted in industries where manufacturing or transport of physical goods plays an important role in the supply chain, including automotive, consumer packaged goods, and pharma (Figure 14).

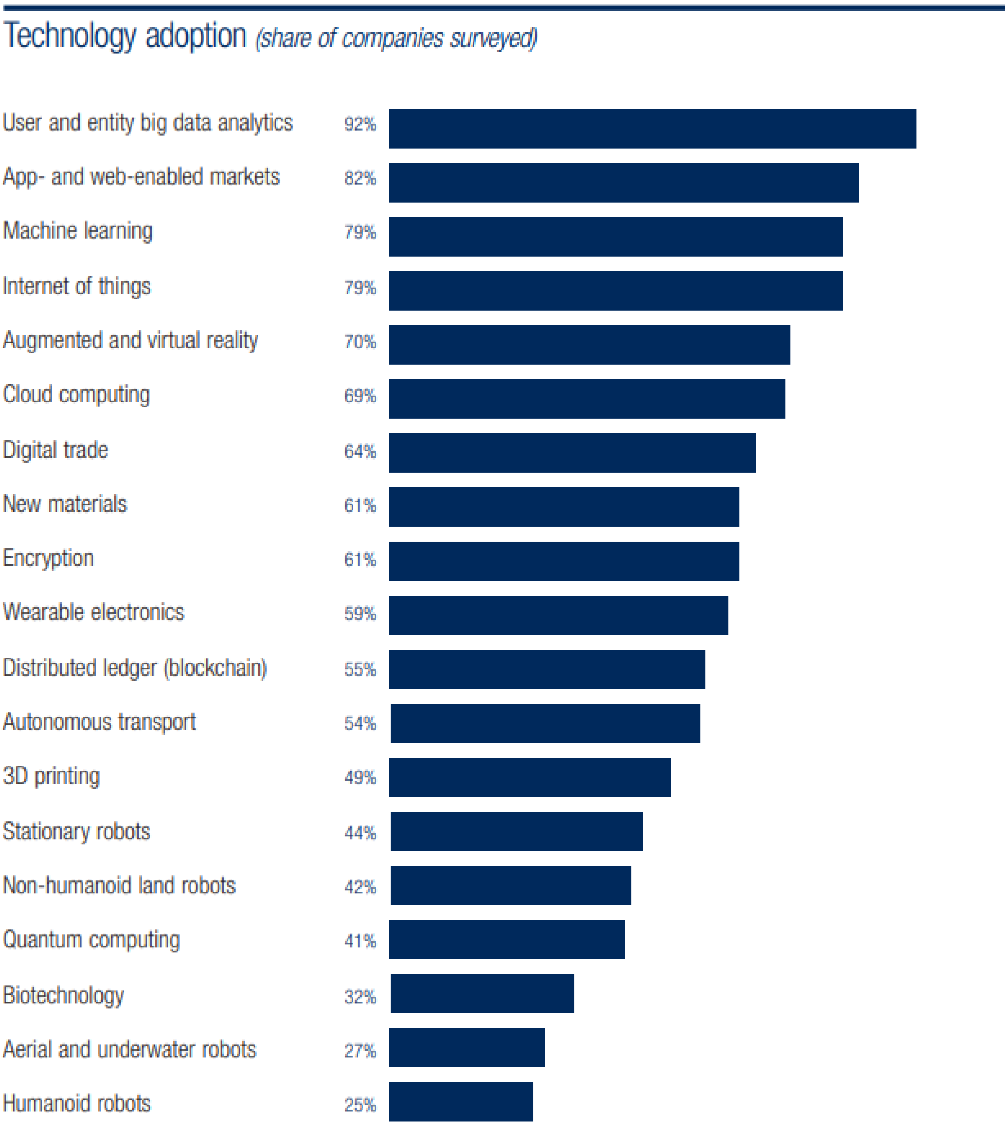
Figure 14. Organizations' AI capabilities



Source: McKinsey & Company (2019)

In Brazil, the World Economic Forum reported (World Economic Forum, 2018) that the main technologies adopted were related to AI (Table 7).

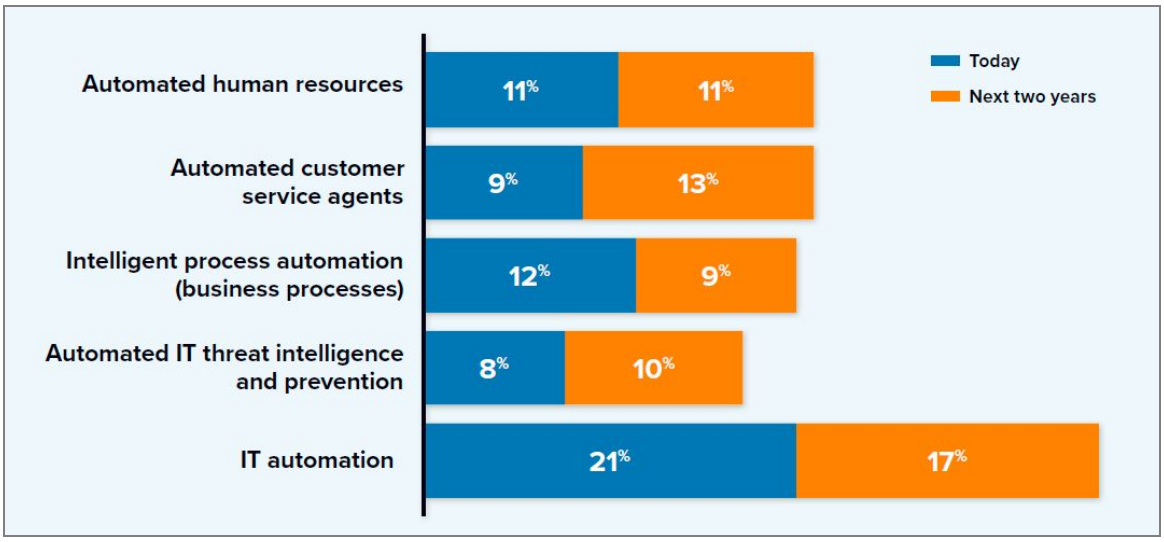
Table 7. Technology adoption in Brazil



Source: World Economic Forum (2018)

IDC (2020a) surveyed use cases for AI solution in 2,056 companies. IDC posed the following question: For what use cases are you currently deploying or investigating AI applications today and in two years? For 2020, IT automation, intelligent process automation (business process), and automated human resources led the ranking. In the next two years, the leading areas are IT automation, automated human resources, and automated customer service agents. Figure 15 illustrates the survey results.

Figure 15. AI use cases



Source: IDC (2020a)

Vanson Bourne (2019) also asked about beneficial business use cases of AI, and the results included communication with customers (59%), predicting customer behavior (53%), Customer Relationship Management (CRM) (51%), employee collaboration (41%), energy efficiency (36%), vulnerability prediction (36%), and recruitment (25%).

Wamba-Taguimdje et al. (2020) developed a study to analyze the influence of AI on the performance of organizations at the organizational and process levels. They reviewed 500 case studies, including IBM, AWS, Cloudera, Nvidia, Conversica, and Universal Robots. They found that AI expresses its potential through its ability (i) to optimize the existing organizational level (financial, marketing, and administrative) and process level, (ii) to improve automation, information and transformation effects, and (iii) to detect, predict, and interact with humans.

For a successful AI technology implementation, companies have to build cognitive capabilities. Davenport (2018) suggested the following steps to form a cognitive corporation:

- Understanding which technologies perform what types of tasks;
- Building on current strengths in big data and analytics;
- Creating a prioritized portfolio of technology matched to processes and tasks;
- Creating a series of pilot or proof-of-concept projects;
- Engaging in cognitive work redesign using design-thinking principles;

- Focusing on scaling and achieving productivity benefits.

Kaplan & Haenlein (2019b) discuss six dilemmas of AI: politics, economics, society, technology, environment, and law. Besides, they develop six directions for large governments, corporations, and society (rulers): enforcement, employment, ethics, education, entente, and evolution. Regarding employment, Kaplan & Haenlein (2019b) state that AI will expressively change some industries, like pink- and white-collar jobs, in the same way as blue-collar workers were affected by automation on the shop floor decades ago.

To face those challenges and changes, management requires strong soft skills in leading an open dialogue and resolving conflict—broadly speaking, a human, ethical, open, and transparent leadership style. Additionally, managers need to identify the skills of their human employees and find a place for them in an ecosystem in which humans and machines will work together (Kaplan & Haenlein, 2019b). This choice includes a stronger focus on emotional or feeling tasks for humans, for which they have an inherent advantage over machines (Huang et al., 2019). In a nutshell, this process needs to be done in a bottom-up versus top-down approach. Involving employees in the process of developing and implementing AI systems makes such systems more successful (Tambe et al., 2019). Managers will need to act as empathetic mentors and data-driven decision makers (Kaplan & Haenlein, 2019b).

Heinen et al. (2017) classified AI impacts on occupations and activities into three groups:

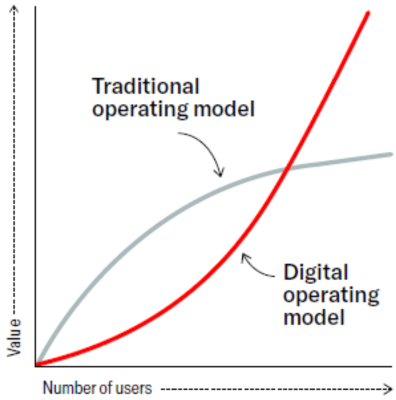
• *Replacement of human work*: complete takeover and performance of activities by machines, even in constantly changing environments;

• *Increased efficiency through intelligent input*: replacement of processes that support the actual creation of value based on intelligent algorithms;

• *New tasks for enterprises and employees*: creation of new value-adding processes due to the execution of standardized tasks by computer programs and machines.

Iansiti & Lakhani (2020) present how machine intelligence changes the rules of business. The age of AI is composed of a new kind of firm, whose value is served up by algorithms rather than by traditional business processes operated by workers, managers, process engineers, supervisors, or customer service representatives. The core of this firm is an “AI factory” with four components: data pipeline, algorithms, experimentation platform, and infrastructure. Iansiti & Lakhani (2020) discuss a collision between AI-driven firms and traditional firms. Figure 16 shows how AI-driven companies outperform traditional organizations: The value that scale delivers eventually tapers off in traditional operating models, but in digital operating models, it can go higher.

Figure 16. How AI-driven companies can outstrip traditional firms



Source: Adapted from Iansiti & Lakhani (2020)

Wade et al. (2020) questioned if the AI solution implemented in organizations is really using AI techniques. Indeed, a survey conducted by the London-based investment firm MMC Ventures (MMC, 2019) revealed that 40% of Europe’s AI startups did not use any AI at all. The offerings of many startups and analytics providers, even if quite advanced, fall short of even basic AI; instead, they use statistical methods and algorithms.

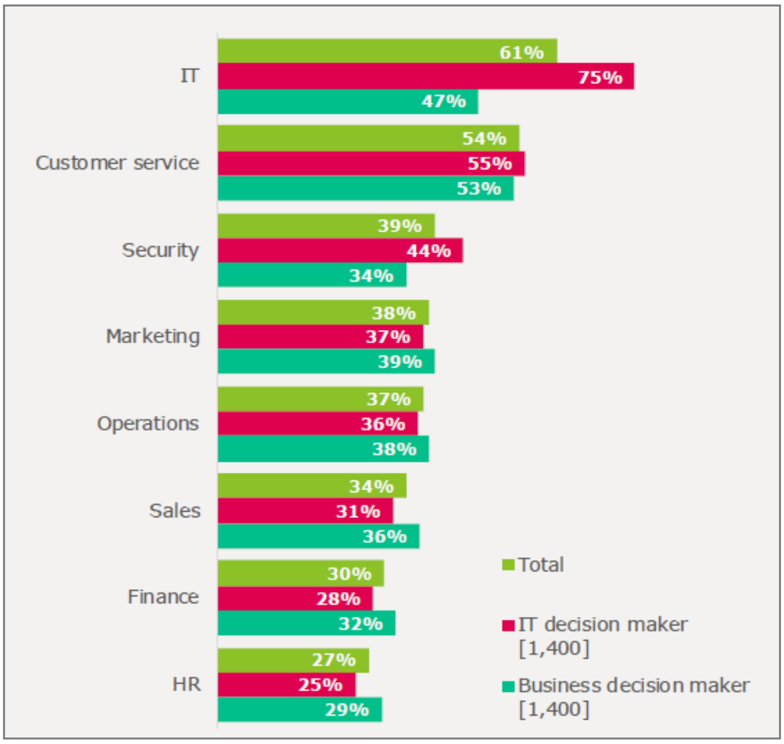
Technological investments in the field of business have shown an increasing interest in exploring conversational agents (Chatbots Magazine, 2019). Conversational agents are “systems that mimic human conversation” using communication channels such as speech, text, facial expressions, and gestures (Laranjo et al., 2018; Radziwill & Benton, 2017). Conversational agents roughly consist of three categories: chatbots without embodiment, virtually embodied avatars, and physically embodied robots. The deployment of conversational agents in service encounters is growing exponentially in industries such as hospitality, banking, entertainment, and healthcare, and it is gradually increasing in other industries (Botanalytics, 2018; Lester, J., Branting, K. & Mott, 2004).

The estimates indicated that the application of these agents will be responsible for cost savings of $11.5 billion by 2023 (Dhanda, 2018).

A Vanson Bourne (2019) survey, *AI in the Contact Center Research*, showed how companies are using AI to drive efficiency in theirs contact centers. The results indicated greater agent productivity (53%), higher first contact resolution rates (51%), increase in the average revenue per customer contact (48%), improvement in the average number of transfers per call (47%), less time spent by supervisors assisting contact center agents (47%), greater number of quality Service Level Agreements (SLAs) met (43%), and no efficiency gains from using AI within the contact center (1%). For the future of contact centers, organizations will have some high aims over the next 12 months: agent assistance and productivity (allowing agents to stay ahead of the customer engagement via predictive analytics) (95%), effortless self-service (allowing customers to help themselves without engaging an agent) (95%), simplified operations (reducing complexity for agents and customers) (94%), smart interactions (create smart, conversational interactions that yield improved results) (93%), smart matching (matching the best agent with each customer) (91%), and empowered agents (using AI to drive agent guidance and suggested actions) (90%) (Vanson Bourne, 2019).

The same survey showed that, outside contact centers, IT is the most likely department (61%) to use AI according to respondents, followed by customer service and security. Figure 17 presents the departments currently deploying AI solutions.

Figure 17. Departments using AI



Source: Vanson Bourne (2019)

Table 8 presents the most likely departments to make AI use cases (Vanson Bourne, 2019).

Table 8. Examples of AI use cases

Department	Use case
IT	Monitoring infrastructure and applications
Finance	Financial analytics
Sales	Analyzing customer buying patterns
Marketing	Communicating with customers
Customer service	Responding to customer queries
Human Resources	Performance management
Operations	Manufacturing analytics
Security	Threat detection

Source: Vanson Bourne (2019)

Concerning the development of AI solutions, the survey showed that 52% of companies mixed in-house and a third party's alternatives, 24% developed in-house solutions, and 24% bought a third party's option (Vanson Bourne, 2019).

2.4 Business process management and operational process

A process is triggered by an event that may originate inside or outside an organization, such as a travel request or a customer order. A coordinated and targeted action in response to such event is called a process. In case the organization is a company, this is referred to as business process (Fleischmann et al., 2020).

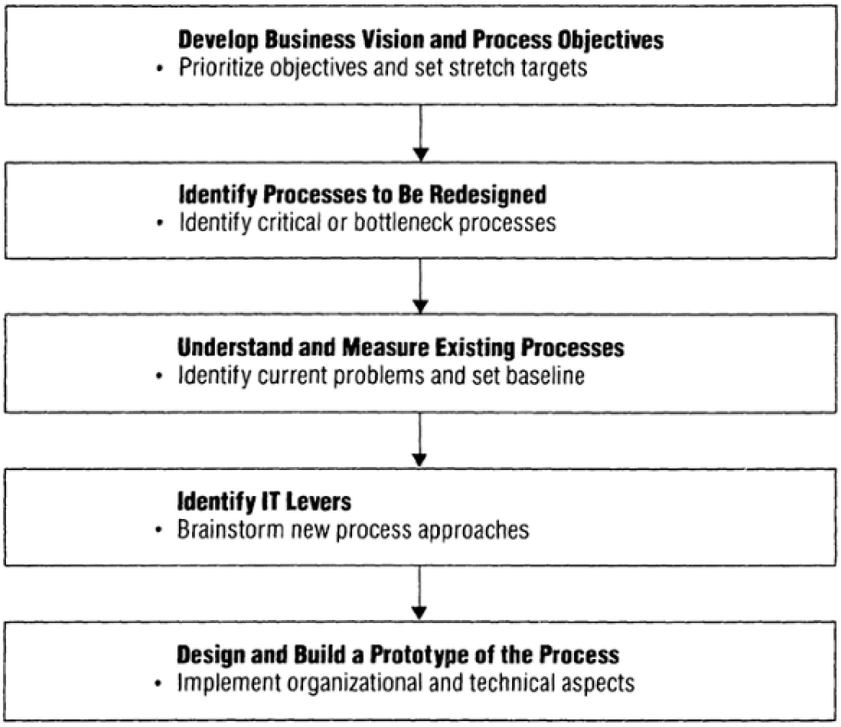
The business process management field encompasses the design, control, and optimization of the business processes of a company (England & Miller, 2016; Hammer, 2010; Lee & Dale, 1998). This field primarily focuses on improving the efficiency of organizations by automating tasks and eliminating bottlenecks, among other strategies (Enríquez et al., 2019). An extensive variety of business terms, such as process redesign, continuous improvement, business process reengineering, is related to this concept of improving quality and efficiency by analyzing and refining business processes (Zellner, 2011).

Hammer & Champy (1993) defined business process as a collection of activities that takes one or more kinds of input and creates an output that is of value to the customer. These same authors belong to the research stream of business process re-engineering, "*an approach used to create a computer-based system for the management of the supply chain traceability information flows*".

On a standard project, a specialist analyzes the current state of processes (as-is model) to detect any room for improvement; then he/she designs a new version of these processes (to-be model) to solve the problems (Dumcius & Skersys, 2019). This process model serves as a basis for the next stage: process implementation. When changes are implemented, the process is moved to the new state so that performance goals can be achieved. Once changes are completed, process execution data is collected and analyzed, new goals are defined, and their respective actions are taken (Dumas et al., 2018).

Davenport & Short (1990) presented five major steps of process redesign: to develop the business vision and process objectives, to identify the processes to be redesigned, to understand and measure the existing process, to identify IT levers, and to design and build a prototype of the new process. Figure 18 illustrates the flow of steps.

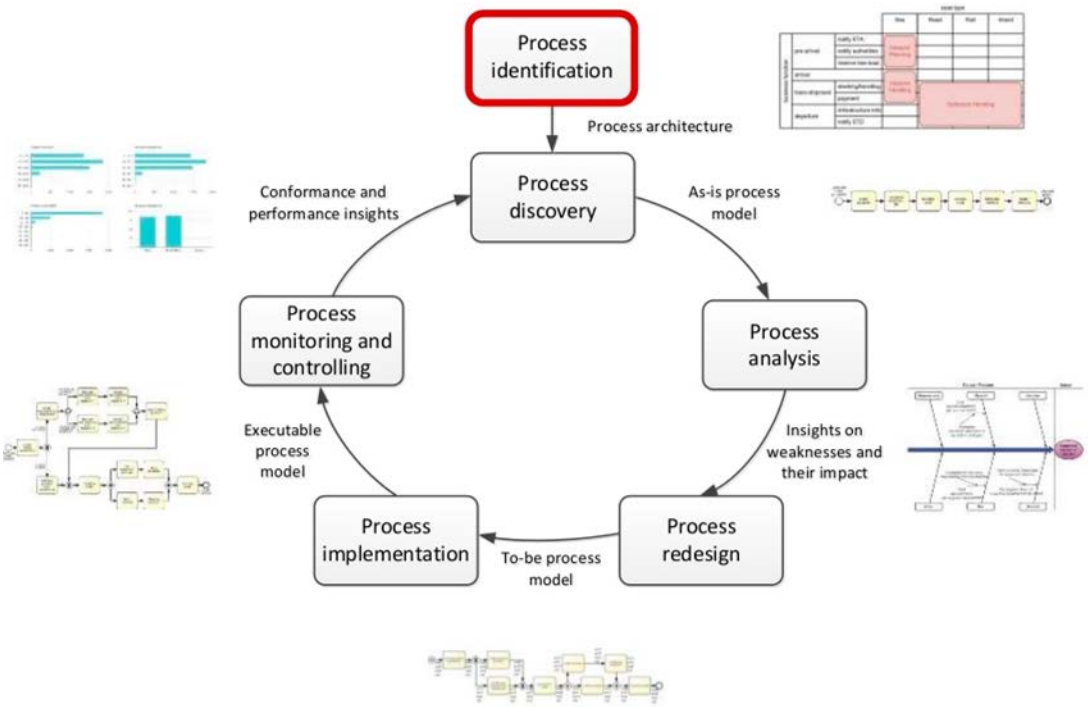
Figure 18. Five steps in process redesign



Source: Adapted from Davenport & Short (1990)

These models are usually described using a graphical representation created for this purpose and called Business Process Management Notation (BPMN) (BPMN, 2019). The latest version of BPMN, 2.0, was released in January 2011. It describes the elements that can be used to model a business process, including activities, flows, gateways, events, and others (Enríquez et al., 2019). Business Process Management (BPM) can be considered as a continuous improvement lifecycle framework with six main phases, as shown in Figure 19 (Dumas et al., 2018):

Figure 19. The BPM Lifecycle

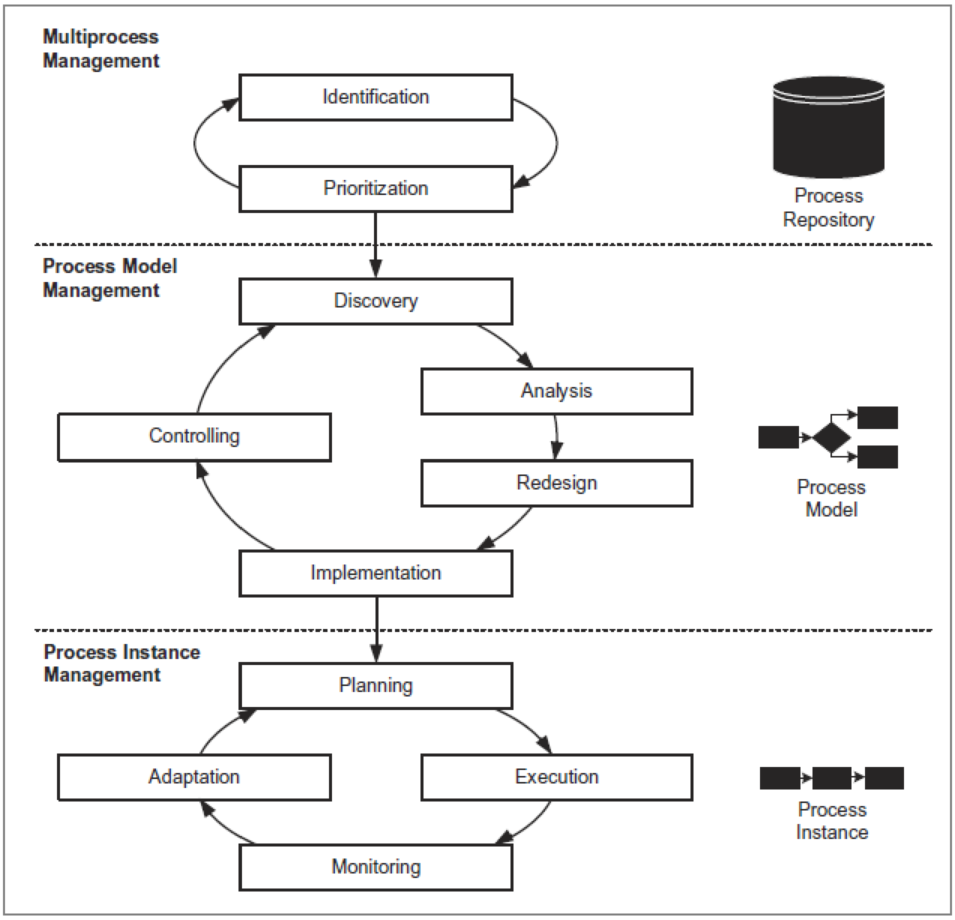


Source: La Rosa & Dumas (2016)

Business processes can also be described using five fundamental perspectives (Zeising et al., 2014): the chronological behavior of the included process tasks (behavioral perspective), the functional elements of a process (functional perspective), the assignment of tasks to human participants (organizational view), the implementation of an atomic activity (operational perspective), and the information entities handled during individual tasks (informational perspective) (Curtis et al., 1992; Mansar & Reijers, 2007; Zeising et al., 2014).

Mendling et al. (2017) distinguished three different levels of business process management. The top level is often referred to as multiprocess management. It identifies the major processes of an organization and regularly evaluates the priorities assigned to these processes. These activities interrelate with issues of strategic management and the overall process organization. The middle level relates to the management of a single process. Management activities on this level are often referred to as the BPM lifecycle (Dumas et al., 2018). The focus of the bottom level is the management of singular process instances. Instances can be planned according to the schedule of their activities and the resources that should be involved. Figure 20 represents these three levels.

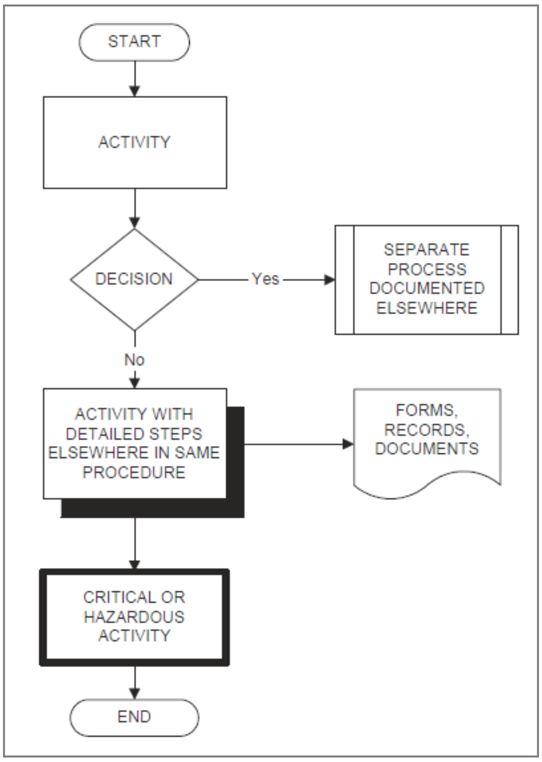
Figure 20. Three levels of BPM



Source: Mendling et al. (2017)

In this study, we built a macro level of the business process affected by AI cases in BPMN to understand and analyze the differences in tasks and processes before and after AI implementation. We considered the process model level by Mendling et al. (2017) and developed a flowchart. Figure 21 illustrates a flowchart example with notation.

Figure 21. Flowchart with notation



Source: Adapted from Hey (2016)

Process is a "specific ordering of work activities across time and place, with a beginning, an end, and clearly identified inputs and outputs: a structure for action" (Davenport, 2013). More specifically, business process is a set of logically related tasks performed to achieve a defined business outcome (Davenport & Short, 1990). According to Chesbrough & Rosenbloom (2002), business processes should be based on the way a business activity is conducted in a company, which has to generate revenue to survive. Pall (1987) and Schein (1988) also converged these ideas into their definition of process: "the logical organization of people, materials, energy, equipment, and procedures into work activities designed to produce a specified end result (work product)" (Pall, 1987; Schein, 1988). Davenport (2013) proposed a business process classification into operational processes and management processes, which we adopted in this study.

A set of processes form a business system: the way in which a business unit, or a collection of units, carries out its business. Processes have two important characteristics according to Davenport & Short (1990):

1. *They have customers; that is, processes have defined business outcomes, and there are recipients of the outcomes. Customers may be either internal or external to the firm;*

2. They cross-organizational boundaries; that is, normally they occur across or between organizational subunits. Processes are generally independent of a formal organizational structure.

Earl (1994) classified processes by their value chain target and process structuredness as follows:

- Core processes are central to basic business operations and directly related to serving external customers. They are usually the primary activities of the value chain;
- Support processes frequently have internal customers and consist of the supporting activities of core processes. Usually they are the administrative, secondary activities of the value chain;
- Business network processes extend beyond the boundaries of the organization, including suppliers, customers, and allies;
- Management processes are those by which the company plans, organizes and controls resources.

Other examples of processes meeting these criteria include developing a new product, ordering goods from a supplier, creating a marketing plan, processing and paying an insurance claim, and writing a proposal for a government contract.

Operations are processes that take in a set of input resources that are used to transform something, or transform themselves, into outputs, services, and products. Although all operations conform to this general input–transformation–output model, they differ their specific inputs and outputs (Slack et al., 2014).

To meet high customer expectations, companies must accelerate the digitization of their business processes. But they should go beyond simply automating an existing process; they must reinvent the entire business process, including cutting the number of steps required, reducing the number of documents, developing automated decision making, and dealing with regulatory and fraud issues. Operating models, skills, organizational structures, and roles need to be redesigned to match the reinvented processes. Data models should be adjusted and rebuilt to enable better decision making, performance tracking, and customer insights. Digitization often requires that old wisdom be combined with new skills, for example, by training a merchandising manager to program a pricing algorithm. New roles, such as data scientist and user-experience designer, may be needed (Markovitch & Willmott, 2014).

An example of task-and-occupation redesign is the use of machine vision systems to identify potential cancer cells—freeing up radiologists to focus on truly critical cases, to communicate with patients, and to coordinate with other physicians. An example of process redesign is the reinvention of the workflow and layout of Amazon fulfillment centers after the introduction of robots and optimization algorithms based on machine learning (Brynjolfsson & McAfee, 2017).

Kakatkar et al. (2020) present four different case studies of AI in action based on previous work in the field. They highlight the benefits and limitations of using AI in innovation and conclude by presenting strategic implications and additional resources for innovation managers. Related with implications for innovation managers: AI draws considerable value from big data, empowers innovation managers to work closely with data scientists to delegate tasks of greater creative complexity to the computer and enables those engaged in the innovation process to better answer existing questions and also to ask better questions based on AI models.

Gust et al. (2017) described how a Swiss electricity utility (SUC) conducted a seed project—a bottom-up initiative to develop an analytics ecosystem of business, organizational and technological capabilities. The project's main challenges and insights are presented in Table 9.

Table 9. Analytics challenges, insights, and lessons

<table>
<tr><th></th><th>Challenge</th><th>Seed Project Experience</th><th>Lesson</th></tr>
<tr><td rowspan="3">Business</td><td>Establish a business case for analytics</td><td>• Analytics reduces overhead of internal processes
• Several future business opportunities identified through interaction between domain and analytics experts</td><td rowspan="3">Leverage process focus</td></tr>
<tr><td>Use analytics to improve decision making</td><td>• Analytics increases planning process accuracy</td></tr>
<tr><td>Measure customer value impact</td><td>• Planning process has reduced response time and can be initiated more flexibly</td></tr>
</table>

Organization	Overcome resistance to change	• Resistance to change originates from both internal, entrenched processes, and external industry norms and standards • Involving users during development helps overcome internal resistance to change	Foster data awareness Adopt agile development practices
	Develop analytics and data skills among staff	• Involvement of stakeholders in agile development facilitates learning on the job • Employees begin to implement new applications	
	Produce credible analytics	• Analytics improves reproducibility by removing subjective manual procedures	
Technology	Provide data access	• Agile development helps to reveal data sources and to flexibly implement additional applications (quick wins)	Move from isolated tools to open platforms
	Manage restrictions of existing IT platforms	• Existing software does not support multi-purpose analytics • Open analytics platform is suited to integrating data from fragmented IT systems	
	Generate appropriate data to support analytics	• SUC's physical infrastructure generates extensive data	
	Manage data quality	• Incompatible databases revealed data consistency problems across SUC's systems	

Source: Adapted from Gust et al. (2017)

Digitalization in the economy or in organizations in general means digitalization of business models, products, and services, as well as of whole processes or parts thereof. For processes, however, this does not necessarily mean full automation without any human intervention (Fleischmann et al., 2020).

Digital technologies are already changing existing work practices and will do so even more in the future, enabling and forcing organizations to redesign their business processes (Allen, 2015; Matt et al., 2015). The problem is that many organizations still lack knowledge on digital technologies as well as on identifying which technologies they should adopt to boost their business processes (Harvard Business Review Analytic Services, 2015).

Process digitalization comprises the technological toolkits that companies use to interact with their channels, including salespeople, independent contractors, or distributors. The goal of process digitalization is operational excellence, with a focus on automating information processes among employees internally so that the engagement between channel members and customers is as informed as possible. Organizational decision making is critically intertwined with an understanding of these enterprise data assets held by incumbents (Khatri, 2016).

Slywotzky & Morrison (2000) coined the term digital business design as the new way in which a firm can capitalize on strategic options available through digital technologies. They suggest that organizations that are able to incorporate digital technologies into their business models will be better able to increase margins and establish competitive advantage. Digital business design means serving customers by creating unique propositions, leveraging talent, and improving productivity and profit.

At present, companies across different industries are infusing AI into their business processes. For example, an AI assistant can access and “learn from” hundreds of customer touch points and can share this data with other systems in an integrated way so that the customer enjoys a consistent experience and is made to feel that the company “knows” him/her. Well-executed AI-powered chatbots improve NPS through speed to resolution, around-the-clock accessibility, and channels in which users are most comfortable. Likewise, as the labor market continues to tighten, employee experience is rapidly evolving to be on a par with customer experience. AI-powered enterprise digital assistants (EDAs) have emerged as groundbreaking tools that can transform the way business professionals work. EDAs are effective applications that act as an interface with other systems to aid humans augment and automate tasks and processes. It does not aim to replace employees but to make their daily work more productive, as well as increasing their engagement, creating connection with colleagues, reducing manual effort, and speeding up time-consuming workflows (Bailey et al., 2020).

Hartley & Sawaya (2019) performed a study based on interviews with supply chain professionals in 14 large, mature manufacturing and service organizations, outlined the promise of digital technologies (RPA, AI/machine learning, and blockchain), and forecast their broad-scale adoption potential. The applications for AI/machine learning were data mining directed to supplier e-mails in order to reduce costs and explore data analytics in demand forecasting and planning, in automated inventory replenishment, and in a cognitive sourcing platform. Many companies do not have the specialized knowledge and expertise to develop and deploy machine learning in supply chain processes on their own. Table 10 shows the progress of cases in DT.

Hartley & Sawaya (2019) suggest the following organizational planning for a successful digital adoption:

(1) Identify a supply chain technology visionary who can guide the organization through the maze of digital technologies: effectively communicate with the company’s executive team members, who are often unfamiliar with digital technologies and unsure of applications, and garner support for technology investments in order to improve supply chain processes.

(2) Develop a digital technology roadmap for supply chain processes: create a competitive advantage using an integrated strategy with digital technologies, business strategy and IT strategy (Bharadwaj et al., 2013).

(3) Update foundational information systems: Many companies are still struggling with outdated or disparate Enterprise Resource Planning (ERP) and/or e-procurement systems. Difficulties in retrieving and sharing information from these systems lead to inefficiencies, errors, and suboptimal decisions.

Table 10. Progress in DT

Degree of Transformation		Company[a]	RPA	AI/ML	Blockchain	Digital roadmap	Cloud-based ERP	Cloud-based e-Procurement
	Medium	Packaging	Pilot	Pilot		Yes	Yes	Yes
		Electric		Yes		Yes	Implementing	Yes
		CPG1	Pilot		Studying	Yes	Partial	
		Health		Yes	In 5 years	Developing	Evaluating providers	Implementing
		Equipment1	Yes			No	Yes	
	Low	Building			Studying	Developing	Yes	Evaluating providers
		Energy				Yes	No	Evaluating providers
		ProServices				Yes	No	Implementing
		CPG2			Studying	Yes	In 5 years	In 3 years
		Auto1		In 5 years	Studying	Developing	No	
		Transport			Studying	No	Partial	Evaluating providers
	Very low	Equipment2				No	No	Yes
		CPG3				Provides Input	No	
		Auto2	In 5 years			Provides input	No	In 5 years

[a] The annual sales of all companies exceeded $1 billion. Health, ProServices, and Transport are service companies and the other companies are manufacturers.

Source: Adapted from Hartley & Sawaya (2019)

Organizations face hurdles when adopting new IT resources (e.g., user resistance) as well as new challenges from the rapid pace of digital technology changes. In addition, DT journeys must overcome challenges common to organizational change, including lack of investment, lack of skills to evaluate and implement new technologies, and resistance to change (Polites & Karahanna, 2012).

2.5 Research Structure and Study Framework

This section presents the research structure with the research category dimensions, guiding frameworks and research structure to research development. The research structure was based on the literature following the main phases adapted proposed by Eisenhardt (1989).

Hess et al. (2016) proposed four dimensions for a DT framework: use of technologies, changes in value creation, structural changes, and financial aspects. With some variation, Vial (2019) designed building blocks of the DT process considering the use of digital technologies, disruptions, strategic responses, changes in value creation, structural changes, organizational barriers, and positive and negative impacts.

Brock & von Wangenheim (2019) presented a framework for implementing AI in the context of DT, offering specific guidance in the areas of data, intelligence, being grounded, integrated, teaming, agility, and leadership. El Sawy et al. (2016) outlined the need for defining and enhancing enterprise capabilities in digital leadership for successful digitalization. El Sawy et al. (2016) illustrated a successful digitalization strategy, where six aspects required consideration and change, namely: business strategy, business models, enterprise platform integration, mindset and skill set, the corporate IT function, and workplace.

Regarding challenges in digital technology implementation, McAfee & Brynjolfsson (2012) identified five challenges for organizations becoming data-driven: leadership, talent management, technology, decision-making, and company culture. Nerur et al. (2005) explored the organizational implications of migrating from traditional software development to agile software development using a model with four dimensions: (1) organization and management, (2) people, (3) process, and (4) technology. Vidgen et al. (2017) found through a Delphi survey the following categories: value, people, technology, data, process, and organization. Also, in their survey, shortage of data science skills, resistance to change, and lack of integrated data management were the main difficulties in three large companies.

We developed a model to understand the organizational changes on business and operational processes with an AI solution, having the DT journey as a background. This study primarily focused on the business process management changes after an AI project was implemented in the companies.

For the study purpose, seven category dimensions were considered (Braganza, 2018; Brock & von Wangenheim, 2019; Colbert et al., 2016; Davenport, 2018; Dwivedi et al., 2019; Earley, 2014; Hess et al., 2016; Maedche, 2016; McAfee & Brynjolfsson, 2012; Nerur et al., 2005; Špundak, 2014; Vial, 2019; Vidgen et al., 2017; Watson, 2017; Yeow et al., 2018): AI in the DT journey, AI projects, business process management, business impacts, organizational aspects, AI integration, and AI implementation challenges. As the reference model, the dimensions followed Yin's (2017) recommendations and presented categories that guided data collection, classification, analysis, and comparison. Table 11 displays these components.

Table 11. Research category dimensions

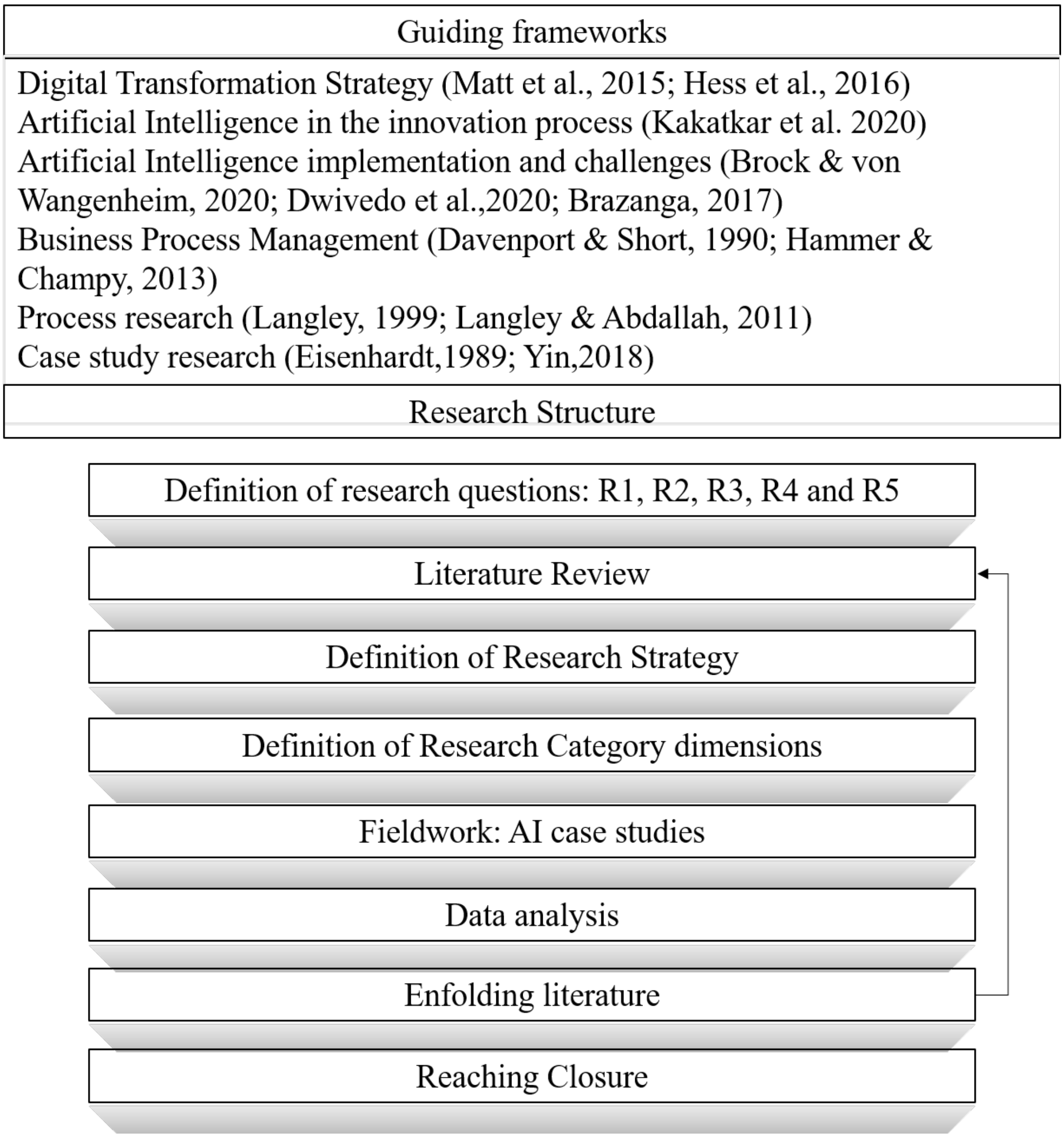
Category Dimension	**Description**	**Source**
AI in the DT Journey	This dimension is related to the effect of DT on a company's portfolio, how DT and ongoing projects are implemented, the search for organizational structure that project governance belongs to, the future planning operation with digital technologies, and the DT roadmap	Brock & von Wangenheim, 2019; Hess et al., 2016; Vial, 2019
AI Projects	This dimension is related to the description of AI projects in the company. It identifies AI technologies, the date when initiatives started, the project management methodology, and if the companies partnered with third parties.	Dwivedi et al., 2019; Špundak, 2014; Vial, 2019
Business Process Management	This dimension is related to the main business process changes. It identifies the main tasks and activities affected by DT and the internal and external SLAs within an AI project.	Dwivedi et al., 2019; Hess et al., 2016

Business Impacts	This dimension is related to finding the extent to which firms use AI in their business and if it is for internal or external purposes—particularly process performance and process redesign.	Brock & von Wangenheim, 2019; Dwivedi et al., 2019; Vial, 2019
Organizational Aspects	This dimension is related to new roles and positions, training, capability sessions, development of specialized groups, relationship with customers and employees, and organization structure.	Colbert et al., 2016; Earley, 2014; Maedche, 2016; Watson, 2017; Yeow et al., 2018
Artificial Intelligence Integration	This dimension is mainly related to the challenge of integrating new digital technology with existing technology in the firms, AI processing, and investments in equipment.	Brock & von Wangenheim, 2019
Challenges	The implementation of AI technologies can present significant economic, social, technological, data, organizational, managerial, political, legal, policy and ethical challenges. This dimension focus on the analysis of the main implementation challenges of an AI project.	Braganza, 2018; Davenport, 2018; Dwivedi et al., 2019; McAfee & Brynjolfsson, 2012; Nerur et al., 2005; Vial, 2019; Vidgen et al., 2017.

Source: The authors.

Figure 22 illustrates our guiding frameworks and the research structure. The guiding frameworks included the following references: Digital Transformation Strategy (Hess et al., 2016; Matt et al., 2015); Artificial Intelligence in the Innovation Process (Kakatkar et al., 2020); Organizational Adoption and Implementation; Process Research (Langley, 1999; Langley & Abdallah, 2011); and Case Study Research (Eisenhardt, 1989; Yin, 2017).

Figure 22. Research Structure



Source: The authors.

3 RESEARCH METHOD

This research studied the main business process transformations after the implementation of an AI project. This is a qualitative research as defined by Denzin & Lincoln (2000) and Theóphilo & Martins (2009).

Some characteristics may also classify this study as an "explicative" investigation. According to Gil (2019), this kind of investigation aims to identify factors that cause a certain phenomenon. Differing from the exploratory research, the explicative study is deep and complex.

The process research recommended by Langley (1999) was employed because it is useful to understand the business processes and because it captures the evolution of phenomena over time in detail. This research used the methodology of studies of business processes as an empirical phenomenon, based on qualitative data from the cases studied (Langley & Abdallah, 2011).

Due to the nature of this research, as well as the scarcity of cases of AI implementation in Brazil, the multiple case study was adopted as an exploration method, because it allows a detailed visualization of the phenomenon and its implications within the context of companies (Voss et al., 2002).

Even though this work does not propose the construction of a new scientific theory, it contributes to the literature by confronting empirical evidence with the literature reviewed, hence validating or challenging some of its results (Eisenhardt, 1989). Questions extracted from the theory were taken to the field, but without limitation, allowing new elements to be added to the final study model. For this purpose, we adopted the case study model classified as theory elaboration by Ketokivi & Choi (2014).

As a structured reference, the protocol proposed by Eisenhardt (1989) was used for case studies, which comprises the following steps:

- Getting started: definition of research questions and constructs *a priori*;
- Selecting cases: specification of the scope of the research and selection of cases based on suitability, and not at random;
- Crafting instruments and protocols: development of a research instrument to guide fieldwork;
- Entering the field: simultaneous work of data collection and analysis, search for flexible data collection instruments that take advantage of the opportunities found;
- Analyzing data: analysis of data within each case and search for patterns between cases;
- Shaping hypothesis: organization of the evidence for each construct, replication of the logic between cases, and search for evidence about the reason of relationships;
- Enfolding literature: crossing data with literature that conflicts with or confirms the results observed;

- Reaching closure: reaching theoretical saturation whenever possible.

A questionnaire with open questions was designed to conduct in-person interviews and ensure that concepts extracted from the literature were addressed in a standardized manner, allowing multiple cases to contribute to the same theoretical structure (Appendix C) (Eisenhardt, 1989).

3.1 Case study variation

According to Yin (2017), case studies is adequate to investigate the how and why for a set of contemporary events. He states that a study case is an empirical investigation of a contemporary phenomenon within its real-life context, especially when the boundaries between the phenomenon and the context are not clearly defined. Yin (2017) also claims that conducting multiple case studies is generally even more challenging, because the researcher has a broader and more robust task than the detailed study of a single case. However, multiple case studies can reward the researcher with expanded possibilities of theoretical replications and generalizations of findings and intersections of cases.

We conducted a multiple case study, as advised by Yin (2014). The study was carried out in companies operating in Brazil in different industries and at varied high stages of DT maturity and AI implementation.

Data were collected in meetings and interviews with multiple departments from the companies. In the meetings, we defined the general profile of each institution, the main changes and challenges of AI implementation, and the solutions provided by AI technology. The results of interviews were tabled and validated.

As secondary sources, to validate the statements from interviews, we analyzed folders and reports made available by the companies, publications in hard copies and electronic media, articles and other sources available on the topic of DT and AI.

3.2 Case selection

Case selection followed the intentional sampling method (Theóphilo & Martins, 2009). As this work aimed to investigate business process changes and impacts in AI projects, we selected companies that had already carried out or were carrying out AI projects in their business processes at the time of the interview.

Another key criterion for case selection presented in the literature was digital maturity. To be an updated and technologically mature company is a prerequisite to adopt new technologies (Davenport, 2018; Hartley & Sawaya, 2019; Kane, 2017). The companies selected had a structured data infrastructure and database to work with AI technologies.

The level of companies' digital maturity was identified through research results outputs from consultancies and market research companies reports specialized in digital capabilities. In these surveys, evaluation criteria were adopted to develop rankings of digital maturity in different industries.

The companies were selected due to their:

(a) pioneering, having completed at least one phase of implementation of an AI project;
(b) high DT maturity;
(c) distinct industries.

In the case selection, one of the sources analyzed was a study performed by McKinsey & Company: *Valor Econômico*: *Índice de Maturidade Digital 2018* (2018 Digital Maturity Index) (McKinsey & Company, 2018). It was a reference of companies that invested in DT. This research was conducted in 128 companies operating in eight industries in different regions of Brazil. It assessed nine dimensions: (1) customer centrality, (2) DT, (3) talent and culture, (4) organization, (5) technology, (6) customer experience, (7) analytics use, (8) operations, and (9) results. Table 12 presents the companies with higher digital maturity in 2018.

Table 12. Companies with the highest Digital Maturity Index

Industry	**Companies**
Finance	Bradesco XP Santander Mongeral Banco Votorantim
Payment methods	Visa Multiplus VR

	Edenred
Retail	Dafiti Pernambucanas Via Varejo Gupo Uni.co GPA
Telecom & Technology	Atento Vivo Stefanini Flex
Infrastructure and Transport	MRV Tecnisa
Basic industry, basic materials, agriculture, and energy	BASF Gerdau EDP
Advanced industry	Sotreq Scheider Eletric
Consumer business	Ambev L'Oréal Natura Dental Cremer
Other industries	Saint Paul Strong Educacional Grupo Fleury

Source: Adapted from McKinsey & Company (2018)

To support the case selection with the digital maturity criteria, we also considered the survey *Digital Transformation in Brazil 2019*, led by E-Consulting in partnership with Centro de Inteligência Padrão (CIP), of Grupo Padrão (E-Consulting, 2019). This survey interviewed 800 executives from the largest 1,000 companies in Brazil to identify companies that were still discovering the role of DT in their business and those that were already driving DT. The categories evaluated were positioning (branding), focus, digital culture, investments, structure, innovation, offers, and customers. Table 13 presents the results of this survey.

Table 13. Prominent companies in DT

Industry	**Companies**
Agro, chemistry, petrochemistry	BASF Cosan Braskem
Food and beverage	Coca-cola Ambev Nestlé
Retail, logistics, and distribution	Makro Martins Profarma
Automobile	FCA Volkswagem Hyundai
Aviation	Gol Azul American Airlines
Banking	Santander Itaú-Unibanco Bradesco
Digital banking and fintechs	Nubank Original XP Investimentos
Durable consumer goods	Samsung Whirpool General Electric
Cosmetics – personal care and beauty	Natura P&G Unilever

Education	Ser Educacional Kroton Estácio
Engineering and construction	Tecnisa MRV Direcional
Pharmaceutics	Novartis Roche Merck
Industry 4.0	3M WEG Embraer
Media, internet, and cable TV	Netflix SKY TV Globo
Health	Hospital Israelita Albert Eisntein Fleury DASA
Insurance companies and health operators	SulAmérica Porto Seguro AMIL/UHG
Digital services	Google Apple Uber
Financial services and payment methods	Stone Pagseguro Serasa Experian
Technology, consulting, and contact center	Accenture IBM TOTVS

Telecom	Telefônica/Vivo Claro/Net/Embratel TIM
Utilities	EDP Elektro Energisa
General retail	Amazon Magazine Luiza Mercado Livre
Retail services, tourism, and entertainment	McDonald's Starbucks Localiza
Retail – Supermarket and drugstores	Carrefour RaiaDrogasil Walmart

Source: Adapted from E-Consulting & CIP (2019).

In addition, the raking published by the Fortune Global 500 was used as a supporting source (Fortune, 2020). The Fortune Global 500 is the annual ranking of the largest 500 corporations worldwide according to their total revenue. All companies on this list publish financial data and report partly or completely their figures to a government agency. Revenue figures include consolidated subsidiaries and reported revenues from discontinued operations but exclude excise taxes. For banks, revenue is the sum of gross interest income and gross noninterest income. For insurance companies, revenue includes premium and annuity income, investment income, realized capital gains or losses, and other income, but excludes deposits (Fortune, 2020).

In order to search for the AI service providers of the selected companies, we used the HFS Enterprise AI Services Top 10 Report, which examines the part service providers are playing in the rapidly growing AI landscape. The report examines 21 service providers across a defined series of innovation, execution, and voice of the customer criteria. HFS's inputs to conduct the survey were detailed Request for Information (RFIs) from service providers, briefings with leaders of AI practices within service providers, interviews with reference and non-reference AI clients, a HFS survey with 262 Global 2000 enterprises, and publicly available information sources (HFS, 2019). Table 14 presents the top 10 AI service providers according to this research in 2019.

Table 14. Top 10 AI service providers

AI service provider
Accenture
IBM
KPMG
Cognizant
TCS
Genpact
Atos
Infosys
Wipro
Deloitte

Source: Adapted from HFS (2019)

We listed the companies mentioned in the sources to organize the data and discover the most frequent companies in each source and ranking. Our company list was classified according to economic sector and industry.

From this list, a search was carried out to find if these companies had AI projects. For each industry, we searched the keywords “company name” and “artificial intelligence” in a web search engine to validate if the companies met our research requirements (high digital maturity and presence of an AI project). In case of a positive result, we identified the stage of AI implementation and the company’s industry. Therefore, the selection of case candidates occurred according to our research requirements. So, this research helped to understand at which stage of the AI journey the candidate company case was at the moment.

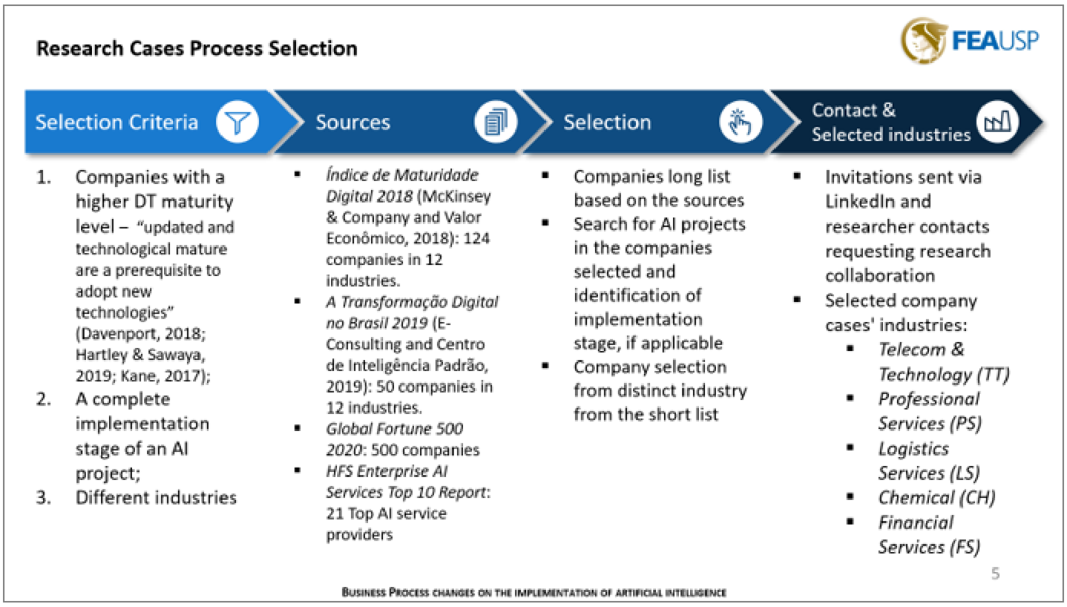
In the next selection step, invitations were sent through a professional social network (LinkedIn), requesting companies to collaborate with our research. Some industries, such as healthcare, utilities, and consumer business replied in the first contact, however they did not respond formal requests for interviews. An IT employee and the head of IT Product Platforms for Customers from a life sciences and pharmaceutical company agreed to collaborate, but the legal department hampered the study continuity.

Our case selection resulted in five companies belonging to five different industries. They fulfilled all the requirements established in this research and agreed to participate:

- Financial services;
- Telecom & technology;
- Chemistry;
- Professional services;
- Logistics services.

Figure 23 summarizes the workflow of case selection.

Figure 23. Research Case Process Selection



Source: The authors

3.3 Data collection and analysis

The primary data were collected from the selected companies. Primary data are defined as the information extracted from the object of study (Theóphilo & Martins, 2009)—in our case, members of the companies.

Companies' stage in the DT journey is the background and start of AI initiatives. Previous AI project documents obtained in the first contact were analyzed to assist the selection of projects for a more detailed investigation.

A semi-structured interview was conducted with the companies' managers/leaders from different departments and areas to collect information on AI and DT projects (Appendix B; Appendix C). The respondents were from the following areas: Digital Transformation, Audit Innovation Technology, IT, Process Digitalization and Continuous Improvement, Digital area, Data Management—Algorithms & Innovation, Operations, and Project Management Office (PMO).

The fieldwork phase took six months, from February to July 2020. We interviewed people in different positions in the companies' hierarchy and in a consulting firm in many rounds. Each main interview had an average duration of 90 minutes and additional interview rounds had an average duration of 30 minutes. Due to COVID-19 social distance restrictions, the interviews were performed via video conferences on Zoom, Citrix Platform, and Microsoft Teams.

For confidentiality reasons, each company received a code according to their industry. Table 15 presents the code and industry of each case, as well the number of interviews, number of interview rounds, interviewee's role, area, and years of work experience.

Table 15. Interviewee's role profile

Company	**Industry**	**# Interviews**	**# Interview rounds**	**Interviewee's role**	**Area**	**Years of experience**
FI	Financial services	2	2	Vice President	Data Management—Algorithms and Innovation	12
			2	Consulting Manager	Project Management	8

TT	Telecom & Technology	1	2	Senior Manager	Digital Transformation (Process Digitalization and Continuous Improvement)	12
CH	Chemistry	1	2	Data Scientist	Digital	16
PS	Professional Services	3	1	Managing Partner	Data & Analytics	20
			1	Systems Coordinator	IT	11
			2	Supervisor Senior Auditor	Audit Technology Innovation	10
LS	Logistics Services	2	2	General Manager	Digital Transformation	20
			1	Solutions Design Manager	Operations	12

Source: The authors

The interviews were recorded for analysis and case writing. After writing, the cases were submitted to revision by the interviewees in an iterative process. Multiple interview rounds were made in order to validate the information provided during the interviews.

Chapter 4 describes each company's AI project implementation following the Research Interview Protocol structure presented in the Table 26 in the Appendix:

1. Company information;
2. Interviewee information;
3. DT Journey;
4. AI Projects;
5. Business Process Management;
6. Business Impacts;
7. Organizational Aspects;
8. AI Integration;
9. Challenges.

4 CASE STUDIES

This section presents the results of our multiple case study. After presenting the cases, we compared our findings in the Discussion section. In the Conclusion section, we exhibited the general conclusions, research limitations, suggestions for further studies, and contributions for management practice.

The companies belonged to the following industries: telecommunications & technology, professional services, logistics services, chemistry, and financial services. All of them met the criteria of having a high DT maturity and an implemented AI solution.

4.1 Financial Services (FI)

FI is one of the biggest banking and financial services companies in Brazil. It has 4,400 branches, almost 98,000 employees, 4,025 service stations, 70 million customers, and 40 million correspondent banks (2018). Customer segmentation comprises corporate clients and natural person. The main products and services are banking, investment banking, private equity, asset management, private banking, insurance, and retail banking.

The interviewees were a Vice President of the Data Management – Algorithms and Innovation department and a Management Consultant responsible for the AI Project Management Office (PMO). The Vice President has 12 years of experience in the technology field and the consultant has 8 years of work experience. In addition to the information collected in the interview, we collected public data from FI’s websites, sustainability and annual reports, and corporate events.

4.1.1 FI DT Journey

The DT journey in the company goes back to the proper development of the financial services industry. In the past, DT projects were developed, such as instant banking, Automated Teller Machine (ATM), internet banking, and mobile solutions.

Annually, the company invests R$ 6 billion in technology considering IT infrastructure and cybersecurity programs (risk management). The innovation strategy is centered in three axes:

1. Digital innovation: new products, services and available technologies on digital channels, which complement physical channels, simplify

customers' lives and ensure convenience, agility, and security. This is the pillar where the AI solution reported in this work stands;

2. Open banking: a regulatory initiative for sharing information between financial and non-financial institutions. Banks have the possibility to establish external partnerships to offer new lines of business and meet new niche markets;
3. Digital bank: digital native bank designed to transform the relationship with an audience hyperconnected with money. It is a 100% digital bank platform.

The company has projects that involve the use of big data and advanced analytics oriented to create offers that are more relevant for customers. One example is the CRM project, which aimed to reorganize the decision governance of offers with intense use of analytics. This project included hiring 80 data scientists and implementing specific technologies in partnership with a reference company in CRM decision software. Another example is a business intelligence project, which used data intelligence to transform credit offering for customers by integrating journeys, processes, price, and credit, supported by new technologies and decision making in real time.

In 2018, FI developed an innovation ecosystem hub (open innovation) to support corporate strategy and foster innovation through collaborative work with employees, business areas, customers, companies, startups, partners, technological investors, and mentors. This innovation platform allows users to share future business visions, accelerate the search for new solutions, and materialize corporate innovation with the goal of meeting customer needs and ensure business sustainability in the long run. Furthermore, the company has a Labs department with internal and third-party tech companies to work with internal cases related to DT and data & analytics.

Other digital initiatives include biometrics in ATMs and voice biometrics in call centers—and there are tests on facial recognition. Another digital solution is cash deposit with banknote reuse. With this solution, the customer no longer uses envelopes: cash value is credited in real time in the recipient's account, and the notes deposited may remain available for other customers to withdraw them. The self-service channel offers the option of sending the deposit receipt by e-mail and not printing it, reducing paper consumption. Part of FI's business partners (bank correspondents) receive tablets with more operational functionalities. The bank was a pioneer in enabling a mobile service for check deposits. The customer photographs the check in the app and sends it to his/her own account.

In the bank app, opening a natural person account is 100% online. The company also provides an exclusive digital account for individual microentrepreneurs, which can be opened via mobile. Since its implementation in May 2019, 21,100 accounts were opened via this mode.

In the Health Insurance business, in 2019, about 40% of medical reimbursement orders were carried out digitally, while refund claims via digital channels reached 92.6%. In the Auto Insurance area, more than 8% of inspections and 16% of towing services were scheduled via app. In the Life and Social Security area, 175,000 proposals were electronically signed.

To support HR processes, innovation and digital solutions were used to ensure scalability and a better internal audience experience. FI carried out partnerships with startups and system updates and launched an integrated HR platform. This solution emerged to improve and integrate three pillars: the corporate university, the human capital management area—responsible for performance assessment and succession process—, and the recruitment area.

4.1.2 FI AI Projects

An AI virtual assistant initiative was implemented with the support of the innovation ecosystem hub. This project represented one of the greatest drivers of DT in the bank.

In 2015, the company signed a contract with IBM and started working in this solution. In the first phase, in 2016, the AI solution was used as an internal support solution for employees in the branch network by answering questions about products and services of bank accounts. In August 2017, the AI solution started to interact by voice and text with customers at the company’s application in natural language, considering its cognitive capacity supported by an AI engine. The Research and Innovation director said:

> *“As the result was very positive [in 2016], we started to implement for the customers and in 2017 we put it on the bank’s app: ‘Ask the AI’”.*

In 2016, one of the drivers that stimulated the leverage of AI was the acquisition of another bank in Brazil with 851 branches, 464 service points, 669 electronic service points, 1,809 self-service environments, and 4,728 ATMs. At the time, a huge effort was made to train the “new” commercial force to understand systemic screens, business processes, etc. All processes had to be done without burdening customer service. Thus, the AI initiative could be offered in a scalable way to deal with this issue.

Currently, in addition to knowing products and financial services, the AI solution enables users to check their account’s balance, latest entries, financial ratios, and network of nearest branches by geolocation.

Since August 2019, the solution achieved a new level of experience, with a project that enabled voice-controlled bank transfers. The solution understands the customer’s intention to make a bank transfer based on his/her verbalization, without the need for any typing.

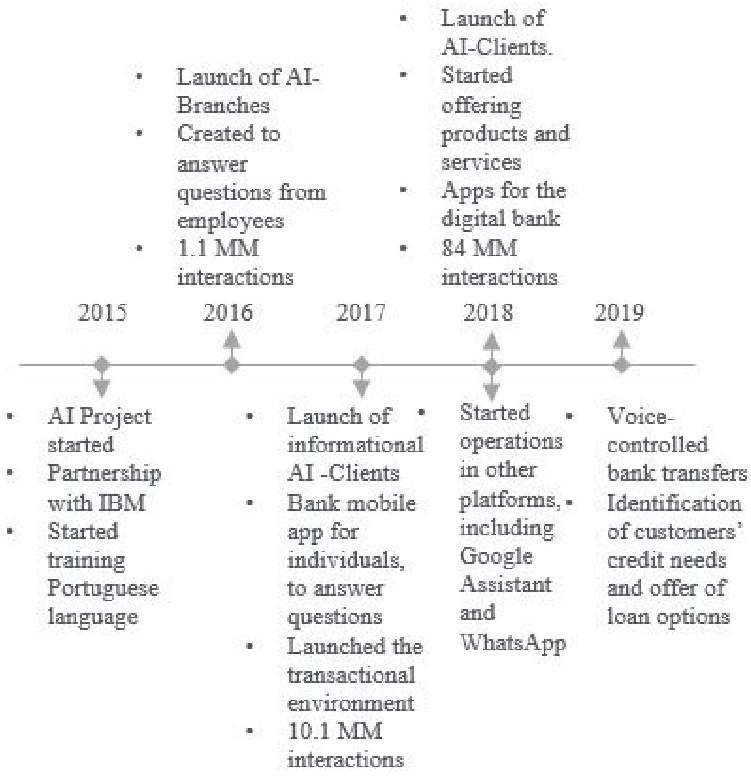
In the second half of 2019, FI implemented a skill that allows the AI solution to identify a customer’s credit needs and to offer loan options. These options can be contracted in the mobile journey. A Development and Research Manager commented on this solution:

> *“We see human interactions with artificial intelligence systems as the future customer relationship in banks, streamlining communication with the customer and making bank systems more efficient.”*

In addition to the mobile app, the AI virtual assistant is available in the digital banking and insurance apps. The assistant answers questions on WhatsApp via text messages and it is integrated with Google Assistant, Alexa (Amazon service), and Apple Business Chat.

The AI solution also has the service "How is the economy?", where the customer receives updated information on the economic scenario, generated by the FI’s Research and Economic Studies department, and a link to the bank’s current Economy portal. Figure 24 represents the AI solution timeline.

Figure 24. FI's AI Solution Timeline



Source: Adapted from Financial Services (2020)

The AI technologies used were RPA, machine learning, NLP, IoT, blockchain, neural networks, Optical Character Recognition (OCR), and deep learning. The AI tools used were IBM Watson Assistant and Watson Discovery.

In addition to AI virtual assistants, the company works with predictive models, prescriptive models, speech analytics, and text analytics. Third party consulting companies participated in the development of AI tool and PMO.

The project management methodology for DT and AI projects had some characteristics from agile. The company seeks to combine PMI (PMBOK) and agile. For example, the agile methodology does not work well for reporting to regulatory bodies.

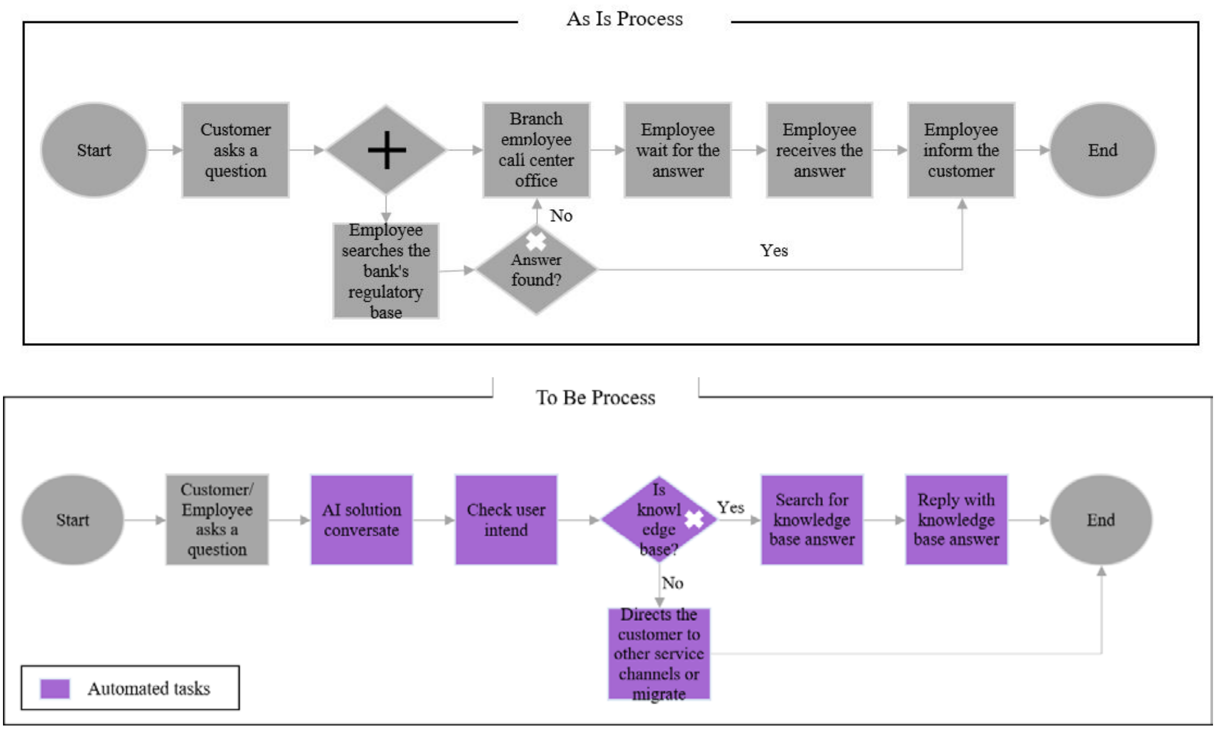
4.1.3 FI Business Process Management

The automated business processes affected employees (AI branches) and customers (AI customer).

Before the AI system, branch employees had to call a central office for answers to unresolved queries. As the employee waited, customers also waited, and sometimes those waits were lengthy. Another alternative was to search the bank's regulatory base (using keywords to streamline the process), but employees did not trust the system—many said it was not necessary in the search and did not deliver the correct document, which made the process as slow as calling the central office. However, even if the system delivered the right document quickly, another problem arose: the extremely technical vocabulary. Many employees were unable to clearly understand what the document explained and many resorted to the internal call center, causing more delay.

In the to-be process, the AI solution analyzes the user's input to determine his/her intent or what he/she is trying to achieve. The intent corresponds to the topic of the question (e.g., payments, query balances and statements, nearest bank branch, transfers, currency exchange, etc.). Then there is a decision in the intent architecture in two categories: knowledge base or not. If the question exists in the knowledge base, the AI solution brings it and answer the user. If not, the AI solution directs the user to another service channel or migrates him/her to human assistance in specific cases. Figure 25 represents the business process management changes.

Figure 25. FI's Business Process Changes



Source: The authors

4.1.4 FI Business Impacts

The impacts of DT on business processes started in the internal process (employee relationship and training purpose) and then moved to the external process (customer relationship), representing a new channel for services and transaction operations.

According to FI's Development and Research Manager:

> *"the AI initiative generated a new demand for delivering information to customers through platforms such as the website and applications developed in the partnership [with IBM]. This resulted in a decrease in waiting time, assistance to bank managers and employees in solving problems and questions about services and products, among many other features."*

In general, the use of AI has generated efficiency, technological updating, customer satisfaction, quality, and standardization of service. It represents innovation in business models and in the work of professionals involved with the service.

After five months of training, the AI solution understood 100% of written questions and 83% of spoken ones. After ten months, the system was answering 96% of all questions correctly. Then, the solution was trained on 62 products and answered 283,000 questions a month with a 95% accuracy rate, with an answer time shorter than three seconds. Only 5% required calls for further assistance.

The AI virtual assistant registered more than 363 million interactions, 133.9 million of them on WhatsApp. In total, 3.5 million people already talked to the AI solution. The agility and quality of service are benefits for customers. Currently, the assistant understands customers' intent 94% of the time with 90 products available.

In the IVR (Interactive Voice Response) call center, the AI solution had an average of 471,000 iterations a day, with 198 redirect tags and 94 answers in the knowledge base.

In the bank acquisition case, without the cognitive assistant, FI would have to grow its service structure. Nevertheless, it was not necessary to meet the intensification of calls at the bank's call center.

Another impact was brand awareness. With the talk capability, customers engaged more and elevated DT.

Throughout 2019, the digital bank held partnerships with companies from other industries, such as a large Brazilian cosmetics company. Thus, a new business model was created. FI offered a set of important benefits for beauty consultants, who had access to a 100% digital account and a free credit card machine, hosted by another bank partner. The purpose of these partnerships is to achieve new accounts, which will centralize card receivables in their accounts and will become distributors of the bank for the general public. In addition to this new distribution model, the digital bank started to operate with corporate payrolls that have employees with customer digital bank profiles.

4.1.5 FI Organizational Aspects

Since 2017, the company has focused its structure on data and analytics, which act as a CoE. There are more than 200 data engineers and scientists, who interact with specialist cells from the most diverse areas of business and support activities. In addition to projects focused on improving customer experience, FI has worked in application algorithms and models in various use cases to increase their operational efficiency and improve controls.

The Data & Analytics team has four value streams:

- Control improvement: identification of anomalies and fraud, path and money laundering;
- Operational efficiency: optimization of internal processes, operational dimensioning, and cash logistics;
- Customer experience: predictive and prescriptive models to understand customers' moment and satisfaction;
- Generation of business value: ability to capture information and develop accurate models to generate revenue in a sustainable manner.

For the AI solution, FI built a multidisciplinary team. There was a core team to develop the AI strategy by analyzing the newest trends and giving directions. There was a team of developers to connect the strategy to the bank systems. And there was an entire team responsible for curatorship, which trained the virtual assistant to give appropriate answers. This team understood question trends to give the best answers to customers. The project has almost one hundred professionals allocated in several areas: Innovation, Channels, Development, Infrastructure, Architecture, Support, and Business. The company invested in the employees' career by creating new functions and developing specialists to build new experiences with AI.

The knowledge curatorship area includes people who have already operated in the call center. Instead of serving customers directly, they train the virtual assistant. This team of curators specialized in digital information is dedicated to improving the platform, which has undergone language training suitable for the millennial public, and to provide a friendly service to the digital bank customers. This curation has been carried out by the Artificial Intelligence Center (CIA), a team of employees specialized in the content and verification of answer accuracy.

The bank has a Corporate Governance area, which is directly linked to the Executive Board. The area of IT Governance is strictly linked to the area of IT and is directly subordinated to the IT Executive Vice Presidency. Thus, IT is seen as a whole and is accountable to the Board, because it captures all initiatives, evaluates and observes what happens in technology. The IT Executive Vice President establishes a link with the Board, since he/she participates in the Executive Board (the committee) along with other vice-presidents, directors, and board members.

The Technology and Business department monitors and manages all the demands of the business areas and captures opportunities at the sources. By being simultaneously close to business and IT areas, this department can capture the needs of the moment and quickly produce the documents that will be interpreted by the technology and translated into systems. As the company has many, varied and extensive demands, this department disciplines prioritization according to importance and emergency—for example, the government announces a legal determination to take effect on a set date.

There were some layoffs as a result of DT and AI initiatives.

There were several training sessions, such as AI tool utilization and design thinking.

4.1.6 FI AI Integration

The IT department is composed of more than 3,000 employees. The company departments are structured and prepared to meet business needs with specialization. The company has areas that exclusively deal with financing, credit, IT, cards, loans, sales, promotions, etc. So FI is structured in business areas. The company operates in all Brazilian municipalities, with more than 200 million transactions processed every day (on average, as some days register 320 million transactions).

There were AI integration complications due to system instability and rollout of new features.

Intent recognition is processed by IBM. Speech-to-text transcription is done in the device, and from time to time it goes to the cloud. The AI solutions were processed on-premise, especially for information security and privacy issues, and on IBM cloud.

4.1.7 FI Challenges

The main challenge reported in AI projects was how to scale solutions. The use cases for internal bank users is very different from customer users. Solutions must consider infrastructure and technical issues on the journey topics. In that way, some questions emerge: “How does the company take organizational learning to generalize?” and “How does the company acquire capabilities?”.

Another challenge was to manage qualified workforce turnover in agile DT deliveries. Additionally, there was a scarcity of skilled labor in AI. In this scenario, investment in training and acquisition of new skills becomes essential.

Another difficulty was the attempt to applicate DT/AI solutions without understanding the real problem. Because of the “hype”, some teams wanted to solve problems using robust mathematical methods in cases where simpler solutions would be more effective.

No difficulties were found in demonstrating the value of AI projects, because the top management already had a clear direction.

Other great obstacles pointed by the IT department included handling the large volume of demands from the business areas, dealing with teams’ anxiety to have their products in production, and maintaining a high system availability in production and processing areas so that customers were not affected by systemic downtime on a daily basis.

4.1.8 FI Summary Table

Table 16 presents the case study summary analysis for the FI company.

Table 16. FI Summary Analysis

Category Dimension	Description
AI in the DT Journey	• 2015: IBM Partnership; • 2016: AI - Branches: internal; • 2017: AI informational - Clients: external; • 2018: AI - Clients - external and Innovation hub; • 2019: More functionalities available for AI Solution.

AI Projects	• AI chatbot and virtual assistant designed to provide immediate customer and employees responses in multiple platforms. Built from the Watson cognitive computing platform in partnership with IBM; • Open banking; • Digital banking and financial services; • CRM; • Automation on ATMs and biometrics; • Digitalization of medical reimbursement health and insurance; • HR Platform.
Business Process Management	• Scope: Customer Service Business process changes started internally and then moved to customer service.
Business Impacts	• Decrease in waiting time; • Support to bank managers and employees in solving problems; • AI understands 94% of the intention; • 90 products available; • 363 million of interactions (133,9 million on WhatsApp); • Enable bank acquisition without increasing organizational structure; • Brand awareness.
Organizational Aspects	• Areas: Data & Analytics, Innovation, Channels, Development, Infrastructure, Architecture, Support, business areas and Technology and Business Department; • Create Artificial Intelligence Center (CIA); • Creation of teams specialized in AI content, verification and curatorship; • Cases of job dismissal.
Artificial Intelligence Integration	• More than 200 million transactions processed per day on average (peaks of 320 million transactions); • AI integration complications due to moments of systems instability and the roll out of new features.
Challenges	• Projects prioritization and selection; • Digital solutions scalability; • Lack of specialized AI workforce and deal with team's turnover;

• Diffusion of AI Knowledge in the company teams.

Source : Authors

4.2 Telecom & Technology (TT)

This case is of one of the largest telecommunication companies in the world by market capitalization and number of customers. It provides fixed, mobile and broadband networks. This company had 122,000 employees in 2018 and operated in 14 countries, split into two geographic regions: Europe and Latin America. In Brazil, it has approximately 100 million clients, including Business-to-Customer (B2C) and Business-to-business (B2B).

The employee who collaborated with the research interview was a Senior Manager from the Digital Transformation (Process Digitalization and Continuous Improvement) department. He has been working in this department since 2018 and had 12 years of experience in the field at the time of the interview.

In addition to the information collected in the interview, we accessed public data from the company's websites and a recorded interview with the Chief Data Officer (CDO), who was the main officer responsible for the cognitive solution implementation and material presented in corporate events.

4.2.1 TT DT Journey

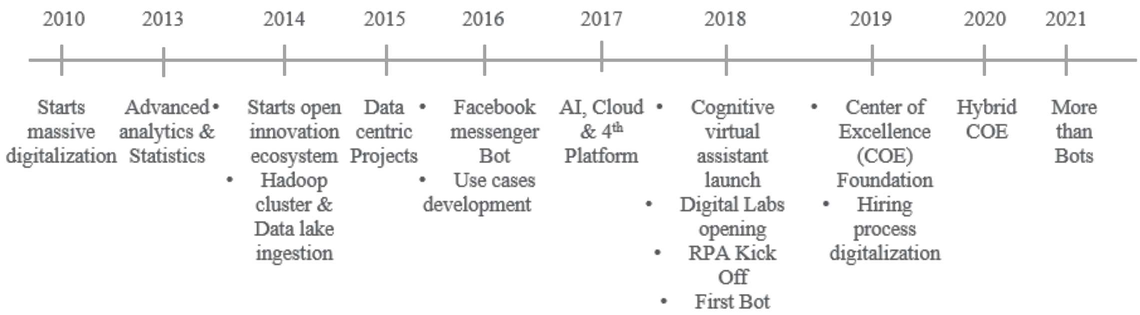
The entire telecom industry has undergone a long-term fundamental transformation driven by over-the-top (OTT) providers, voice over Internet Protocol, and the exponential growth of network traffic. Therefore, TT has also been challenged by digital disruption and changing customer preferences.

The company has a strong market share in its core markets. Thus, it is exposed to multiple countries and economic vulnerabilities in the markets where it operates. In order to address these challenges, the telecom company needed a new strategy—one that would transform its applications and operations and make use of data to better serve customers and employees, while providing a robust foundation for the future of the organization.

The company's DT started in 2010, when it committed to a massive digitalization project to make its platforms intelligent and modernize the business. In 2014, the company inaugurated an open innovation ecosystem in Europe with acceleration programs for startups. Starting in 2015, data centric projects have been encouraged, and a cognitive virtual assistant was launched in 2018. In the same year, the company opened in Brazil their own Digital Labs, a Bot Training Center, and an RPA Kick Off to implement its first bot. On the following years, more bots and a Center of Excellence (CoE) were developed to provide quality and efficiency to technology project deliveries. The company also managed to digitalize its hiring process using video bots, SMS, and a digital platform. Until 2021, there is a goal to achieve R$ 1.6 billion in financial savings through digitalization.

TT's Global Digital Transformation Program was built on four pillars: digital value proposition, end-to-end digital customer experience, process automation, and cutting-edge technology. In Brazil, the company created the BOTS program of process automation. Figure 26 presents these main events on a timeline.

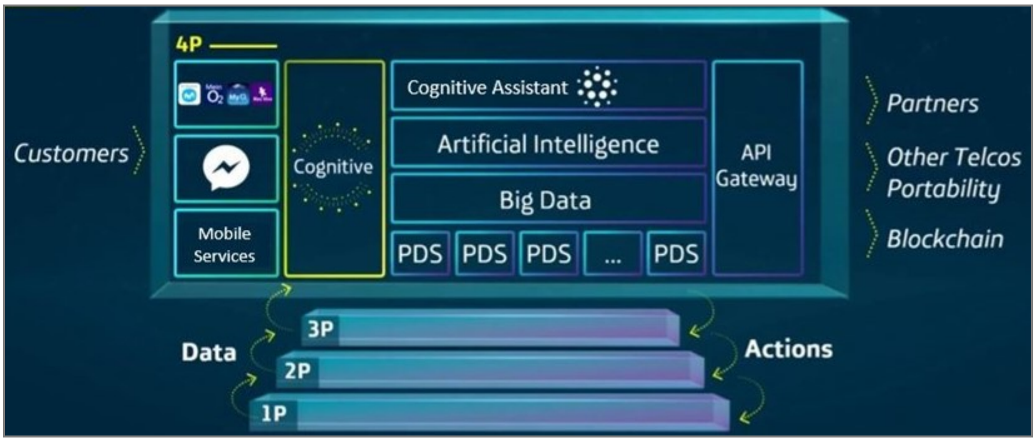
Figure 26. DT timeline of TT



Source: Telecom & Tech company (2020)

The business strategy was redesigned into four platforms: 1st level: telephony, which includes the company's networks and other physical assets; 2nd level: links, which encompass unified IT systems; 3rd level: all digital products and services offered to customers; 4th level: services that arise from data utilization (for example, integration with personal assistants, behavior understanding to personalize products and services, active customer interactions and suggestions, data utilization applications). Figure 27 illustrates TT's 4th platform framework.

Figure 27. TT 4th Platform framework



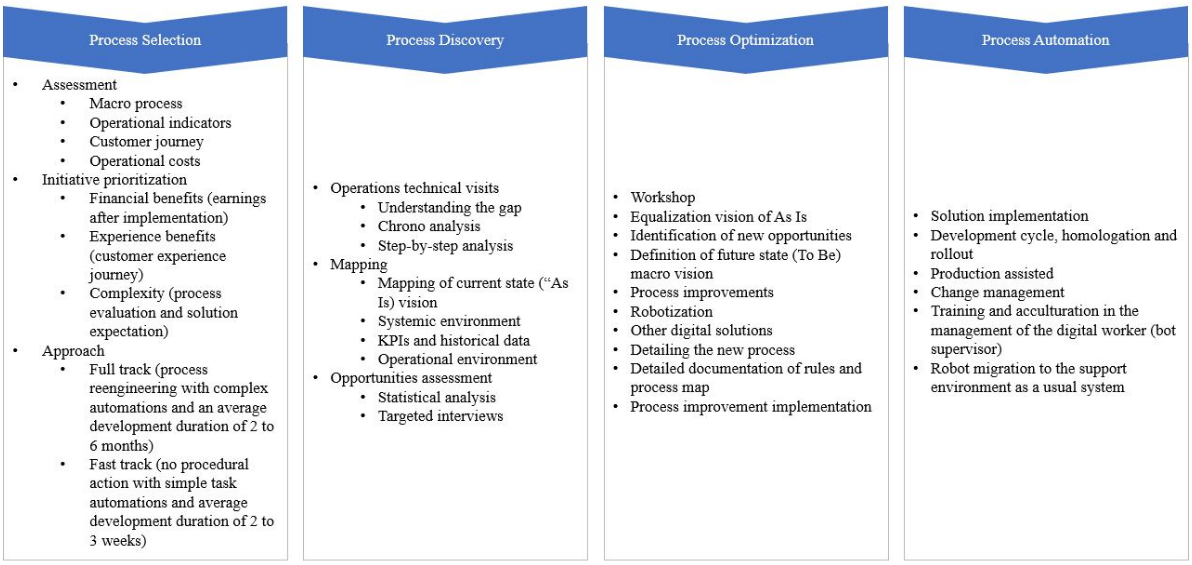
Source: Telecom & Tech company (2020)

Since 2012, TT has invested approximately €48 billion in this whole process to deploy networks and other state-of-the-art infrastructures, to integrate IT systems, or to develop new digital products and services.

4.2.2 TT AI Projects

The project selection process for DT and AI initiatives followed a framework of four phases: (1) process selection—benefit estimate, complexity assessment, and approach definition; (2) process discovery—operation visits, process documentation, and assessment of optimization opportunities; (3) process optimization—simplification and exclusion of no value activities; (4) process automation—digital solution implementation and training, and acculturation of the new process. Figure 28 presents the projects selection framework for the TT company.

Figure 28. TT's selection framework for digital initiatives



Source: Telecom & Tech company (2020)

For the Telecom & Tech company, DT projects can start in the business areas or through the Digital Transformation (Process Digitalization and Continuous Improvement) department.

TT decided to implement an AI solution, and its CDO highlighted some relevant points of the strategy:

> *"We started about three years ago [2015] with a big project internally, a big transformation using data to make decision. We started to think about [the company] as a data-centric organization. So, we put the data in the core of all our decisions. So when we were doing this, we realized that we wanted to give full control of all the data to our customers, our customer-generating, our assistant, and we needed to create an interface that was easy enough to be managed by all of our customers, so we decided to go through artificial intelligence technology to create a cognitive intelligence in which our customers could just talk to the assistant and get things done in real time."*

TT's first AI project was a digital assistant, which had three core principles: transparency, control, and security of customers' personal data. Customers can use the assistant to ask questions about the products and services they use, create and track a claim, manage and unblock device access to Wi-Fi routers, and receive data consumption alerts. Customers can search, sort, change channels or watch content on the TV, as well as on the company's pay TV, and receive personalized recommendations based on their watch history and preferences.

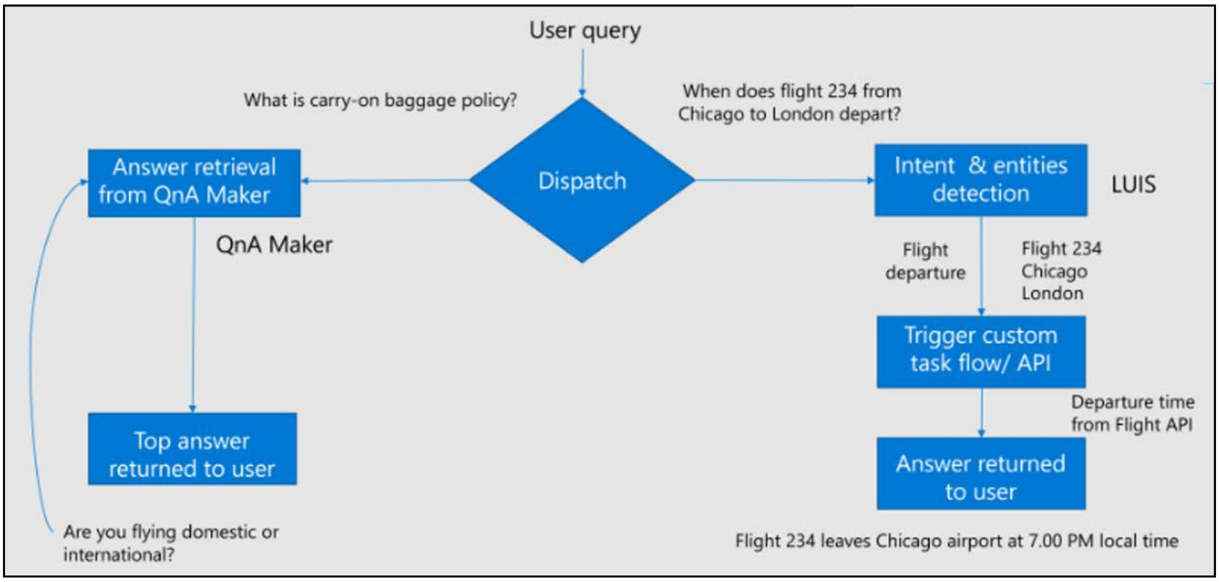
Depending on the country, the cognitive assistant is delivered to customer devices via mobile app or through third-party channels, like WhatsApp, Facebook Messenger, and Google Assistant. The assistant can leverage the power of AI to provide customers with customized experiences and to facilitate the adoption of new value-added products, based on data insights. Another functionality is the collaboration with partners through integration with other technologies and digital services.

The agile project management with scrum was used. Additionally, TT applied Lean Six Sigma and Kaizen concepts, mainly on the process optimization phase. Currently, the company is organized in 20 squads with 30 ongoing projects and more than 100 backlog projects.

The AI technologies implemented included RPA, machine learning, deep learning, OCR, IoT, neural networks, and NLP. For RPA projects, TT hired consulting companies to implement and integrate the process automation tools. Investments were made in contracting tools, virtual machines, and IT park structuration.

The cloud features involved in the AI project were Bot Framework, QnA Maker (a cloud-based API service that creates a conversational question-and-answer layer over the company's existing data), and LUIS (Language Understanding—a machine learning-based service to build natural language into apps, bots, and IoT devices) from Microsoft Cognitive Services. The QnA Maker returns an answer to a question from a customized knowledge base, while LUIS determines the user's text intent; thus, the service does not return an answer to the question. Figure 29 exemplifies the QnA and LUIS services (Microsoft, 2020).

Figure 29. QnA and LUIS utilization



Source: Microsoft (2020)

4.2.3 TT Business Process Management

There have been many changes in TT's business process due to process automation and DT projects. These changes affected both B2B and B2C work processes, i.e., administration, human resources, IT, legal, sales, engineering, and customer services.

One example of B2B change is the automation of the billing process. The invoice contestation analysis in the back office was transformed through process reengineering, combined with the automation of more than 70% of activities.

Regarding B2C, changes occurred in the technical service for fixed internet customers. In the as-is process, a customer reports a problem on the assistance phone; the call is answered at the call center (N1), which is the first level of service assistance. The call center team tries to solve the problem, but, if they cannot do it, they open a defect ticket in the system. The defect ticket is then directed to a technician, who must go to field service (usually the customer's house).

TT redesigned this process and implemented a to-be process, which follows the same sequence as the as-is process from reporting a problem to opening a defect ticket. Once the ticket system is opened, a robot captures the tickets and performs a series of tests, for example, scope tests and network tests with more than 20 systems to identify the type of product, type of customer, recurrence, or if it has physical issues. Based on the test results, the robot sends them to a second routing robot, which starts online commands to try to solve the problem. This second robot has three output flow options:

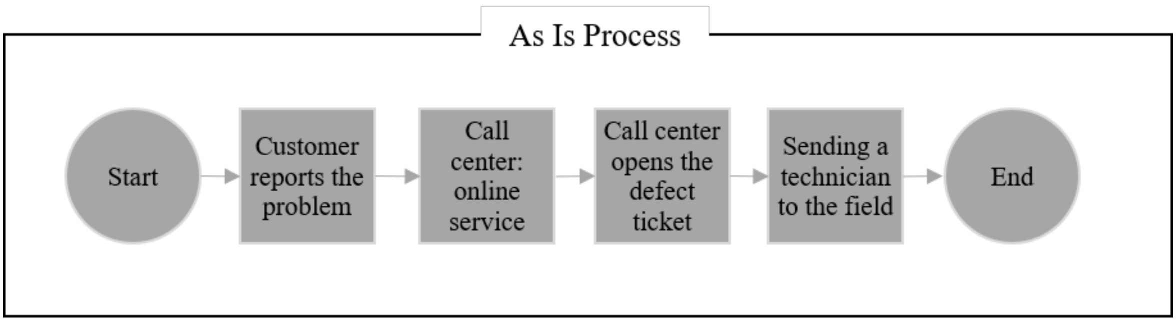
(1) if the commands are successful, the robot automatically closes the defect ticket. When it is closed, the robot interacts with the customer via WhatsApp using the AI platform to check and close the defect ticket.

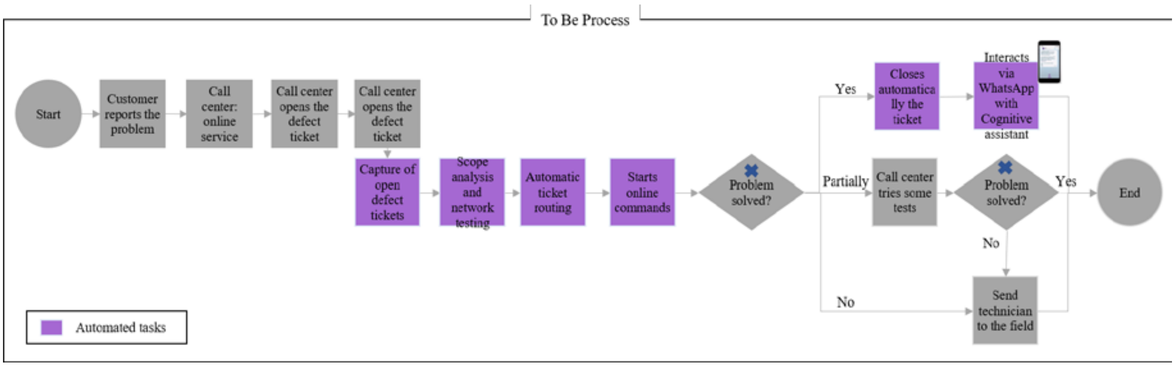
(2) if the problem has not been entirely solved but it has potential to be resolved online, the robot directs the problem to the call center team to do some tests and solve the problem. If it is successful, the ticket is closed. If it is not (the problem remains), a technician is sent for field service.

(3) If the defect is physical, the defect ticket is directed to field service.

The flowchart in Figure 30 illustrates the as-is process and the changes in the redesigned process (To Be).

Figure 30. TT's Business Process Changes





Source: The authors

4.2.4 TT Business impacts

The main business processes affected in the company were internal processes (employee relationship) and external processes (customer relationship—B2C and B2B).

In the B2C billing case, the technological changes reduced the risk of fraud and increased control over operations. The main project outcomes were: 54% reduction in analysis time, lower lead response time—which resulted in important operational and financial benefits—, 73% of automated activities, 134 headcounts released with reskilling, and more than R$ 10 million in savings with insourcing of activities related to third party contracts.

In the B2C case, TT has more than 150 robots working on the process, more than 20% retention of defect tickets, 24 systems involved with more than 160 automated tests, more than 100 business rules, upskilling to create a new team, 75% of SLA improvement for defect tickets automatically treated, integration of RPA and AI for customer interactions, and R$ 100 million in savings. The cognitive assistant promoted one channel with a single technology to interact with the customers. As a result, it reduced the number of interactions in more expensive channels for the company, such as the call center. The cognitive solution was able to retain more than 20% of call center demands. The AI solution is available on more than 20 channels and is responsible for more than 15 million calls per month, without user waiting time.

Currently, TT has around 900 "digital employees" with more than 100 automated processes in eight departments. At the interview time period, bots had performed more than 1.5 million transactions, with more than 400,000 working hours with 87% of robotic efficiency (metrics: % of correct automated planned tasks).

Other business process changes affected 75% of the billing process, which became an e-billing process. Sales expenses decreased due to lower expenses with commissioning, call centers, billing, and marketing. This department also benefited from digitalization initiatives, having 55% of payments made through digital platforms.

4.2.5 TT Organizational aspects

Concerning organizational structure for DT projects, TT created an area of Strategy & Governance Structure, which is responsible for governance, key performance indicators (KPIs), results, and sourcing strategy. Another area, Innovation & Synergies, is responsible for proof of concept (POC) development, digital solutions, relationship with startups, and prioritization assessment for possible process automation. Other two areas are responsible for project management, starting in the first mapping process until the project deliverables. At certain stage, the IT team was involved in the project: digital factory, CoE, and support team.

In 2018, a Bot Training Center was created to analyze whether the cognitive solution correctly understands customers' queries. If it does not, the center generates inputs for correction and trains the bot so that it hits the next time. The Bot Training Center's team also assesses whether the cognitive solution's answer really clarifies customers' queries in order to guarantee the continuous improvement of user experience with the bot. The leaders aim to create a Bot Supervisor position, i.e., a robot manager.

The company dismissed some employees. Nevertheless, it made an effort to reuse resources. TT emphasized the importance of upskilling and reskilling for career transfer, as the departments were prepared to work with AI and robots.

4.2.6 TT AI Integration

The company has around 2,000 running systems, which imposed some challenges to system integration. Some departments have particular systems that are not supported by the IT corporate team or third-party systems, so they have little control over these systems due to different IT security firewalls and business rules. The IT systems work mainly by Application Programming Interface (API) to obtain more stability. However, managing robots when the system environment changes is a challenge (e.g., changes on a website or a screen). During the AI project implementation, a full technology revision was made in the cognitive solution, data, and APIs, which helped TT discontinue many legacy systems and technologies.

For dashboards, TT uses business intelligence tools, such as Grafana and Power BI to monitor AI/robot operations. Regarding robot governance and control, each robot has an ID under a network manager in an Enterprise Resource Planning (ERP) system, as if it were a human user.

Some processes have some volume processing issues because of the data size. Data is processed by on-premise virtual machines, but there is a movement to migrate to cloud processing.

4.2.7 TT Challenges

The main challenges encountered in the AI and DT projects were how to manage the multiple demands from the whole company, considering the resource restrictions of people and budget: How to ensure that resources are being allocated to projects of greater value?

Another issue is the project prioritization approach: "How to deal with complex and simple demands competing for the project portfolio?". For example, minor requests from Human Resources (HR) may be never be granted comparing to higher initiatives. For that reason, TT created two lines of project approach:

(1) Fast track: no procedural action, simple task automations, and average development duration of 2 to 3 weeks, which is managed by the business area; and

(2) Full track: process reengineering, complex automations, and an average development duration of 2 to 6 months.

A challenge was reported in terms of a real understanding of each process to be transformed in the process discovery phase of the digital initiatives' selection framework. The company had to comprehend accurate process gaps and the environment and had to measure time to be close to each business area.

The challenge of overcoming cultural resistance was highlighted: people feared either to lose their jobs or to be taught how to do their activities.

4.2.8 TT Summary Table

Table 17 presents the case study summary analysis for the TT company.

Table 17. TT Summary Analysis

Category Dimension	Description
AI in the DT	• 2010: Digital Transformation started;

Journey	• 2014: Open innovation ecosystem; • From 2015: Data centric projects are encouraged; • 2018: Cognitive virtual assistant.
AI Projects	• AI digital assistant to provide customers services. Built from cognitive computing services in partnership with Microsoft; • RPA for the billing process and technical services.
Business Process Management	• Scope: Customer Service Business process changes in technical assistance for B2C.
Business Impacts	• 150 robots working on B2C case • More than 20% retention of defect tickets • 75% of SLA improvement • R$100 million in savings • Reduced the number of interactions in the contact center • Available on more than 20 channels • 15 million calls per month, without user waiting time
Organizational Aspects	• Areas: Strategy & Governance Structure, Innovation & Synergies, Digital Transformation, Digital factory, CoE and IT • 2018: Bot Training Center • Creation of "Bots Supervisor" role • Cases of job dismissal but there is an effort for upskilling and reskilling
Artificial Intelligence Integration	• 2,000 systems • Integration challenges to work with specific department systems • Robot’s governance and control
Challenges	• Projects prioritization and selection • Real understanding of the process to be transformed • Cultural resistance • System environment changes can cause malfunction and risks for the automated process

Source : Authors

4.3 Chemistry (CH)

The chemical company is a global gas producer with 3,800 employees in South America. In Brazil, it has 3,136 employees. Globally, CH is in more than 100 countries and has more than 80,000 employees (2020). The main activities of the company involve production and commercialization of gases for three product lines (industrial, medicinal and special offers), which are offered to a portfolio of small, medium and large customers from varied industries.

The interviewee was a Data Scientist from the Digital department. She has been working in this department since 2019 and she has 16 years of experience in the field. In addition to the information collected in the interview, public data were collected from the company's websites, sustainability and annual reports, and corporate events. We also accessed a presentation from July 2020 by the company's Analytics & Digital Transformation Manager and the Partner & co-founder from the partner firm involved in the AI solution.

4.3.1 CH DT Journey

In the end of 2017, CH created the Digital department and directly affected the way employees work and the way the company presents itself to the market. The objective of the Digital department is to develop solutions for different areas of the company, including AI and IoT in operations. The Digital team is formed by specialized professionals with experience in AI algorithms.

One of the first projects implemented by the Digital area, in partnership with the CRM department, was a sales dashboard tool, which helped the Sales Force to manage their portfolio more strategically and proactively. The dashboard is an online platform that integrates strategic information from different sources about the company's main customers. The sales dashboard tool gives the level of customer satisfaction, sales figures, and the location of competing plants nearby. Two other dashboards were created in a three-month period: one for customer portfolio management (it identified the sales from each customer per product line and anticipated the risk of losing customers) and one to cost to serve analysis (it assessed production and distribution costs to serve customers in the company's portfolio according to each product line).

In 2018, the company started using the design thinking approach in projects, launched one application with daily news about the company, implemented the WhatsApp tool channel in the call center (customers can request orders, delivery forecast, assistance, among other services), started using tools in the Recruitment and Selection area, and created a Digital Management area with an AI specialized team.

As a primary aspect of CH’s DT, the company will consolidate, by 2024, a new model of information management, communication and operation, establishing a new technology level, business intelligence, and innovation. Among other investments, this means developing a new and complete digital management platform.

The Digital area is a corporate structure and has the following mission: to lead the replication and customization of global digital solutions; to have a close contact with business units and to develop unique solutions for local needs; to be agile in developing simple and complex projects. There is a Digital Committee for portfolio review and prioritization. The department’s main capabilities are machine learning, AI, statistics, optimization, and utilization of Business Intelligence (BI) tools.

The portfolio projects from the Digital area were categorized into four pillars with the following main themes:

- Supply chain optimization: optimized liquid production, distribution planning, and cylinder inventory and transfer;
- Hyper automation: process automation with RPA, virtual assistants, and AI;
- Customer engagement: digital solutions to answer customer needs (applications and e-commerce platforms);
- Business process improvement: customer management with greater convenience and practicality, pricing tools, and lead identification.

In 2018, the company partnered with an innovation platform from German, American, and Singaporean hubs—which connects over 30 startups with a host of partners from industry and from the research and scientific community—to create Europe’s largest innovation network. CH’s technicians and customer operators trained in a virtual reality environment long before the plant was built. Other teams developed algorithms to predict customers’ orders and used data glasses to remotely support service and maintenance work in complex modules.

4.3.2 CH AI Projects

The company develops projects with AI solutions in several areas, such as demand forecasting systems, driver fatigue monitoring (Seeing Machine), process automation, virtual reality, IoT, and production and supply chain optimization.

In the fourth quarter of 2019, many manual tasks could already be performed automatically. The Digital area carried out a POC in the supplier registration process with an ERP system. A POC business case was made considering the workload effort in manpower and work readjustment. The case was built in two weeks and its value was demonstrated to the Board. A consulting sourcing was made to select third-party partners, and a workshop was made to engage the team at *Fábrica de Startups* (Startup Fabric, in English). *Fábrica de Startups* is a corporate accelerator that develops innovation for large companies from startups.

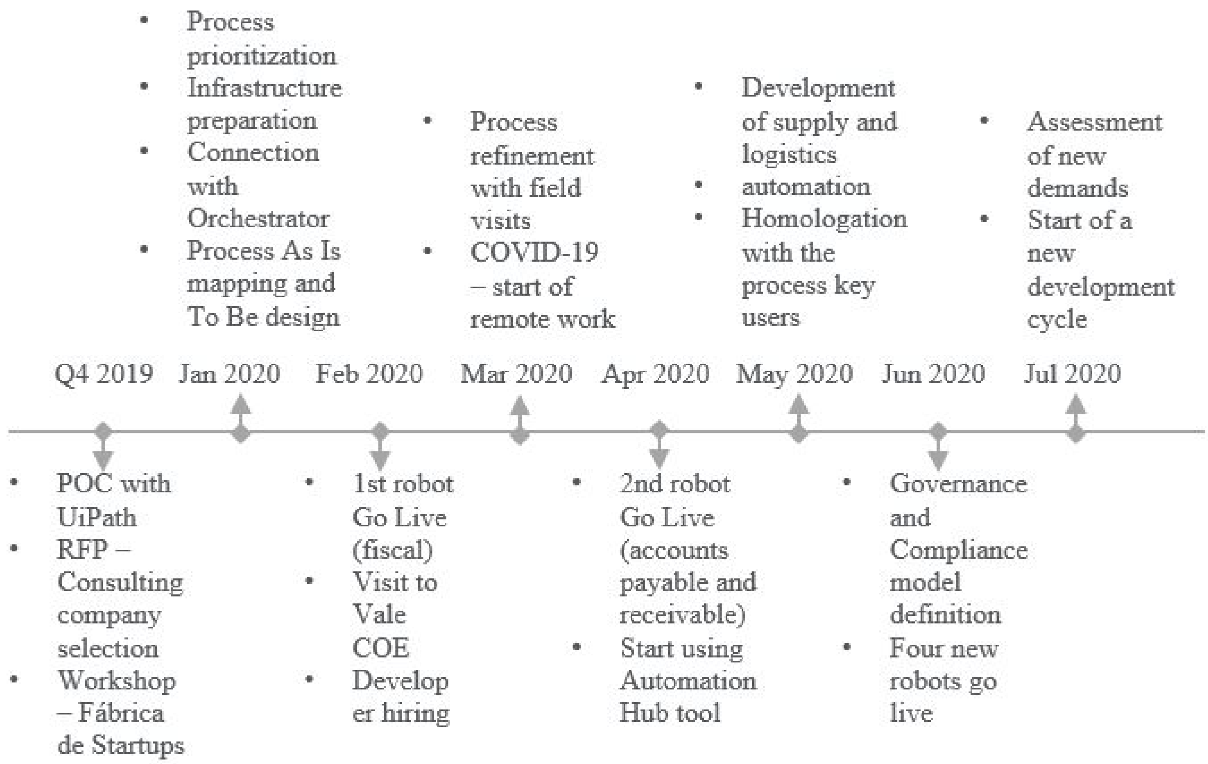
In 2020, the Digital department started to assess the Finance process and they found more than 50 processes to automate. Due to the high number of candidates, a prioritization was made considering higher value x less effort. The IT department was involved to discuss the project infrastructure. The process mapping (as-is) and the to-be process were performed. The first process automated was a fiscal one for city duties.

For benchmarking purposes, CH visited the CoE of Vale S.A. in Rio de Janeiro (Vale had four years of automation experience at that time) and hired another developer to the Digital team. In March 2020, The Digital team made technical visits to verify the automated fiscal process for further understanding. However, the remote work started because of COVID-19. At the first moment, the fiscal process was working with an unattended robot. In April 2020, a second robot was built for the billing process, and the Automation Hub was implemented.

The Automation Hub is a process prioritization application from the RPA tool provider. The system user can register a process automation idea on the platform. The tool provides a first sense of the process complexity, ROI evaluation, task capture with a functionality that registers the process walkthrough, and estimations of future headcounts needed in the automated process (UiPath, 2020).

In May 2020, CH developed an automation for supply and logistics process with homologation by key users. In June 2020, four new robots were delivered, and a Governance & Compliance model was defined with Global teams (e.g., robot behavior, tracking, logs control, etc.). In July 2020, a new cycle of development started with new demands of assessment. Figure 31 shows the RPA journey in the company.

Figure 31. CH's RPA Journey



Source: Adapted from the Chemical company (2020)

The Digital team also developed, in partnership with the Liquid Logistics area, an AI solution ranging from the treatment and verification of quality of telemetry data on the level of customers' tanks to accurately forecast demands based on consumption history. This solution included a delivery optimizer with routing and a new demand forecasting and refueling planning model, greatly increasing reliability.

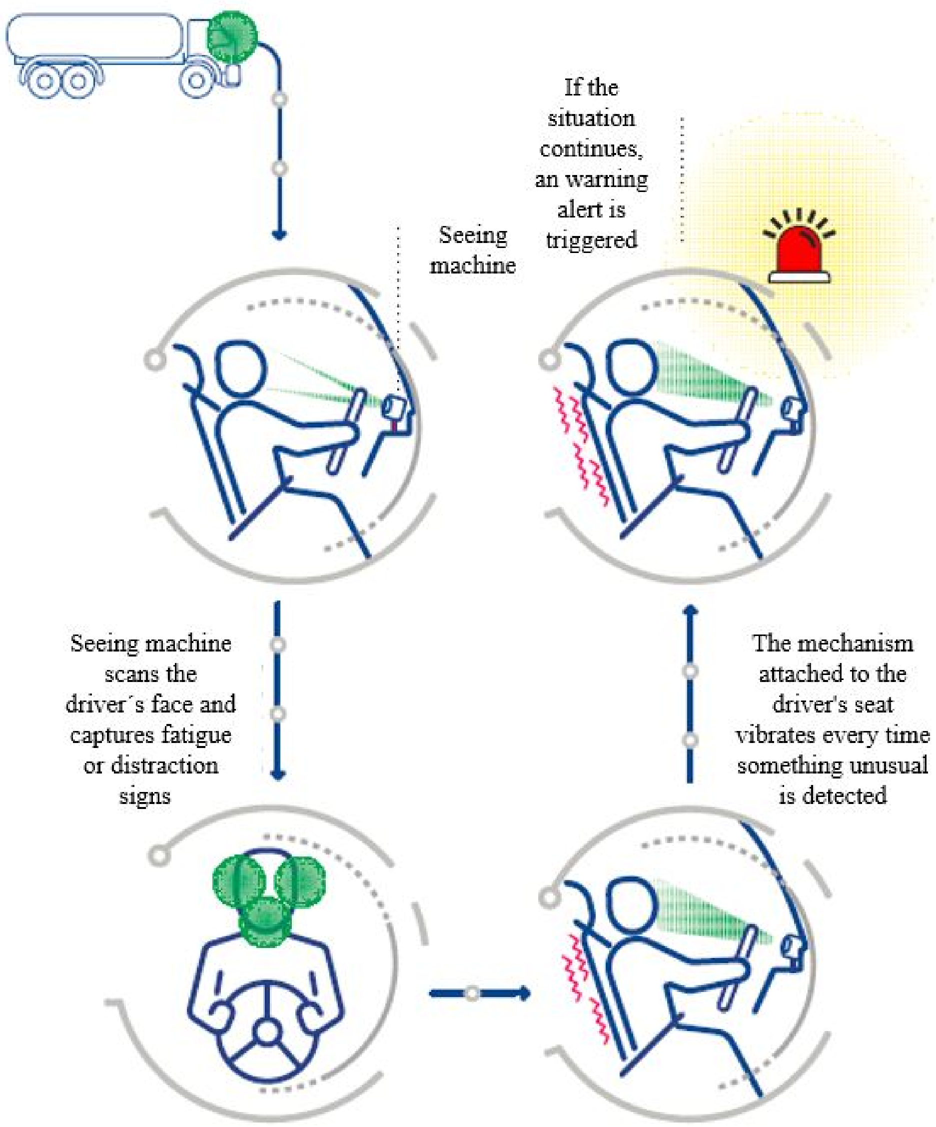
The robotics field also had a role in digitization. A decrease in the number of welders available in the market over the years led to a change in the scenario of welding activities, so this service started to be done by remotely operated robots.

CH also invested in monitoring technologies to reduce the number of accidents in roads and improve safety and working conditions for trailer and truck drivers. The company installed a system of facial recognition in the vehicle fleet that identifies signs of fatigue or distraction in the drivers through an AI algorithm, the Seeing Machine. It captures the driver's image in the driving position, analyzes his/her facial features and creates a base with reference information, such as eye size and shape of the face. During travel, the camera aims to capture if the driver shows any abnormal behavior in real time and send the images to a monitoring central.

When identifying a fatigue event or distraction, the system triggers the bank cart, which vibrates to attract the driver’s attention. If the behavior continues, a new alert is triggered, a short horn sound. For months, the company carried out tests to improve the use of this tool, which adds safety, health, and well-being for drivers. The pilot project was deployed in trucks in Brazil and Colombia in 2017; at the end of 2018, about 250 vehicles in the fleet in several South American countries had the equipment installed.

The company strategically prioritized vehicles serving critical (mountain regions) or long routes (more than 400 kilometers long). In the next four years, the company expects to implement this technology in all vehicles and estimates a decrease of 27% in high severity events (collisions) and 28% in vehicle falls. Figure 32 illustrates the Seeing Machine.

Figure 32. CH’s Seeing Machine



Source: Adapted from the Chemical company (2020)

In partnership with a consulting firm, the company developed an IoT device that can transmit and store data about industrial gas cylinder valves in the cloud. Using an app on their computer, laptop, or mobile, users can see “at a glance” exactly where all their cylinders are currently located, what gases they contain, and how full they are. The device also allows the company to provide a unique gas management service to help improve its customers’ operational productivity, reduce their costs, and at the same time ensure they never run out at a critical time.

Another DT project was developed by the Engineering Global Construction department. This team uses digital twins of plants to operate them and train customers even before the plant is built. The virtual reality experience allows customers to become familiar with the plant topology and to be trained in critical procedures.

Third-party partners in the AI and DT projects included consulting firms focused on analytics and process automation, startups, and the RPA tool (UiPath).

Currently, the company has assisted robots, i.e., they depend on a human trigger to initiate the process. However, there are ongoing studies to migrate this technology to autonomous robots, i.e., no need of a human to start automatic operations.

The project management methodology used in digital projects were agile and Cross Industry Standard Process for Data Mining (CRISP-DM).

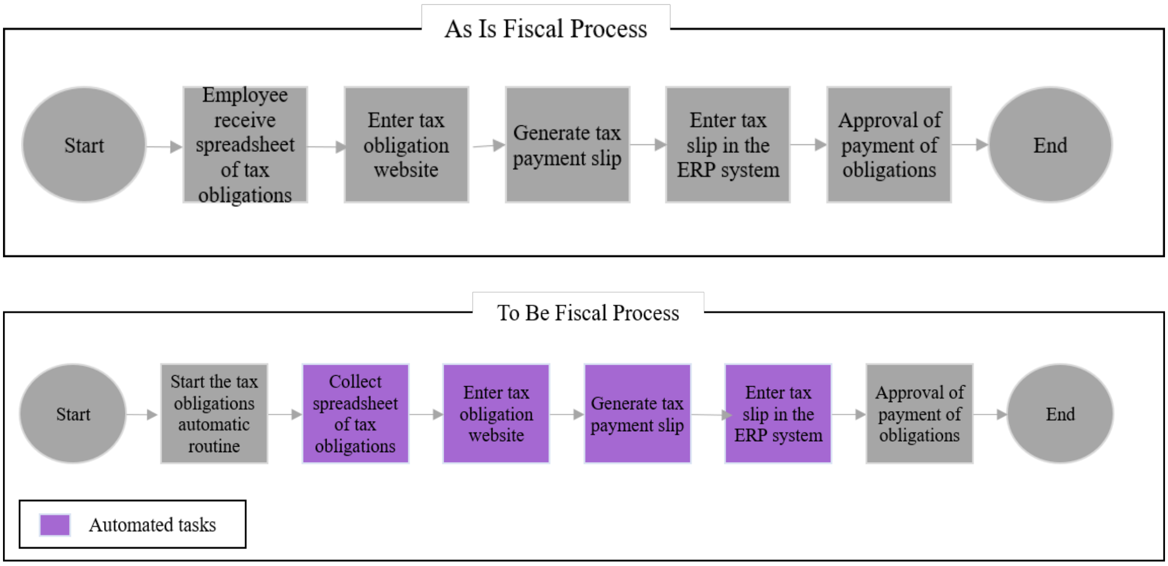
As for AI global solutions, the company used RPA, machine learning, virtual reality, neural networks, robotics, OCR, and IoT.

4.3.3 CH Business Process Management

The business processes automated were from the Fiscal, Finance, and Supply Chain & Logistics departments.

Concerning fiscal issues, in 2015, a Brazilian constitutional amendment regulated a tax obligation that determined that the person responsible for paying tax in sales to the final consumer would be the sender, which generated an obligation for the company and a back office cost for the vendor. In the as-is process, a third-party employee received a spreadsheet and accessed a website to generate the tax obligation payment slip. This process was performed three times a day. In the to-be process, the entire process was automated, and the person was transferred to a more analytical role. Figure 33 represents the changes in the redesigned fiscal business process.

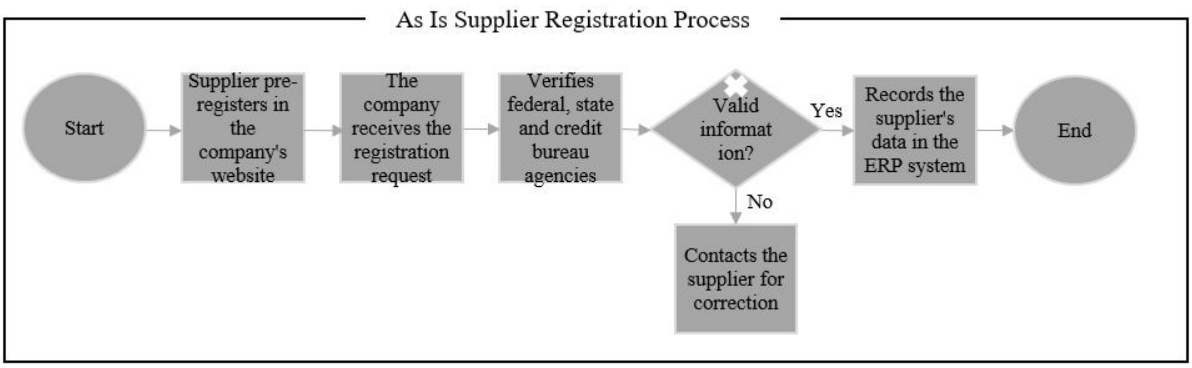
Figure 33. CH's Fiscal Business Process Changes

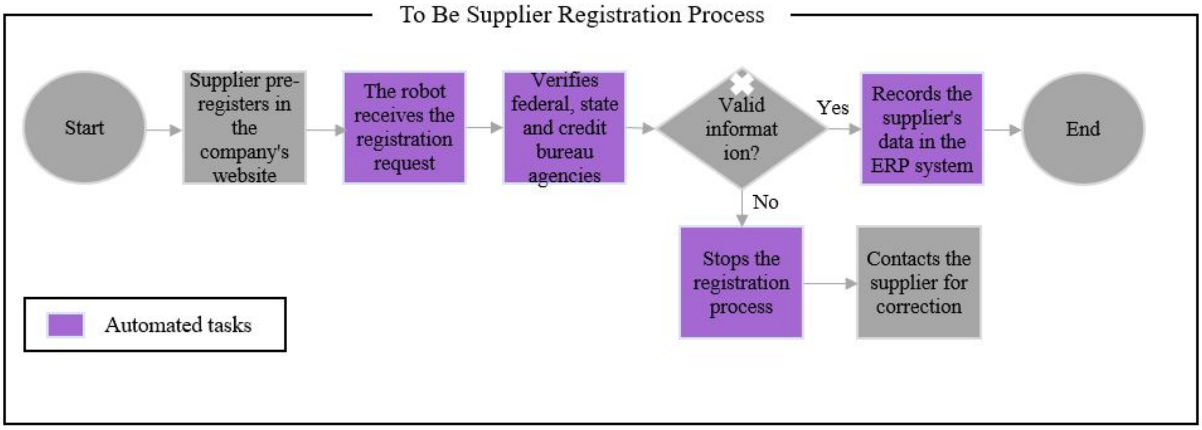


Source: The authors

Business processes in the Procurement area for supplier registration also changed. In the as-is process, the new supplier inserted their data in the website for pre-registration. Then, an employee searched information about the new supplier information on websites, such as Credit Bureau, Federal Revenue Office, and State Registration. If the requested information were active, the employee would effectively register the supplier's data in the ERP system. In the to-be process, these activities were automated in two steps: (1) new supplier's data captured from sources; (2) data uploaded to the ERP system. If any inconsistencies are found in the automated process, the robot stops and generates a report for manual analysis, and the registration process is interrupted. Figure 34 represents the changes of the redesigned procurement business process.

Figure 34. CH's Procurement Business Process Changes





Source: The authors

Concerning Supply Chain & Logistics, most of CH’s sales are delivered via road transportation. In this process, many transportation documents are generated, such as the Electronic Transportation Bill (CTE – *Conhecimento de Transporte Eletrônico*). In the as-is process, the entire input information process was manual. In the to-be process, there was a pilot project in the Campinas unit. In the redesigned process, the solution captures the CTE via API from the Federal Revenue Office’s website and verifies if the values are correct according to the contract (audit activity). After that, it uploads the information to the ERP system.

In the Finance department, a debt management solution was implemented. As the company decentralized purchases, there was the risk of a gap between the invoice arrival at the company and the effective payment term agreed with the supplier. To avoid it, the digital solution weekly monitors the notary public’s and the credit bureau’s websites, checks if there is any pending issue regarding the company’s CNPJs (Brazilian Corporate Tax Registration) and triggers the person in charge of the unit for the pending issues. The machine collects data, generates a dashboard in Tableau (a business intelligence tool) and sends an email to the unit’s Accounts Payable area.

4.3.4 CH Business Impacts

CH’s business process changes affected its internal relationship (employees), even though the company also has digital initiatives to interact with external members in the value chain management.

One example of project for external relationship is an American pilot for home care assistance. This digital solution will monitor every minute if there is a gas demand in residences. It will be interfaced with a logistics tool to find the nearest driver and update the gas demand at the administrative center.

In the Fiscal process, the issuance of payment slips was not fully served throughout the day; the as-is process did not guarantee that all payments due were made on the correct day. In the to-be process, the company complied with the tax issues. The project feedback was highly positive. The tax process is a 100% automated, with human approval at the end.

In the supplier registration process, CH estimates that 80% of cases are performed automatically. Nowadays, there are some exceptions, like foreign and restricted suppliers.

For Supply Chain & Logistics, 80% of the business processes are served by robots (current volume: 8,000 documents per month). The main gains included financial benefits and compliance.

The AI roadmap planning includes the use of CTE information, such as geolocation of origin and customer destination, mileage, and product. If a more significant database is built, the company plans to use it for forecasts themes.

4.3.5 CH Organizational Aspects

In 2018, CH created a group of experienced professionals, who participated in projects in the different offices around the world. Their aim was to choose the new generation of monitoring and control software for factory operations.

The Digital team has a technical (data scient developers and RPA developers) and a business profile. This department promotes initiatives to reinforce the importance of new technologies for the company and conduct trainings on business technology tools (e.g., Tableau). Globally, it is involved with R&D, CoEs, and the Digitalization department.

A partnership was made with the HR department. A training plan aimed to change the personnel profile, management, and internal communication. With trained employees, it is expected that in the future the simplest processes can be automated by the business areas themselves.

At the beginning of the AI projects for fiscal and supplier registration process , an IT functional professional was involved to set the environments and systems appropriately.

The main differences between AI projects and other projects are the time and the high volume of requests: digital projects had a faster deployment and deliverables to business areas than ERP implementation so that many departments demanded automation in their processes.

Digital projects had the goal to remove routine work processes from employees and move them to tasks with greater specialization. There is a concern that new generation workforce does not seek activities that do not set a challenge for them. No cases of layoff were reported during this process.

4.3.6 CH AI Integration

The company relies on IT systems and networks for business and operational activities, where it also stores and processes sensitive and proprietary information. Currently, the company is on an ERP system migration project.

The robot's orchestrator is globally managed. Since 2016, the company's global guideline is to use the UiPath platform. An improvement in data quality is sought with AI projects.

An integration challenge was reported due to a management deficiency in the current ERP system. The integration is not native, so the CH company could install plug-ins to access the ERP information. However, a direct installation on ERP could pose great risk to automation. The alternative method was inserting data in ERP using image recognition with OCR.

CH invested in IT infrastructure, machines for developers and robots, virtual machines, and licenses. Processing is performed on-premise and it consumes some cloud data from the global orchestrator.

For solution support and maintenance, the business areas received a training on low complexity processes. More complex processes are supported by a consulting firm.

4.3.7 CH Challenges

The main challenge reported in AI projects is that the company was working in silos, i.e., there was a defective connection between business areas.

Another challenge concerned portfolio project prioritization in searching for the business processes that would achieve greater return.

One risk of the projects implemented is that if any database template is changed, the automated solution may not work properly.

4.3.8 CH Summary Table

Table 18 presents the case study summary analysis for the CH company.

Table 18. CH Summary Analysis

Category Dimension	Description
AI in the DT Journey	• 2017: Created Digital Department; • 2018: Services app tool for customers and Innovation platform partnership; • 2019: POCs and workshops; • 2020: Robots Go Live.
AI Projects	• RPA solution for fiscal and supplier registration process automation (Hyper automation); • Customer engagement: CRM, sales dashboard tool and demand forecasting systems; • Order management; • Seeing machine: driver fatigue monitoring; • Supply Chain Optimization; • Business Process Improvement; • IoT to transmit and store customer data in the Cloud; • Digital Twins and virtual reality for training and projects;
Business Process Management	• Scope: Internal Process Business process changes in fiscal and supplier registration flow
Business Impacts	• 4 macro-process with automation: Fiscal, Finance, Registration and Supply Chain & Logistics; • Enable tax compliance; • Increase finance monitoring and control • 100% fiscal process automated (human approval); • 80% Supplier registration automated.
Organizational Aspects	• Areas: Digital and IT; • No employees lay-offs; • No open formal positions opened.
Artificial Intelligence Integration	• ERP migration Project ongoing; • Integration challenge with the current ERP system.

Challenges	• Projects prioritization and selection; • Low integration between company´s departments; • Database changes can cause malfunction and risks for the automated process.

Source : Authors

4.4 Professional Services (PS)

PS is divided in five main areas: Audit, Assurance, Advisory, Tax, and Risk. The company has a partnership with an innovation hub ecosystem with startup connections, and it has an area focused on the development of digital solutions. Globally, the company has more than 207,000 employees in 153 countries (2018). In Brazil, it has 24 offices, with more than 4,000 employees and 5,000 clients.

Three employees were interviewed: a Systems Coordinator from the IT department— who has been in this department since 2012 and has 11 years of experience in the field—; a Supervisor Senior Auditor from the Audit Technology Innovation department—who has worked in this department since 2018 and has 10 years of experience—, and a Managing Partner from the Data & Analytics area, with 20 years of experience.

In addition to the information collected in the interview, we collected public data from PS's websites, sustainability report from 2018/2019, and internal material provided by the interviewees.

4.4.1 PS DT Journey

In 2018, the company started a partnership with an innovation hub, which is an open innovation platform that connects more than 12,000 startups of different maturities in the development of non-traditional solutions for any type of problem. The experience of being part of an innovation and transformation ecosystem with agile methodologies had the following objectives: new businesses, skills, partners, products, ways of hiring, and people development.

Another significant movement was the development of a Data & Analytics area with four values: data, people, technology, and clients. This area assists the company in DT in order to automate processes and insert AI into the organization's day-to-day activities. The first initiatives took place in the back office: legal, purchasing, financial, tax, accounting. Automation solutions were implemented to read and analyze unstructured data information, which allowed the organization to extract abstracts, correlate information with increased efficiency, and reduce operational costs. These initiatives took place in partnership with Google, IBM, and Microsoft.

4.4.2 PS AI Projects

AI projects started in 2019 in the Tax department, with a virtual assistant that answered queries regarding individual income tax. For example: “Can I claim deduction of my child’s school fees?”, “Can I claim deduction of my English course?”, and “How do I declare my dependents’ health insurance expenses?”. This AI solution used machine-learning techniques.

In the US Tax company office from a PS client, there was a case of R&D tax relief. Tax professionals and engineers in R&D departments spent thousands of hours manually reviewing materials to discern appropriate evidence to claim R&D tax relief. The company made a partnership with IBM Watson and trained an AI solution using 10,634 documents on five different R&D models by 13 tax professionals. After training, the solution recommended the correct tax treatment in about three out of four times.

In the Risk department, PS developed a virtual assistant to build a knowledge base about the company: documents, materials, described procedures, and document templates.

In the United Kingdom office, a financial PS client had a regulatory obligation to record almost all voice activity to maintain records of orders and transactions in the bond, equity, and derivative markets. For that purpose, the institution should clearly inform each customer about the recording and obtain their explicit consent to record and transcribe the call. For very large organizations, this procedure may produce 100,000 hours of audio or more every day. Transcribing all those recordings and manually searching them for compliance risks can take weeks or months and cost millions of dollars. Thus, the company made a partnership with Microsoft Cognitive Services to develop a cloud-based service. A customer risk analytics solution was offered using multiple components of cognitive services such as speech services, text analytics, and LUIS to transcribe recorded calls, detect specific text patterns and keywords, and flag compliance risks.

In the Audit area, there were some digital initiatives, such as:

- Cognitive: reading documents using AI and preparing audit working papers. This is the company’s AI project reported in this work;

- Confirmation portal: automated balance confirmation (circularization), with evidence of digital and electronic signatures and digital certificates;
- Smart Audit Platform: digital collaboration platform—project management, calendar, announcements, project team, education, control deficiencies, statutory audit tracking, tasks, and insights.
- Chrono: automation of 45 substantive audit procedures, such as voucher testing, recalculations, Enterprise Resource Planning (ERPs) and standard working papers;
- Signatures Portal: a platform for managing and signing proposals, contracts, and other documents with Brazilian legal validity;
- BIP (Bank Intelligent Platform) & DIP (Digital Insurance Platform): automation of substantive procedures for the Banking and Insurance segments;
- Fund in a box: automation of procedures for the Funds segment;
- FC APP & Drones: solutions for physical inventory.

The audit cognitive solution started in September 2019 and took six weeks to be developed. The solution passed by PS's approval workflow and compliance. The development was made with the internal IT team.

In June 2019, PS started the development of another virtual assistant to support the whole company on internal topics. In the previous scenario, the business departments had difficulties in accessing HR information. Consequently, HR responded to many simple demands. This solution was built by the internal IT team with the quality and development teams, which took a month to release the first version. The project had the following structure: partner, project manager, and a coordinator. The project management methodology used was agile.

The kickoff version started with HR topics, such as information on employees' vacation. Later, new features were implemented: active notifications, feedbacks, team scheduling, customized answers, presentation of the company's flows, balanced scorecard information, workload register, citizenship, service desk applications, institutional and virtual assistant own persona assistant questions.

On new releases, PS plans to open automatic calls when the cognitive assistant is unable to help, to fully integrate it with RPA tools, to schedule team entries, and to transfer calls to a service desk human assistant. It also plans to increase accessibility by integrating other virtual assistants and WhatsApp and implementing image identification of personal documents through OCR and speech-to-text (STT) recognition.

The two main basic components of the company's virtual assistant front end and back end orchestrators. When a message is sent to the robot, it decides the flow direction, receives the messages, and determines where information will be obtained: to pull RPA, database, systems, cognitive service, or API. On the back flow of answer, the system returns with a probability of answer by evaluating the percentage of the answer in the cognitive service.

The cooperating third partner was Microsoft, with the cognitive services LUIS and QnA Maker. These tools were used to build a knowledge base by extracting questions and answers from a semi-structured content, including FAQs (frequently asked questions), manuals, and documents. Figure 29 presents an example of use of QnA and LUIS.

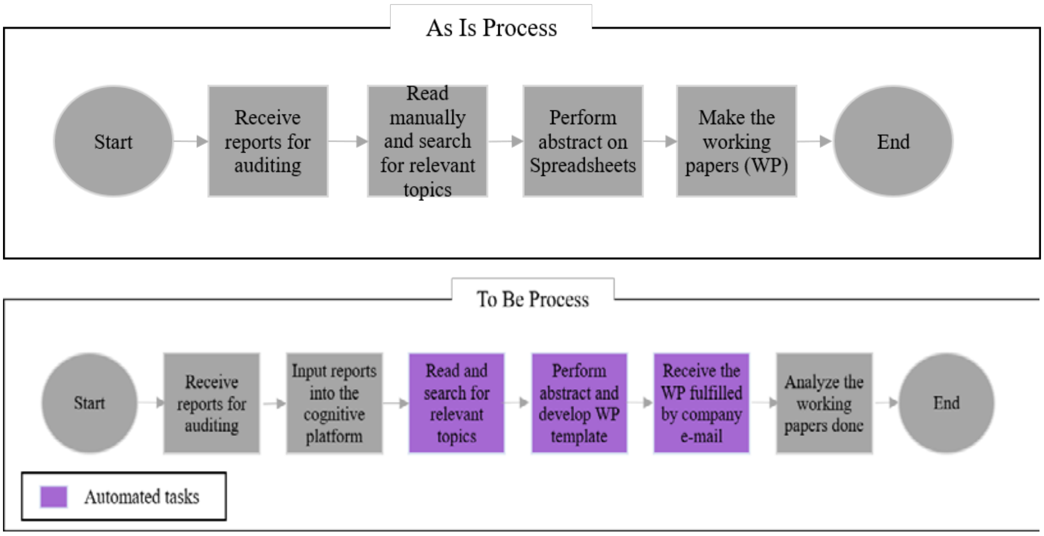
In the Advisory department, AI was used to develop a cognitive contract reader with IBM Watson. The platform, which is already being used by Brazilian customers, was trained to read contracts in Portuguese and carry out compliance assessments and risk analyses in large amounts of documents. The same technology can be used for invoices and audit purposes. ABBYY technologies were used with deep learning methods, multi-level analyses, and OCR. The main points of analysis in the contracts read by the AI document reader engine are object, contracting party, contracted party, deadlines, payment methods, readjustments, billing rules, termination clauses, liability limitations, confidentiality, penalties, subscriptions, and witnesses.

The AI project technologies implemented were RPA, machine learning, OCR, neural networks, and NLP. The project management used was agile for these projects.

4.4.3 PS Business Process Management

The cognitive contract reader has been used internally by audit teams, and it changed some business processes. In the as-is process, once the teams received the reports for audit (e.g., funds, meeting minutes, financial statements, fund regulations, letters of attorney), they read them manually and searched for relevant topics in the documents. Next, the team produced an abstract in spreadsheets and prepared the audit working papers. In the to-be process, after receiving the documents, the audit team now uploads the documents to the cognitive platform. The cognitive solution reads and searches for the relevant topics and prepares the abstract in a working paper template. The user receives an e-mail with the template filled. The working papers are analyzed and revised by the audit team to finalize the process. Figure 35 shows the business process changes for that activity.

Figure 35. PS’s Audit Business Process Changes



Source: The authors

Another AI project was a virtual assistant available for all employees. Previously, PS’s employees made direct telephone calls, e-mails, and in-person questions to the HR and IT service desk teams. These teams manually treated each information request and provided it to the requester. After the cognitive virtual assistant, the employees ask their questions through a web application. The message is sent to the orchestrator, which consults the cognitive services (Microsoft Azure Cognitive Services) and produces customized queries, if necessary. All logs are recorded in the administrator, and the answer is sent to the employees.

4.4.4 PS Business Impacts

The business process changes in the company affected mainly the internal process (employee relationship). The external process (customer relationship) was indirectly affected.

Until April 2020, the main results of the Audit Technology department’s solutions were:

- Cognitive: 20,850 documents analyzed (solutions in progress—certificates, loans, contingencies, funds, and insurance);
- Confirmation portal: 2,479 project engagements created (clients, banks, lawyers, suppliers, related parties and stakeholders), 38,166 letters prepared, 15,970 letters sent, and 6,379 letters received. Currently, the company has a postal expense of R$ 1.5-1.7 million per year, which highlights an economic benefit;
- Smart Audit Platform: fiscal year 2018: 121 portals; fiscal year 2019: 139 portals; fiscal year 2020: 398 portals (until April 2020);
- Chrono: 1,916 registered project engagements, 875 routine engagements performed, and 13,466 routines performed.

These solutions increased the productivity of teams in audit engagements and decreased the number of the bottlenecks in operational tasks.

During the first nine months, PS's virtual assistant had the following results when serving all the company's areas (internal relationship):

- 5,723 user accesses;
- 520.000 queries answered;
- 91% index of queries answered;
- 93% satisfaction survey;
- 1,561 support requests;
- 10 department databases involved.

Nowadays, the assistant receives an average of 500 questions a day; with seasonality, some months register 4,000-5,000 questions a day. The number of calls to the IT and HR service desks decreased.

With the AI solution for the UK financial institution, PS reduced the time, effort, and cost of call transcription and analysis by up to 80%, which resulted in an economic benefit.

4.4.5 PS Organizational Aspects

To support the DT journey, PS deployed a strategic PMO, which controls accomplishments, deadlines, and strategies of the organization, providing project tracking, redirection, prioritization, and focus. An Innovation and Investment Committee was created as a subcommittee of the Executive Committee, with the fundamental role of guiding the DT journey of the company and services (from core to transformational) by using technology.

In Audit, PS created the Audit Innovation Technology area, which is dedicated to identifying and implementing innovative approaches and tools to advance audit quality. PS significantly invested in innovative technology, such as Data & Analytics, AI, cognitive technologies, and robotics, and in strategic work with companies such as Microsoft and IBM.

The development and support of AI projects were assumed by the company’s IT team, and one person from the support team was trained to start training the bots. No new formal positions were created, and layoffs did not happen.

4.4.6 PS AI Integration

The company’s IT structure has 110 physical and 328 virtual servers, which support 116 systems and 5,700 notebooks. For the AI projects, the company used its own IT servers and acquired Microsoft cognitive services in a software as a service (SaaS) contract mode. System integration was facilitated because the teams were familiar with the current systems. APIs and databases were developed by PS’s IT team.

The company has been developing the process mapping of personal data information to comply with *Lei Geral de Proteção de Dados* (LGPD), which is the Brazilian law for personal data protection, like the General Data Protection Regulation (EU GDPR).

Data processing was made on-premise (front end, orchestrator, databases, dashboards) and on cloud (cognitive services).

The virtual assistant has integrations with databases, external APIs, and cognitive services for standard responses and machine learning for customized answers.

4.4.7 PS Challenges

One of the main challenges imposed by the virtual assistant has been selling to the company's leader the need for maintaining and updating the curatorship. The objective is to maintain the bot growing with effective answers. At the moment, the company has shortage of people to curate and correct wrong answers and include new subjects.

Another issue is the huge scope of subjects to be addressed by the AI solution, which requires a large neural network. For instance, the word "hours" has multiple meanings, so the assistant may search in different areas, such as programming, training, citizenship etc.

4.4.8 PS Summary Table

Table 19 presents the case study summary analysis for the PS company.

Table 19. PS Summary Analysis

Category Dimension	Description
AI in the DT Journey	• 2018: Partnership with an innovation hub; • 2019: Data & Analytics area development.
AI Projects	• AI virtual assistant for reading and preparing audit documents (Working papers) and tax reports; • Cognitive Contract Reader, • AI virtual assistant for tax, risk, HR and IT topics; • Cloud-based service to transcribe recorded calls, detect specific text patterns and keywords, and flag compliance risks; • Confirmation portal; • Digital collaboration platform (Smart Audit Platform); • Automation of audit procedures and Funds; • Digital Insurance Platform; • Solutions for physical inventory process;
Business Process Management	• Scope: Internal Process Business process changes in the audit operational activities for documents analysis
Business Impacts	• 20,850 Documents analyzed (solutions being developed - certificates; loans; contingencies; funds and insurance); • Higher productivity in audit teams with a decrease in bottlenecks for operational tasks.
Organizational Aspects	• Areas: Strategic PMO (Project Management Office), Innovation and Investment Committee, Audit

	Innovation Technology, Data & Analytics and IT; • No new formal positions were created and neither lay-offs happened.
Artificial Intelligence Integration	• 110 physical and 328 virtual servers, which support 116 systems and 5,700 notebooks in Brazil; • System AI integration facilitated due to IT team experience on internal systems.
Challenges	• Structuring a specialized curatorship team; • Deal with the huge scope of subjects addressed by the AI solution.

Source : Authors

4.5 Logistics Services (LS)

The LS company has six main divisions: Postal Service, Express, Global Forwarding, Freight, Supply Chain, and e-commerce. It operates globally and has 380,000 employees (2020). In Brazil, LS has 12,000 employees and 56 operations centers.

The participants who collaborated in the research interview were a General Manager and a Solution Design Manager. The General Manager is from the Digital Transformation area; he has been working in this department since 2015 and has 20 years of experience in the technology and management field. The Solution Design Manager has 12 years of experience. In addition to the information collected in the interview, we collected public data from the company’s websites, specialized magazines, and sustainability and annual reports from 2019.

4.5.1 LS DT Journey

In 2019, a 2025 Strategic Plan was elaborated and launched to continue the exploitation of opportunities enabled by globalization. The flourishing e-commerce department and the associated intense global exchange of goods have driven the company’s growth. The ongoing digitalization of operations has picked up speed and it will significantly improve processes. By 2025, LS will be investing €2 billion to improve customer experience, operational performance, and working conditions. This plan is expected to generate at least 1.5 billion euros annually towards earnings by 2025.

Digitalization is the key cornerstone of the company’s strategy. The main objectives of the company’s digitalization is to increase standardized processes, to enhance transparency, to improve customer interaction, and to simplify interactions. The company has five global CoEs to perform processes like finance, sales, master data management, HR, reporting + management services, control tower, and process automation technology.

Figure 30 illustrates LS's strategy framework. The company's CEO made the following announcement:

> *"In the future, we intend to bring together our technological capabilities in global Centers of Excellence in order to centrally develop key technologies such as IoT and supply them to our divisions. In this way, we can take advantage of the Group's strength to drive digitalization".*

Figure. LS's strategy framework

Source: Adapted from Logistics Services company (2020)

In the 2025 Roadmap, the company has initiatives to maximize synergies to increase the use of postal services and preserve parcel CAPEX, such as automatic sorting of small-format e-commerce shipments in letter sorting centers and optimization of existing hubs, for example by installing 3-5 side readers at sorters to reduce rejects (98% machine sorted), delivering digitalization with a new generation of handheld scanners, and digitalizing site management and staff deployment.

At the Post Service & Express business, the company has a roadmap-based development/simplification of the IT landscape presented in Table 20.

Table 20. Digitalization at the Post Service & Express business at LS

Themes	Example
Renewal of IT infrastructure	Data network upgrade Personal workspace hardware renewal

	Renewal and enhancement of scanner
Revision “Legacy”	Harmonization of billing systems for parcel Yard logistics system Transportation Management System
Removal of redundancies	Customer service rollout Harmonization of sales management tools IT management tools
Simplification of customer contact	Lean parcel locker pilot and rollout Customer portal for business and private customer Digital franking and pre-advise
Improvement of customer experience	Route navigation and customer advice Digital Dialogue Marketing Next generation parcel app
Operations automation	Digitalization of depots & sequence optimization Applicant management and resource planning Permeability of post and parcel network

Source: Logistics Services company (2020)

The lifecycle of a shipment is a complex process. For that reason, LS has made technology investments in the following solutions: online quotation tools, app-based tracking tools, IT system upgrades, and real-time tracking platform.

The company has an approach to boost the deployment of new technologies on some trends: RPA, machine learning, drones, robotics, NLP, OCR, autonomous vehicles, 3D printing, IoT and wearables, virtual and augmented reality, supply chain visibility, transportation optimization, warehouse optimization, and blockchain.

In 2017, the company established a startup lab to assist kickstart innovative business models and implement new technologies in the corporate business. LS also have an incubation program and offers services to facilitate innovation within the Group, both at an individual and department level.

4.5.2 LS AI Projects

The company has AI projects on many themes, like demand forecast, handling, cargo, and freight. In Brazil, the company is testing an algorithm that predicts delivery refusals using different sources of information, such as cargo volume, day of the week, weather conditions, etc. This algorithm learns and becomes more accurate as new deliveries happen—either successfully or unsuccessfully. By doing this, the company seeks to reduce the number of delivery refusals, improve the service level, and reduce transportation costs. With this new technology, refusals are expected to decrease by up to 30%.

In 2017, LS developed a warning system that uses machine learning and NLP to detect disruptions in a supply base before they could cause financial losses or long-lasting reputational damage. With this solution, the company added a broad range of new risk categories to the system's existing portfolio to monitor supplier risks on a company level, including financial indicators, mergers and acquisition, environmental damages, supply shortages, quality issues, and labor disputes. The company monitored and collected public data from online and social media sources.

In 2019, the company conducted a part of its recruitment process via WhatsApp for its German branch. When accessing the recruitment address, applicants received a phone number for registration via WhatsApp. Then they were guided by a chatbot to send their documents and complete the HR process in the app.

Some RPA fronts in the company are related to process automation. Currently, 350 RPAs are running in areas such as legal, tax, and registration. Internal repetitive processes are migrating to RPA with the RPA tool UiPath.

The company has one chatbot, called Logistics Artificial Intelligence (LIA), that can be reached by WhatsApp and internal system network (intranet). The goal is to answer questions from employees. The most common topics concern the HR department: vacation, health insurance reimbursement, and software licenses.

The company acquired Tinbot, which is a collaborative robot (cobot) that shares tasks with people side by side. Tinbot is a Brazilian robot that brings together AI, cognition, and IoT. It was developed in C# and .NET programming languages (Tinbot, 2020). Cognitive intelligence is responsible for resources like speech synthesis or text-speech, facial and image recognition, photo capture, movement of hands, arms and torso, and system integrations, such as Slack, Github, Google Calendar and Microsoft 365. LS is preparing cobots to monitor feedbacks from the new integrated system of individual employee indicators, to open pyramids, and to ask operation questions in the field. Figure 36 shows an example of Tinbot.

Figure 36. Tinbot

Source: Tinbot (2020)

The LS's AI project reported here started in June-July 2019 in the Health, Safety and the Environment (HSE) department. This project aimed to automatize open topics on safety and health issues in the company's system. At the beginning, LS conducted a survey to discover which and how startups and companies were working in this field. A startup in Campinas was selected to develop the POC phase. The main steps followed in the project were minimum viable product (MVP), POC, pilot, and rollout.

In the POC phase, 10 people from the HSE department were selected to perform tests: opening and closing safety and health tickets in a systemic simulation. After that, the tests were expanded to become a project deliverable. The solution was a direct link with IBM Watson.

Regarding safety events, there were some examples: cracked or imperfect warehouse floor, broken chair wheels, incorrect car parking in the parking slots, misbehaving on the cell phone—walk and talk at the same time is not allowed in the company. On new releases, LS plans to incorporate quality procedures and Kaizen forms.

Regarding the project management methodology, the company follows the Project Management Institute (PMI) framework Project Management Body of

Knowledge (PMBOK). In addition, it has started working with some agile methodology features.

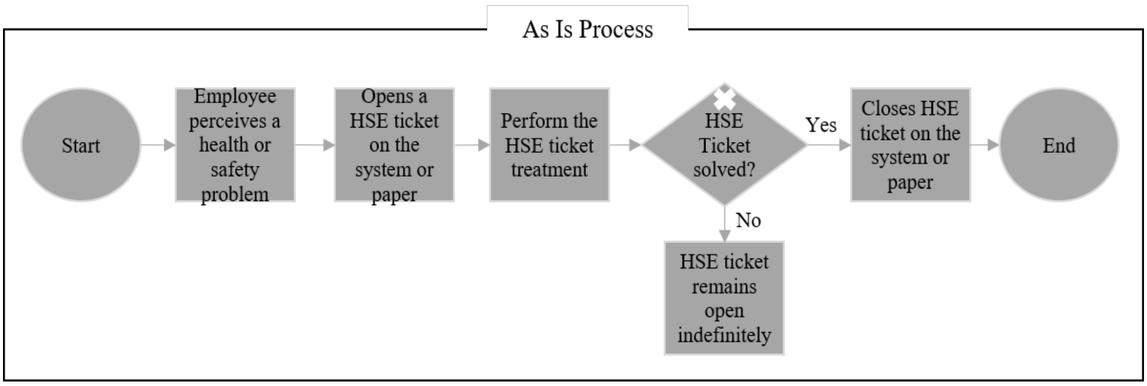
Concerning third parties in the digital projects, the company involved startups for implementation and IoT and a consulting company.

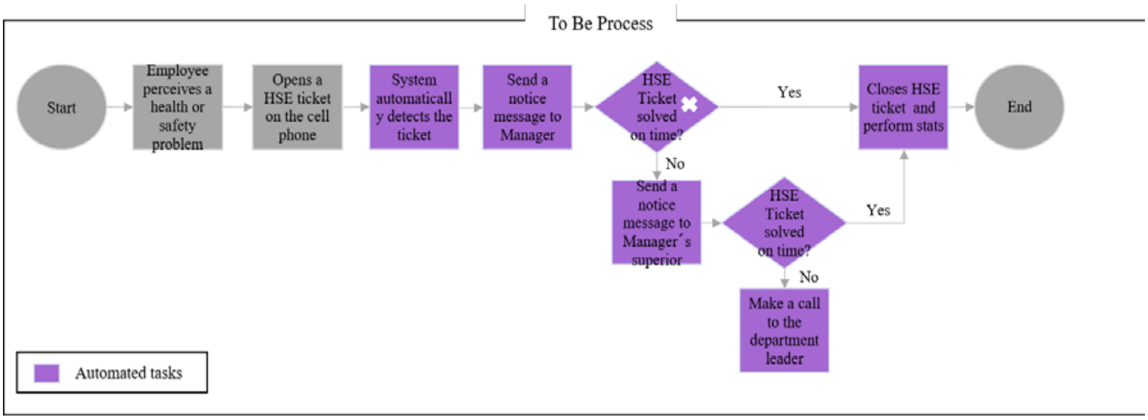
4.5.3 LS Business Process Management

In the as-is process of the HSE case, the safety and health ticket (called pyramid in the company) was manually opened in a paper or computer by employees. The treatment for closing it was also manual depending on the manager's wishes. In the to-be process, the ticket can be opened in a cell phone, where the system automatically identifies the geographic location and verifies that there is an open issue. The system checks this open pyramid and sends a notice message to the direct manager of the person involved in the issue (via WhatsApp, Telegram, SMS, or e-mail).

In the next steps, if the direct manager does not treat this pyramid within a specific lead time, the AI system sends a message to the manager's superior. If the inadequate treatment remains, the AI system triggers a voice phone call to the person responsible for that department. Figure 37 presents the business process changes in the LS company.

Figure 37. LS's Business Process Changes





Source: The authors

This AI solution also identifies superficial dealings, performs statistics and analysis between operations, and creates a database with methods to close pyramids in the best possible way focusing on people's safety and health.

4.5.4 LS Business Impacts

Changes in LS's business processes mainly affected internal processes (employee relationship).

The main initial aim of cobots in the operational business was to make operators' routine smoother and with more information, given that cell phones are not allowed in certain operational areas (e.g. restricted warehouses).

The main benefits of the HSE ticket implementation was increased engagement in the safety team and in the company, greater system visibility, and easy opening of pyramids, which resulted in more safety and health. The estimated degree of process automation was 90% in the pyramid opening process.

Concerning administrative processes that were automatized, there was greater productivity in the teams involved. For example, simple questions via e-mail are answered automatically.

4.5.5 LS Organizational Aspects

The Digital Transformation and Innovation area deals with digital culture issues in the company and responds directly to the Board. In the beginning, the area was focused on product, packaging, and customer development and it was developed to serve the entire company concerning digital issues. Now, this department is responsible for innovation and digitalization. In the company's hierarchy, it is under the Operations area.

The Continuous Improvement team operates the Innovation Projects and Incremental Projects. The Process Engineering area supports the implementation of projects in local operations with the IT team.

There were no layoffs in the company, and new positions were opened in the Digital Transformation and Innovation area.

Some internal IT programmers use the RPA tool. Regarding training, sessions with startups and Lunch & Learn were made during project implementation.

4.5.6 LS AI Integration

LS's IT infrastructure is composed of 60 servers and 700 workstations, with more than 30 software applications related to its business activity.

For AI projects, the company invested in developing and programming startups and consulting companies, increasing the number of tablets in operations, and in three Tinbot robots.

No major AI integration difficulties were identified within the core system or databases. The processing is being done in Amazon's cloud services.

4.5.7 LS Challenges

In the first year, the challenge was to get the support from the company's leader to connect with the startup ecosystem and open the company to innovation. Another obstacle was to obtain the proper budget for the AI project, since the deliverable does not generate a direct return on investment (ROI) at first sight.

The lack of specialized workers and companies was a challenge due to their high cost of working hours and availability restrictions. In particular, some companies did not necessarily have an AI solution but would sell it as if they did.

Another challenge was demystifying AI in the sense of the solutions were simple project implementation that can solve all the issues with a push of a button. The LS company employee has superficial AI information in general.

4.5.8 LS Summary Table

Table 21 presents the case study summary analysis for the LS company.

Table 21. LS Summary Analysis

Category Dimension	Description
AI in the DT Journey	• 2017: Startup Lab; • 2019: Launched the Strategy 2025 Plan to promote company´s digitalization
AI Projects	• AI solution for Health, Safety and the Environment (HSE) events in operations; • Automation of package sorting, prediction of delivery refusal, demand forecast, supply chain risk and optimization • Digital recruitment process; • Cobots; • RPA for legal, tax and registration; • Chatbot for internal issues.
Business Process Management	• Scope: Internal Process Business process changes in the safety & health ticket
Business Impacts	• 350 robots working in the company; • Cobot acquisition and utilization; • Increased security engagement of the security team and in the company; • Greater system visibility • Easiness in opening the safe and security tickets • Estimative of 90% of process automation
Organizational Aspects	• Areas: Digital Transformation/digitization and Innovation, IT, Continuous improvement and Process Engineering • No employees lay-offs • New open formal positions opened
Artificial Intelligence	• 60 servers and 700 workstations, with more than 30 software applications;

Integration	• No major AI system integration difficulties.
Challenges	• Obtain the company leaders support and the financial resources; • Lack of AI specialized workforce and companies; • Diffusion of AI Knowledge in the company teams.

Source : Authors

5 DISCUSSION

This section is dedicated to the comparison and analysis of the study cases. A cross-case analysis was performed to achieve the general objective. The specific objectives were stated on 1.2 Objectives. The cross-case analysis seeks patterns when crossing cases and listing and discussing similarities and differences between them (Eisenhardt, 1989; Langley, 1999).

The companies analyzed, as previously mentioned, were given fictitious ID codes: TT for Telecom & Technology, PS for Professional Services, LS for Logistics Services, CH for Chemistry, and FI for Financial Services. Table 22 presents an overview of the companies' profiles.

Table 22. Overview of companies' information

ID	Industry	Products & Services	Main Markets	Number of employees (Global)
TT	Telecom & Technology	Fixed, mobile and broadband networks	B2B and B2C	122,000 (2018)
PS	Professional Services	Audit & assurance, advisory, tax, and risk	B2B	207,000 (2018)
LS	Logistics Services	Postal service, express, global forwarding, freight, supply chain, and e-commerce	B2B and B2C	380,000 (2020)
CH	Chemistry	Industrial, special and process gases	B2B	80,000 (2020)
FI	Financial	Banking, investment banking, private	B2B and B2C	98,000

	Services	equity, asset management, private banking, insurance, and retail banking		(2018)

Source: The authors

We analyzed seven main topics: DT Journey, AI Projects, Business Process Management, Business Impacts, Organizational Aspects, AI Integration, and Challenges. A summary of the cross-case analysis was made considering the transformational content in Appendix D.

5.1 AI in the DT Journey

Concerning the DT journey, TT (year 2010) and FI (year 2015) started earlier compared to the other companies (PS, LS, and CH). One of the reasons is that these industries have been challenged by digital disruption and changing customer preferences, added to a huge customer database (TT: 100 million customers; FI: 80 million) in their local markets (Battistella et al., 2013; Kilkki et al., 2018).

Digitalization is the basis of LS's 2025 Business Plan. In FI, DT is the main efficiency driver to decrease operational total costs. For PS and CH, DT plays a central role in the business roadmap in either internal or external initiatives. TT built a level of its strategy platform (the 4th level) dedicated to digital and data solutions. This DT and digitalization phenomenon is demonstrated by Bharadwaj et al. (2013), Fleischmann et al. (2020), Hess et al. (2016), Piccinini et al. (2015), Singh & Hess (2017), Vial (2019), and Westerman et al. (2012).

All companies in the study cases are connected with open innovation environments, either partnering with third parties or innovation hubs, creating their own spaces for startups, or developing their own acceleration programs. Recent research suggests that cooperation with other firms whose activities are interdependent is essential to enable technology advancements in highly interconnected business ecosystems (Adner & Kapoor, 2010; Iansiti & Levien, 2004; Pisano & Teece, 2007). Engel (2011) and Kohler (2016) proposed a closer cooperation and regular exchange between incumbents and startups in order to accelerate entrepreneurial transformation. Incumbents should recognize startups as a source of external innovation and develop suitable models for collaboration (e.g., corporate accelerators) (Nadkarni & Prügl, 2020). In particular, incumbents are advised to implement three common best practices from successful startups in order to facilitate transformation: (1) working in small omni-functional teams, (2) goal-driven rapid development instead of bureaucratic processes, and (3) field-level exploration of market potential instead of complex and tedious quantitative models (Engel, 2011).

The AI solutions proved to be a very recent business phenomenon, even though the AI field of study dates back to the 1950s. The first solutions started in 2015, and the last ones in 2019. Even TT, which is a technology provider, started the movement in 2010, but the AI initiative only went live in 2018.

5.2 AI Projects

As presented in the case reports, the companies have an extensive, varied project portfolio relating to DT/AI in their roadmaps. As presented in section 3.2, these companies have high maturity in DT and are present in varied significant industries. Hartley & Sawaya (2019) identified that most companies with a higher degree of transformation have an already well-structured digital roadmap.

TT presented a structured process for selecting projects with digital solutions encompassing four main phases: process selection, process discovery, process optimization, and process automation. The first phases maintain a proximity to the BPM lifecycle presented by Dumas et al. (2018). This BPM framework includes process identification, process discovery, process analysis, process redesign, process implementation, and process monitoring and controlling. Moreover, TT's project selection process presents some aspects from the Lean Six Sigma approach on process improvement (Harmon, 2019).

CH started using a process prioritization application from its RPA tool provider (UiPath, 2020). This tool gives a sense of the process complexity, ROI evaluation, task capture with a functionality that registers the process walkthrough, and estimations of future headcounts needed in the automated process.

Apart from CH, all the other companies presented virtual assistant solutions for both internal and external relationships. Bailey et al. (2020) confirmed this trend by presenting the employee experience and customer experience market movement with chatbots.

Internal cognitive assistants for employees are used specially for IT and HR themes. These assistants answer questions, present information, and locate documents and procedures. For example, in PS, there are projects to automate parts of administrative processes, such as scheduling vacations and scheduling professionals in project engagements. Bailey et al. (2020) calls this AI solution as enterprise digital assistants (EDAs). This groundbreaking tool has emerged to transform the way business professionals work. EDAs are effective applications that act as an interface with other systems to aid in human augmentation and automation of tasks and processes.

External cognitive assistants are used by customers to obtain information about the products and services they use, create and track a claim, contract services, perform operational tasks, etc. This list is aligned with the Vanson Bourne (2019) survey's findings about this technology: improving customer self-service, resolving customer issues faster, automating responses to customer complaints/queries, helping customers navigate around the company's website, predicting customer behavior, using chatbots to interact with customers, gathering contextual insight before routing customers to the best resource and/or content, and mining for sales leads/opportunities. This trend is also verified in the Juniper Research (2018), which highlighted the increasing use of AI in the form of chatbots for customer service applications. These deployments may realize annual savings of $ 439 million globally by 2023.

FI's cognitive virtual assistant solution offers the largest product portfolio (90 products) and has the functionality of understanding customers' natural language in their native language (Portuguese, in this case). Paschen et al. (2020) indicated the increase in AI capability to use unstructured inputs, such as images, speech, or conversations, in addition to structured inputs, like transaction data. Another curious fact is that FI's AI solution learned Portuguese in this project. Before that, only English language was available for native verbal operations.

In omnichannel terms, TT and FI offer the largest range of channels to connect with customers in multiple platforms, such as app, WhatsApp, website, Facebook Messenger, Google Assistant, and Alexa. There is an increasing trend in the omnichannel strategy, including various digital channels for sales and marketing, as presented in Hansen & Kien (2015) and for retail, as reported by El Sawy et al. (2016) in the case of marketing moves launched by the LEGO group.

LS has invested in cobots to act like virtual assistants in the operational field and help the workforce with common questions and operational procedures. Cobots are increasingly being used at work. These systems work side by side with humans, often share their workspaces and tasks, and will be an indispensable tool in different future organizations (Fast-Berglund et al., 2016; Simões et al., 2019). Thus, they are transforming work processes in the industry (Seriani et al., 2018). However, in the case studied, the solution was an informational pilot project for workforce teams.

PS has a cognitive document reader solution that is used both internally, to optimize audit work, and externally, as a sales solution for consultancy clients, e.g., American Tax client reported in the PS case study. The use of cognitive models and architectures to create summaries of texts has evoked interest in the recent years (Guo & Stylios, 2005; Hernes et al., 2015). PS has other digital initiatives to automate processes—and thus reduce administrative processes and physical paper consumption—; for instance, the company is developing an app and drone solutions for the inventory process.

LS has been adopting digital solutions in a wide range of segments, such as handling, cargo, freight, delivery refusal forecast, security, HR, and supply chain disruptions. Dwivedi et al. (2019), Vanson Bourne (2019), and Vial (2019) presented a large range of use cases in similar areas and applications in IT, finance, sales, marketing, customer service, HR, operations, and security.

TT, CH, FI, and LS invested heavily in CRM solutions in order to better understand customers' needs and adopt methods to forecast demands for products and services. These investments were reported by Antonio (2018) and Loring (2018): combining new algorithms with existing CRM platforms may allow the company to analyze and predict selling opportunities, or the salesperson to identify changes in customer status. Those CRM initiatives are relevant to AI projects because they have a great connection with customer database, which results in a series of better insights and understanding of customers' needs and behavior.

Both CH and FI employed facial recognition in their AI solutions. In the case of CH, the Seeing Machine captures the driver's image in the driving position for safety purposes; in the case of FI, ATMs are equipped with biometric authentication. The

Seeing Machine has a larger application since it can be applied to all logistic vehicles and even private cars.

Table 23 presents the scope of AI initiatives classified into external process (customer experience) and internal process (employee experience).

Table 23. Process scope of AI technologies

External process (customer experience)	Internal process (employee experience)
Cognitive and virtual assistants, Customer Relationship Management, documents and audio reader, digital financial services, biometrics in ATMs, insurance, open banking, and medical reimbursement	Cognitive and virtual assistants, document reader, package sorting, delivery refusal forecast, demand forecast, supply chain risk and optimization, recruitment, process automation: billing, fiscal, tax and supplier registration, cobots, Health, Safety and the Environment (HSE), and training

Source: The authors

Concerning the project management methodology, all companies used agile management methods. PS and FI combined agile methods with PMBOK (PMI). This type of combination and customization was studied by Špundak (2014). In addition to agile, CH used CRISP-DM, which is a framework for translating business problems into data mining tasks and carrying out data mining projects regardless of the application area and the technology used (Wirth & Hipp, 2000). Thereby, we observed current project management methodologies for software development.

About AI technologies, RPA, machine learning, and OCR were observed in all case studies. NLP was observed in TT, PS, LS, and FI. Except for PS, all other companies used IoT. Due to the nature of its operations, LS presented a greater diversity of technologies, such as 3D printing, robotics, wearables, and virtual and augmented reality. Robotics and virtual reality were also detected in CH to monitor customer operations. This range of organizational AI applications was shown in McKinsey & Company (2019) and reinforced the technology adoption presented in the World Economic Forum (2018). Table 24 summarizes AI technologies widely adopted due to their general application field, and AI technologies with a more specific application, such as industrial or physical services.

Table 24. AI technologies applied by companies

General applications	Industrial/Physical applications
RPA, machine learning, deep learning, OCR, neural networks, and NLP	IoT, 3D printing, OCR, robotics, drones, wearables, virtual and augmented reality, and robotics

Source: The authors

As for AI technologies, companies used multiple technologies, sometimes in a combined way.

5.3 Business Process Management

For each case, we mapped business processes before the AI solution, which was called as-is process, and after AI implementation, which was called to-be process. The activities that suffered changes or were performed in an automatic model were highlighted to facilitate the comparison and analysis of business process changes. The process mapping approach was based on Dumas et al. (2018) and Dumcius & Skersys (2019). In all cases, business process changes were observed within the areas where the AI solution was implemented.

We detected a decrease in activities performed by humans in a manual mode. This reduction was possible with the replacement of the action agent by robots, which started to perform these activities automatically. Also, companies' combined AI technologies, such as RPA + NLP and NLP + machine learning. Matt et al. (2015) described that the integration of digital technologies enables the DT strategy.

Building organizational AI and machine learning capabilities requires a fundamental reengineering of existing business processes and competencies (Brock & von Wangenheim, 2019; Van der Meulen, 2018). Allen (2015), Davenport (2018), Dirican (2015), and Matt et al. (2015) described process automation.

Regarding business process management, both TT and FI changed their processes of customer services. A similar solution was applied by a train company according to James Wilson & Daugherty (2018) and Van Pinxteren et al. (2020) for conversational agents (chatbots, avatars, and robots).

In FI, first the AI solution was implemented for employees. Then, it evolved to customers but with a more informational nature. At last, FI released operational transactions and service provision for customers.

In TT, the as-is process for technical assistance was completely manual in the beginning. The to-be process inserted automated activities: opening tickets, scope analysis, network testing, automatic routing, communication with the client, and automatic closure integrated with the cognitive solution.

Process changes in PS and CH improved internal teams' productivity. In PS, changes optimized the cognitive document reader for audit services, a solution that is also used in projects for Advisory, Risk and Tax clients. In CH, digital changes improved processes in the fiscal department and in supplier registration using RPA solutions. According to Paschen et al. (2020), the PS and CH AI solution refers to the competence-enhancing process innovation dimension considering improvements to internal processes that result in improvement in efficiency. Davenport (2018) classifies this AI capability as cognitive engagement and process automation for the CH case.

In the CH planning´s roadmap the utilization of AI solutions in Supply Chain & Logistics area. For instance, using machine learning models with information from transportation documents for data science projects.

5.4 Business Impacts

Vanson Bourne (2019) demonstrated AI use cases in internal entities, such as IT, Finance, HR, and Operations, and with external entities, like Sales, Marketing, Customer Services, and Security. In this case study, the AI solutions implemented affected business processes in both internal and external relationships. In TT and FI, the main impacts were on the external relationship (customer services). In PS, LS, and CH, the main impact was on the internal relationship (employee assistance).

Companies with cognitive solutions for costumer services reduced the waiting time and interaction in the costliest channels, such as call centers. In addition, this solution is available in several digital channels and domestic assistants (e.g., Google Assistant and Alexa), which expands the interaction and relationship with customers. According to McLean & Osei-Frimpong (2019), AI in-home voice assistants will have an unprecedented growth. Their findings illustrate that individuals are motivated by the (1) utilitarian benefits, (2) symbolic benefits, and (3) social benefits provided by voice assistants. The cognitive solutions applications and features were described in Davenport (2018), James Wilson & Daugherty (2018), and Mason (2017).

TT has the largest reported number of digital employees, with more than 800, followed by LS, with 350 robots. TT reported a financial benefit since the beginning of the AI implementation (R$ 100 million). Furthermore, its automatic solution retained more than 20% of defect tickets. Bailey et al. (2020) described that good executed AI-powered chatbots improve NPS through speed to resolution and around-the-clock accessibility and through the channels in which users are most comfortable.

In the case of FI, the AI solution enabled the incorporation of another bank without an increase in organizational structure. FI has a wide range of products to be provided for customers, so it created an impacting brand awareness associated with AI, which was explored in the media and in events together with FI's technological partner (IBM, in this case).

In all cases, the increase in productivity was a benefit. In the redesigned processes, at least 80% of activities were automated; in CH's tax solution, the entire process was automated except for the final approval, which remained manual. The relationship between productivity and operational efficiency was observed by Andriole (2017), James Wilson & Daugherty (2018), Paschen et al. (2020), and Wamba-Taguimdje et al. (2020).

In PS, more than 20,000 documents were read by the cognitive document reader. This solution advanced the company's capabilities to sell the solution to its customers, thus bringing financial revenues to the company. FI also started with an internal solution and migrated for an external solution.

LS reported an increase in awareness of safety- and health-related issues, which reduced occupational accidents and absences by 90% with process automation.

5.5 Organizational Aspects

Structural changes (organizational structure and culture, leadership, employee roles and skills) and talent management: people perform a fundamental role in DT/AI initiatives. One way to achieve a cross-functional collaboration among people is by creating a separate unit that maintains a level of independence from the rest of the organization (Maedche, 2016; Sia et al., 2016). Hybrid (Ransbotham et al., 2017) and hub-and-scope (Rock, 2020) happens when a core analytics team supports many different internal groups and work together.

The organizational models of AI/DT projects differed according to the structures of the companies we investigated. However, the IT department was always involved in the digital projects.

Another common aspect between companies was areas that have similar digital functions, such as Digital Transformation, Digital & Analytics, and Digital area. These areas were structured especially for the assessment, process mapping, design, process redesign, development, and implementation of DT/AI solutions. In the cases, these areas cross-collaborated with the business area, mainly in the initial phases, in order to assess and map business processes for the current state (As Is business process).

AI initiatives were led mainly by teams in the areas related to technology, namely: Digital department, Digital Transformation, Data & Analytics, and Data Management – Algorithms and Innovation. These areas collaborated with business areas (customer service, operations, tax, legal, and audit) and IT areas to implement the AI projects.

All companies with AI solutions implemented had partnership with third parties, such as consulting firms and startups with a varied scope (PMO, development, support, tools, and training) and big tech companies for the cognitive solutions, such as Microsoft, IBM, and Amazon. This procedure is in line with the Vanson Bourne (2019) survey: the majority of companies (52%) prefer a mix of pre-packaged AI solution from an outside vendor with their own AI in-house developers.

PS developed DT/AI solutions internally and used the cognitive services of an external provider. In addition, it structured an Innovation and Investment Committee and a specific PMO for these initiatives. FI opted for a PMO carried out by an external consulting firm.

Spyros Samothrakis, quoted by Dwivedi et al. (2019), states that, in the new AI era, new roles will be created either in support of AI or in the design or assurance of AI technologies. The same understanding appears in Markovitch & Willmott (2014): new roles, such as data scientist and user-experience designer, may be needed. Vey et al.

(2017) showed that new roles and action areas for Learning and Development (L&D) professionals have emerged, such as change agents and consultants and positions in innovation labs. Dremel et al. (2017) mentioned the need for a Chief Digital Officer (CDO) and new organizational structures.

The World Economic Forum (2018) indicated AI as one of the main drivers of workforce transformations, followed by ubiquitous high-speed mobile internet, widespread adoption of big data analytics, and cloud technology, which are also related to the AI arena. New positions include data analysts and scientists, software and application developers, and e-commerce and social media specialists, which are significantly based on and enhanced by technology. Roles that advance distinctively "human" skills are expected to grow, such as managers and specialists in customer services, sales and marketing, training and development, people and culture, organizational development, and innovation. Moreover, the World Economic Forum's (2018) analysis found extensive evidence of an accelerating demand for a variety of new specialist roles related to understanding and leveraging the latest emerging technologies: AI, machine learning, big data, process automation, information security analysis, user experience and human-machine interaction design, robotics engineering, and blockchain. Table 25 presents examples of stable, new and redundant roles in all industries.

Table 25. Examples of stable, new and redundant roles

Stable Roles	New Roles	Redundant Roles
Managing Directors and Chief Executives	Data Analysts and Scientists*	Data Entry Clerks
General and Operations Managers*	AI and Machine Learning Specialists	Accounting, Bookkeeping and Payroll Clerks
Software and Applications Developers and Analysts*	General and Operations Managers*	Administrative and Executive Secretaries
Data Analysts and Scientists*	Big Data Specialists	Assembly and Factory Workers
Sales and Marketing Professionals*	Digital Transformation Specialists	Client Information and Customer Service Workers*
Sales Representatives, Wholesale and Manufacturing, Technical and Scientific Products	Sales and Marketing Professionals*	Business Services and Administration Managers
Human Resources Specialists	New Technology Specialists	Accountants and Auditors
Financial and Investment Advisers	Organizational Development Specialists*	Material-Recording and Stock-Keeping Clerks
Database and Network Professionals	Software and Applications Developers and Analysts*	General and Operations Managers*
Supply Chain and Logistics Specialists	Information Technology Services	Postal Service Clerks
Risk Management Specialists	Process Automation Specialists	Financial Analysts
Information Security Analysts*	Innovation Professionals	Cashiers and Ticket Clerks
Management and Organization Analysts	Information Security Analysts*	Mechanics and Machinery Repairers
Electrotechnology Engineers	Ecommerce and Social Media Specialists	Telemarketers
Organizational Development Specialists*	User Experience and Human-Machine Interaction Designers	Electronics and Telecommunications Installers and Repairers
Chemical Processing Plant Operators	Training and Development Specialists	Bank Tellers and Related Clerks
University and Higher Education Teachers	Robotics Specialists and Engineers	Car, Van and Motorcycle Drivers
Compliance Officers	People and Culture Specialists	Sales and Purchasing Agents and Brokers
Energy and Petroleum Engineers	Client Information and Customer Service Workers*	Door-To-Door Sales Workers, News and Street Vendors, and Related Workers
Robotics Specialists and Engineers	Service and Solutions Designers	Statistical, Finance and Insurance Clerks
Petroleum and Natural Gas Refining Plant Operators	Digital Marketing and Strategy Specialists	Lawyers

Source: World Economic Forum (2018)

Note: Roles marked with * appear across multiple columns. This reflects the fact that they might be seeing stable or declining demand across one industry but be in demand in another.

Considering the structuring of new areas, TT and FI created specific departments for the training and curation of robots for the purpose of developing their AI solution. They are strategic areas to update robots and insert new learning content for a constant evolution of the assistants. Part of the teams in these departments was originally from call centers and migrated to the robot management centers. TT additionally structured a CoE to provide quality and efficiency in technology project deliveries. These results corroborate the emerging job roles presented in the World Economic Forum (2018) for Brazil, with a high emphasis on technological aspects: software and application developers and analysts, data analysts and scientists, and database and network professionals. LS also has Centers of Excellence (CoEs) around the world. Nevertheless, its structure is used as a Shared Services Center for transactional process.

The new organizational structures and job roles appeared in the solutions related to customer service. An area for management, monitoring, and training cognitive solutions was structured mostly with teams from call centers. The Bot Supervisor role was created in this new department for AI solution governance and update.

Estimates for work displacement due to automation highlight that up to a third of current work activities may be affect by 2030 (Manyika et al., 2016). Extensive studies analyzed the impact of this significant change and developed a narrative of a changing labor market, which is predicted to focus the human value chain on more creative and cognitive-oriented roles in support of AI technologies (Aleksander, 2017; DIN & DKE, 2018; Jònsson & Svensson, 2016; Kaplan & Haenlein, 2019; Larson, 2010).

This situation was observed in TT and FI companies: employee dismissals. There were specific cases of upskilling and reskilling efforts for the companies’ workforce. For example, employees moved to the bot training center or moved to another function. In the other companies, no layoffs were reported as a direct result of AI projects. Davenport & Kirby (2016) argued that AI-enabled automation will augment the work of humans rather than completely replace them. The collaboration effect between humans and AI technologies was also mentioned by Daugherty & Wilson (2019) and James Wilson & Daugherty (2018).

The business process management changes caused by AI projects changed parts of work functions. In the cases studied, analytical assignments, AI training, and monitoring tasks were more frequent. Davenport (2018) emphasized that current cognitive technologies can automate tasks but not entire jobs. For example, cognitive tools can largely automate tasks like legal research in a few domains of law, rapid review of documents, and extraction of contract provisions; however, these activities and other narrow tasks are still performed by employees. Davenport (2018) also reinforced that the augmentation of AI-assisted roles is a more likely outcome than large-scale job losses due to automation. Heinen et al. (2017) classified these implications in two groups: increased efficiency through intelligent input and new tasks for enterprises and employees.

5.6 AI Integration

Complications in AI solution integration with legacy systems were presented in some cases, such as TT, CH, and FI. IT legacy issues were pointed by Davenport (2018), Leonard-Barton (1992), and Ng (2019), especially in incumbent firms like the ones we investigated. Nadkarni & Prügl (2020) emphasized the need to reach a more comprehensive understanding of “how” and “where” the integration of technology and transformation activities should be embedded within the organizational architectures of incumbent firms.

The difficulties presented were working with specific internal systems, non-native integration with the company’s current ERP system, and problems and system instabilities mainly in times of multiplication of new functionalities and features.

As part of their business nature, TT and FI have a high volume of transactions and data processing in their operations. Some processes may cause some volume processing issues because of the big data size. This issue, regarding quantity and quality of input data, was described in the literature by Dwivedi et al. (2019). Khanna et al. (2013) raised special attention about the need for new and efficient technologies to handle the large volume, variety and velocity of big data, for example in the healthcare industry.

In TT, each robot has an ID under a network manager in the ERP system, as if it were a human user for governance and control. Marijn Janssen, reported by Dwivedi et al. (2019), questioned the challenge of lack of governance, which is needed to unravel complexity and understand how connected AI systems influence business decision-making. Studies have highlighted the implications of lack of AI governance and their potential for unintended consequences (Dwivedi et al., 2019; Zandi et al., 2019). Janssen argued on the criticality of AI governance not just at the algorithm and system level but also across networks of interconnected systems and data levels (Dwivedi et al., 2019).

Currently, CH is going through a period of ERP system migration, which creates particular difficulties. TT conducted a full technology revision during its AI project to check the cognitive solution, data, and APIs. It helped the company discontinue many legacy systems and technologies. Hartley & Sawaya (2019) suggested foundational information systems have to be updated. Difficulties in retrieving and sharing information from these systems lead to inefficiencies, errors, and suboptimal decisions.

On the processing theme, except for LS, all companies run their DT/AI solutions both on-premise and on cloud. LS chose cloud because it offers scalability with less time and costs involved compared to on-premise for their use case. Kane (2015) exemplified some cloud computing benefits: on-demand, elastic resources that do not need to be provisioned, managed and maintained by the IT staff. The use of cloud-based solutions for AI has garnered much public attention in media and publications (Cray, 2019). These results corroborated the Cray survey (*The State of Enterprise AI Adoption*), which found that organizations continue to use on-premise systems to run AI applications due to performance and scale requirements. For organizations that have implemented mainstream AI applications, on-premise systems still hold tremendous value, even with the growth of cloud services. Nearly 65% of respondents stated they need to expand their on-premise systems to keep pace with increasing performance requirements. Performance (26.6%) and data locality and security (26.2%) were the two primary considerations for using on-premise systems (Cray, 2019).

5.7 Challenges

There is considerable research in the literature on challenges for technology transformations (Davenport et al., 2017; Davenport, 2018; Davenport & Ronanki, 2018; Dwivedi et al., 2019; Gust et al., 2017; Loucks et al., 2018; McAfee & Brynjolfsson, 2012; McKinsey & Company, 2019; Nerur et al., 2005; NewVantage Partners LLC, 2019; Vanson Bourne, 2019; Vidgen et al., 2017). The main categories of challenges described were organization and management, people, process, business, data, AI knowledge, organizational constraints, and technology.

Organizations have a set of internal selection pressures (e.g., budget processes, culture, performance management, organization design) that are supposed to make the organization fit for its environment. However, these pressures do not always align effectively with each other or the environment. Particularly in an era of disruption, organizations need internal selection pressures with a different balance between their levels of fitness (Dwivedi et al., 2019). For example, concerning DT, organizations may have insufficient internal selection pressures to support adaptiveness (often resulting in high levels of friction associated with change), thus they struggle to keep pace with changes in their environment (Capgemini, 2018). Beyond these challenges, big companies often also have bureaucratic planning processes and well-established capital allocation processes with little flexibility (Davenport, 2018).

The main challenges faced by TT, CH, and FI in AI implementation were AI prioritization and AI project selection. Their reasons were the high demand for digital projects in the business areas and common resource constraints (budget, time, and people). Davenport & Ronanki (2018) presented the importance of developing a prioritized portfolio of projects. This assessment should be done in three phases: identification of opportunities, determination of use cases, and technology selection.

TT faced an obstacle during the project selection phase. There were demands from business areas that had no financial benefit or were too small compared to other demands. Thus, the company applied full and fast track approaches to deal with this decision. Fast track was used for minor initiatives, which were managed by the business areas with simple automations. Full track was used for more complex, time-consuming processes, involving IT, CoE, and other areas.

LS went through a tough phase in obtaining support from the top management to start and invest in AI projects. The lack of stakeholder buy-in showed up in the Vanson Bourne (2019) survey as a barrier to AI adoption.

Changes in databases and systematic environments were pointed out as challenges by TT and CH, presenting potential risks of malfunctioning or even stopping digital solutions. This issue was pointed out as data challenges in Dwivedi et al. (2019), including lack of data integration and continuity and lack of standards for data collection (format and quality).

Lack of workforce and digital positions is another usual challenge for new technology implementation and new IT-enabling tools. This situation is presented in Davenport et al. (2017), Dwivedi et al. (2019), Loucks et al. (2018), Manyika et al. (2016), and Vanson Bourne (2019). The shortage of skilled workers and companies specialized in AI matters was reported by LS and FI, including team turnover issues.

The study companies also commented on the challenge of disseminating AI knowledge, which was often misunderstood and simplified by staff from the business areas. Likewise, this subject is mentioned in Davenport et al. (2017), Hartley & Sawaya (2019), Harvard Business Review Analytic Services (2015), and Ransbotham et al. (2017). For instance, TT reported cultural resistance and lack of real understanding of the processes to be transformed. This obstacle has been frequently reported in the literature: Fitzgerald et al. (2014), Kane (2016), Lucas & Goh (2009), NewVantage Partners LLC (2019), Polites & Karahanna (2012), Singh & Hess (2017), and Vidgen et al. (2017).

PS presented challenges in structuring a curatorship area for its solution, which is an organizational structure challenge (Dwivedi et al., 2019; Earley, 2014; Maedche, 2016; Selander & Jarvenpaa, 2016). Another big challenge was the wide range of subjects addressed within the scope of the cognitive assistant offered internally by the company.

FI posed problems in scaling a digital solution. As FI has millions of customers in its database, shifting the AI solution from internal to external environment or even creating and propagating a new solution is a challenge. Bharadwaj et al. (2013) argued on the relevance of this challenge as a strategic role of digital technologies. They have affected the scale and the scope of the changes associated with their use along with the speed at which those changes take place. Davenport & Ronanki (2018) reinforced the scale-up challenge and its association with legacy system, process integration and change management issues.

6 CONCLUSIONS

This study proposed a contribution to the understanding of business process changes and impacts with a focus on AI initiatives. Our fundamental research question was: What are the main changes and impacts on business processes in the adoption of AI? This led us to study AI projects, business process management, business impacts, organizational aspects, AI integration, and challenges faced by companies that had AI solutions implemented. We verified that all objectives were achieved, and each specific question was addressed.

The main business process changes in the implementation of AI occurred in different industries were in assistance services: external (customers) and internal (employees) and internal processes (e.g., document analysis, health, fiscal and supplier registration).

According to the changes in the business process mapping (As-Is x To-Be), AI implementation modified parts of job activities by replacing or automating prior manual and human tasks in business processes. It changed people's roles at work but maintained human interaction. In the cases reported, we identified analytical assignments and AI training and monitoring roles.

We also observed the presence of DT/AI projects in companies' roadmaps. Some implementations started internally, for their employee relationship, and later evolved to the external relationship (customer), as in the case of FI's cognitive assistant and PS's cognitive document reader. Therefore, AI initiative is closely related with systemic and it is key for DT engagement.

All companies in the study were connected with open innovation environments by establishing partnerships, participating in innovation hubs, or creating their own spaces for startups or their own acceleration programs.

Some of the business impacts described by companies included process automation with a much higher proportion of automated tasks in the redesigned process (for both cognitive solutions and RPA), an increase in productivity, an increase in the service level, a decrease in human interactions, opening of new multiple channels to interact with customers (omnichannel trend), financial benefits, and support to growth without increasing the organizational structure. Moreover, one of the cases had marketing effects by relating the company to its AI cognitive assistant (AI branding).

Regarding organizational impacts, the companies created new organizational structures and roles, dismissed employees, invested in upskilling and reskilling, and reallocated employees to other functions. The AI solution enabled business growth without an increase in the organizational structure (bank incorporation case). It represents a competitive advantage for companies that adopted AI solutions in their business processes.

AI integration difficulties were differences in specific internal departments' systems, non-native integration with the current company's ERP system, big data issues, robot governance, and system problems and instabilities, mainly in times of multiplication of new functionalities. A big ERP system migration project was mentioned and created particular difficulties. TT conducted a full technology revision during its AI project to check the cognitive solution, data, and APIs. It helped the company discontinue many legacy systems and technologies. Difficulties in retrieving and sharing information from these systems lead to inefficiencies, errors, and suboptimal decisions. The cases show the effort in integrating AI solutions interacting with business processes and current systems.

The main challenges found in implementation were the prioritization and selection of AI projects, and obtaining support and financial resources from senior management to carry out digital initiatives. From the HR's point of view, the scarcity of specialized AI teams and their high turnover were identified as obstacles, as well as cultural and integration barriers between departments. In addition, the companies mentioned issues in scalability of solutions and risks related to databases and systemic environment changes.

The required business process changes were highly specific to each company and had to be developed according to their needs, including the choice of third parties and AI services.

Research Limitations

The main limitations of this case study were process scope, problems complexity, and lack of companies from other industries and geographies. Other limitations included the impossibility to follow up business process updates and the full disclosure of results and project outputs.

Due to the strategic character of some points of this research, we could not obtain complete information or disclose it due to confidentiality terms.

We did not have access to scorecards, internal databases, KPIs, managerial reports or details on the procedures and workflows of each company. The AI portfolio and process selection was not fully accessed.

Some invited companies' legal department created barriers to study collaboration, even when professionals had accepted to participate in the research.

Another limitation was the impossibility of performing in-person technical visits at companies due to social distancing imposed by COVID-19 restrictions.

Contributions for Future Research

Our findings are valuable for expanding knowledge on Technology Management. They lead to some important conclusions, which may guide future research, and even to some valuable practical teachings for managers.

Further quantitative research is needed to develop and test hypotheses regarding, for example, the impact of AI solutions on other industries and segments, changes in business process management with companies from other countries, other AI technologies, and other applications. Future research exploring similar contexts can contribute to the understanding of these business process changes and dialogue with the findings of this exploratory study.

We also suggest the development of studies using internal databases, KPIs, and scorecards, as well approaching AI portfolio selection issues (e.g., small projects x big projects) and implementation approach for AI projects.

Other topics that deserve further analysis are AI processing decision criteria (e.g., performance, locality, security) and business cases for on-premise, on cloud and hybrid systems.

Additional research may help organizations move beyond business process changes in AI solution implementation. Some questions that deserve exploration include: What are key success factors, and do they differ due to AI technology? Which business processes stand to benefit the most from AI technologies, which AI technologies are these, and why they were chosen? How can AI technologies enable new capabilities and lead to a truly integrated company? What are the main impacts of AI on workforce? These and other questions need to be examined at a deeper level.

Managerial Recommendations

As an outcome of this research, we permit ourselves to give some advice and recommendations to the practice of business process changes in AI implementation. For example, before setting up an AI project, a phase of process mapping (As Is) and process redesign (To Be) is recommended to clarify which activities will be transferred to the cognitive solution and at which depth. It also helps to understand the tangible business issues related to the process.

The IT process infrastructure and architecture mapping should be performed as well to decrease integration challenges. From a management point of view, each robot should have an ID under a network manager in the ERP system, as if it were a human user for better governance and control.

In order to reduce cultural barriers and team resistance, teams should be involved in the project since the initial phases. Technical and business teams should be integrated because greater harmony is expected in multifunctional teams. Although these are currently “AI hype” subjects, it is important to provide formal training sessions on AI solutions and on agile project management methods.

“Start indoor and then go outdoor”: we recommend that companies start with an AI solution internally and increase their value in practice; then, it can evolve to external relationships with the help of third-party suppliers.

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APPENDIX

Appendix A: Case Study Protocol

Universidade de São Paulo (USP)

Programa de Pós-Graduação em Administração de Empresas

AS MUDANÇAS DE PROCESSOS DE NEGÓCIOS NA IMPLEMENTAÇÃO DE SOLUÇÕES DA INTELIGÊNCIA ARTIFICIAL

Prezado entrevistado,

O presente roteiro de entrevista foi construído para apoiar a fase de coleta de dados de uma pesquisa acadêmica realizada como parte do programa de Mestrado em Administração de Empresas da FEA-USP. O principal objetivo deste estudo é fornecer uma melhor compreensão das alterações dos processos de negócios na implementação de iniciativas de inteligência artificial em organizações.

Como resultado, o questionário a seguir tem como objetivo orientar a entrevista, ajudando você a compartilhar sua experiência sobre a solução de inteligência artificial de maneira semiestruturada. É importante mencionar que as informações fornecidas durante a entrevista são confidenciais e não serão divulgadas a quem não faz parte da equipe de pesquisa.

Sua cooperação é essencial para o sucesso do estudo.

Obrigado pela atenção.

Atenciosamente,

Oscar do Amaral Adorno
Mestrando

Prof. Dr. Paulo Tromboni de Souza Nascimento
Professor Orientador

Appendix B: Research Protocol

Table 26. Research Protocol

General Research Objective	Specific objectives	Research Questions	Research topic
Assess the main changes and impacts on business processes in an Artificial Intelligence (AI) project / portfolio	Analyze the impacts on operational and management business processes	**(**R1) What are the main business process changes and impacts in the adoption of artificial intelligence solutions?	• Business process management • Macro process mapping • Organizational structure • Training program
	Analyze the implementation of Artificial Intelligence projects / programs in organizations	(R2) How was the AI implementation in the company?	• Digital transformation journey • Artificial Intelligence Projects • Business process management
	Analyze the main implementation challenges in an AI project	(R3) What are the main implementation challenges?	• Implementation Challenges
	Identify whether the AI project / program has performed as expected and the unintended consequences of implementing and using AI	(R4) What are the main business impacts?	• Business impacts • Key performance indicators (KPIs) • Internal and external relationship
	Analyze the integration of new digital technology with existing technology	(R5) How the integration of artificial intelligence solutions interacts with current business operations?	• Artificial Intelligence integration • Database treatment

Source: Authors

Appendix C: Research Script

BUSINESS PROCESSES CHANGES ON THE IMPLEMENTATION OF ARTIFICIAL INTELLIGENCE

Semi-structured interview script

Interview questionnaire:

Date: ____ / ____ / _____

I. Company information

1. Company name

2. Sector

3. Industry / markets

4. Products and services

5. Organization (multiple businesses, business units):

6. Foundation

7. Number of employees

8. Revenue (2019 or available)

9. Supply chain strategy

10. Technological strategy and distinctive processes

11. Other relevant information

II. Interviewee information

1. Name

2. Area

3. Role

5. Academic background

6. What are your main duties / activities?

7. Do you have responsibilities / activities related to Artificial Intelligence?

8. How long have you been working at this company?

9. How long have you been working in this area?

III. Digital Transformation Journey

1. Does this company have a strategy for digital transformation? What are the company’s goals? When did the journey start?

2. What is the order of magnitude of the investments allocated to the digital transformation strategy?

3. What are the current digital transformation projects in the company's portfolio?

4. What is the scope of projects aimed at digital transformation?

5. Who is in charge of the digital transformation journey? Is this responsibility individual or shared?

7. How does the company plan to operate with new digital technologies?

8. Is there a digital transformation/digitization roadmap in the company?

IV. Artificial Intelligence Projects

1. Does the company have a strategy aimed at implementing Artificial Intelligence solutions? When has it started?

2. Is there an Artificial Intelligence roadmap in the company? What are the current Artificial Intelligence technologies planned or already implemented by the company (RPA, machine learning, deep learning, natural language processing, computer vision, etc.)?

3. What were the benefits expected/obtained with Artificial Intelligence projects?

4. What is the stage of implementation of Artificial Intelligence projects under development?

5. What are the main differences between your company’s Artificial Intelligence project and other companies’ projects?

6. What was the project management methodology used?

7. Did third parties (specialized companies, start-ups, consultancies, and IT services) participate during the implementation and operation of the Artificial Intelligence projects? If so, who were these partners and how was their participation?

V. Business Process Management

1. What were the main processes affected by the implementation of Artificial Intelligence projects?

2. Which departments belong to these processes?

3. How was the previous state (As Is Process)?

4. How was the process redesigned (To Be Process)?

5. What were the main changes and impacts in these processes? (operational processes, people, technology, products and services)

VI. Business Impacts

1. How did AI initiatives impact relationships with the customer (external entity) or employee (internal entity)?

2. How was the performance of these processes before and after the implementation of the AI project? Was it possible to measure differences in productivity?

3. Were there changes in the key performance indicators (KPIs) for these processes?

4. How will the AI project transform future operations or business models?

VII. Organizational Aspects

1. In the current organizational structure of the company, where are the responsible people/leaders for the digital transformation located?

2. In the areas where there were Artificial Intelligence projects, were new functions or positions created in the organizational structure?

3. After implementation, were there any cases of layoffs/resignation as an effect of the Artificial Intelligence project?

4. Were specialized groups created to take on Artificial Intelligence-related functions?

5. Were there training and/or qualification programs for the teams involved in Artificial Intelligence-related processes?

VIII. Artificial Intelligence Integration

1. How does the integration of Artificial Intelligence solutions interact with current business processes and operations?

2. Can you provide an overall IT infrastructure information for Artificial Intelligence projects?

3. Were there problems related to databases (access, collection, volume, processing, format, privacy, integration, etc.)?

3. Was it necessary to investment in assets (equipment, infrastructure, etc.)? If so, what was the order of magnitude?

4. What were the main challenges of integrating the Artificial Intelligence project with existing processes and systems?

IX. Challenges

1. What were the main challenges to operationalize the digital transformation journey?

2. What were the main challenges in implementing Artificial Intelligence projects?

3. From the point of view of process, what were the main challenges in Artificial Intelligence projects?

4. What were the main challenges in organizational aspects?

5. What were the main challenges to measure and demonstrate the value of Artificial Intelligence projects?

Appendix D: Cases cross analysis

Table 27. Cases cross analysis

Category	Subcategory	Financial Services (FS)	Telecom & Technology (TT)	Chemistry (CH)	Professional Services (PS)	Logistics Services (LS)
Products & Services	**Main areas, products and services**	Banking, investment banking, private equity, asset management, private banking, insurance and retail banking	Fixed, mobile and broadband networks	Industrial, special and process gases	Audit & Assurance, Advisory, Tax and Risk	Postal Service, Express, Global Forwarding, Freight, Supply Chain and e-commerce
Main Markets	**B2B or B2C**	B2B and B2C	B2B and B2C	B2B	B2B	B2B and B2C
Size	**Global employees**	98,000 (2018)	122,000 (2018)	80,000 (2020)	207,000 (2018)	380,000 (2020)
Digital Transformation Journey	**Digital Transformation Timeline**	• 2015: IBM Partnership • 2016: AI - Branches: internal • 2017: AI informational - Clients: external • 2018: AI - Clients - external and Innovation hub • 2019: More functionalities available	• 2010: Digital Transformation started • 2014: Open innovation ecosystem • From 2015: Data centric projects are encouraged • 2018: Cognitive virtual assistant	• 2017: Created Digital Department • 2018: Services app tool for customers and Innovation platform partnership • 2019: POCs and workshops • 2020: Robots Go Live	• 2018: Partnership with an innovation hub • 2019: Data & Analytics area development	• 2017 Startup Lab • 2019: Launched the Strategy 2025 Plan to promote company´s digitalization
Artificial Intelligence Projects	**Start of AI initiative**	2015	2015	2019	2019	2019

Category	Subcategory	Financial Services (FS)	Telecom & Technology (TT)	Chemistry (CH)	Professional Services (PS)	Logistics Services (LS)
Artificial Intelligence Projects	**AI Case Project Overview**	AI chatbot designed to provide immediate customer response. Built from the Watson cognitive computing platform in partnership with IBM	AI digital assistant to provide customers services. Built from cognitive computing services in partnership with Microsoft	RPA solution for fiscal and supplier registration process automation	AI virtual assistant for reading and preparing audit documents (Working papers)	AI solution for Health, Safety and the Environment (HSE) events in operations
	Project Management Methodology	PMBOK and Agile	Agile	Agile and CRISP-DM	Agile	PMBOK and started working with Agile
	AI related Technologies	RPA, machine learning, natural language processing (NLP), blockchain, neural networks, optical character recognition (OCR) and deep learning, Internet of Things (IoT)	RPA, machine learning, deep learning, Optical Character Recognition (OCR), Internet of Things (IoT), neural networks and Natural Language Processing (NLP)	RPA, machine learning, neural networks, virtual reality, robotics and Optical Character Recognition (OCR), Internet of Things (IoT)	RPA, machine learning, Optical Character Recognition (OCR), neural networks and Natural Language Processing (NLP)	RPA, machine learning, robotics, autonomous vehicles, Optical Character Recognition (OCR), Natural Language Processing (NLP), 3D printing, internet of things (IoT), wearables, virtual and augmented reality
Business Process Management	**Business Process redesigned**	Business process changes started internally and then moved to customer service	Business process changes in technical assistance for B2C	Business process changes in fiscal and supplier registration flow	Business process changes in the audit operational activities for documents analysis	Business process changes in the safety & health ticket

Category	Subcategory	Financial Services (FS)	Telecom & Technology (TT)	Chemistry (CH)	Professional Services (PS)	Logistics Services (LS)
Business Impacts	**Main business impacts and KPIs**	• Decrease in waiting time • Support bank managers and employees in solving problems • AI understands 94% of the intention • 90 products available • 363 million of interactions (133,9 million on WhatsApp) • Enable bank acquisition without increasing organizational structure • Brand awareness	• 150 robots working on B2C case • More than 20% retention of defect tickets • 75% of SLA improvement • R$100 million in savings • Reduced the number of interactions in the contact center • Available on more than 20 channels • 15 million calls per month, without user waiting time	• 4 macro-process with automation: Fiscal, Finance, Registration and Supply Chain & Logistics • Enable tax compliance • Increase finance monitoring and control • 100% fiscal process automated (human approval) • 80% Supplier registration automated	• 20,850 Documents analyzed (solutions being developed - certificates; loans; contingencies; funds and insurance) • Higher productivity in audit teams with a decrease in bottlenecks for operational tasks	• 350 robots working in the company • Cobot acquisition • Increased security engagement of the security team and in the company • Greater system visibility • Easiness in opening the safe and security tickets • Estimative of 90% of process automation
	Case main scope process impacted	Customer service	Customer service	Internal process	Internal process	Internal process

Category	**Subcategory**	Financial Services	Telecom &	Chemistry	Professional Services	Logistics Services (LS)

		(FS)	Technology (TT)	(CH)	(PS)	
Organizational Aspects	**Areas involved and main organizational structure changes**	• Areas: Data & Analytics, Innovation, Channels, Development, Infrastructure, Architecture, Support, business areas and Technology and Business Department • Create Artificial Intelligence Center • Creation of teams specialized in AI content, verification and curatorship • Cases of job dismissal	• Areas: Strategy & Governance Structure, Innovation & Synergies, Digital Transformation, Digital factory, CoE and IT • 2018: Bot Training Center • Creation of “Bots Supervisor" role • Cases of job dismissal but there is an effort for upskilling and reskilling	• Areas: Digital and IT • No employees lay-offs • No open formal positions opened	• Areas: Strategic PMO (Project Management Office), Innovation and Investment Committee, Audit Innovation Technology, Data & Analytics and IT •No new formal positions were created and neither lay-offs happened	• Areas: Digital Transformation/digitization and Innovation, IT, Continuous improvement and Process Engineering • No employees lay-offs • New open formal positions opened
AI Integration	**Artificial Intelligence integration and IT structure**	• More than 200 million transactions processed per day on average (peaks of 320 million transactions) • AI integration complications due to moments of systems instability and the roll out of new features	• 2,000 systems • Integration challenges to work with specific department systems • Robot’s governance and control	• ERP migration Project ongoing • Integration challenge with the current ERP system	• 110 physical and 328 virtual servers, which support 116 systems and 5,700 notebooks in Brazil • System AI integration facilitated due to IT team experience on internal systems	• 60 servers and 700 workstations, with more than 30 software applications • No major AI system integration difficulties
	AI Solution Processing	On premise and on cloud	On premise and on cloud	On premise and on cloud	On premise and on cloud	On cloud

Category	Subcategory	Financial Services (FS)	Telecom & Technology (TT)	Chemistry (CH)	Professional Services (PS)	Logistics Services (LS)
Challenges	**Main challenges on AI solution**	• Projects prioritization and selection • Digital solutions scalability • Lack of specialized AI workforce and deal with team's turnover • Diffusion of AI Knowledge in the company teams	• Projects prioritization and selection • Real understanding of the process to be transformed • Cultural resistance • System environment changes can cause malfunction and risks for the automated process	• Projects prioritization and selection • Low integration between company´s departments • Database changes can cause malfunction and risks for the automated process	• Structuring a specialized curatorship team • Deal with the huge scope of subjects addressed by the AI solution	• Obtain the company leaders support and the financial resources • Lack of AI specialized workforce and companies • Diffusion of AI Knowledge in the company teams

Source: The Authors