On the Journey to AI Maturity—Insights from Enterprise Artificial Intelligence Service Providers

Chuanwen Dong, Akanksha Saxena, Markus Bick (corresponding author) and Andrea Sabia

cdong@escp.eu, akansha.s1995@gmail.com, mbick@escp.eu, andrea.sabia@edu.escp.eu

ESCP Business School Berlin
Department of Information and Operations Management
Heubnerweg 8-10
14059 Berlin

Abstract. In recent years, it has become conventional wisdom that artificial intelligence (AI) will be a game-changer in business. However, it remains challenging to adopt enterprise AI, i.e., enterprise software that incorporates AI techniques, into firms' core and overall data strategies. In this study, we investigate the path to AI maturity and enterprise-wide adoption from a service provider perspective. We collect secondary data from 66 white papers published by leading AI service providers in the past five years and use topic modeling to understand the current themes in AI implementation. Thereafter, we analyze pertinent challenges through the lens of the classical technology-organization-environment (TOE) framework. Our results demonstrate that, even though AI service providers have successfully addressed—at least in part—major questions faced by clients, there still exists a gap between the features demanded by end-users and the skills possessed and focused on by the AI service providers. For example, a vendor thinks his user does not have a clear vision on AI adoption, whereas the user finds it difficult to align the provided AI solution with the firm's vision. We then argue that a holistic review of all TOE contexts is critical for closing the gap on the journey to AI maturity.

Keywords: Artificial Intelligence, Enterprise Systems, Enterprise AI, Topic Modeling, Technology-Organization-Environment Framework.

1 Introduction

The rise of digital transformation has fueled the growth of artificial intelligence (AI) technology, which is now an essential driver of sustainability and scalability. Global corporate investment in AI surges every year and reached almost 94 billion U.S. dollars in 2021 [1]—a figure already exceeding the annual GDP of some European countries such as Bulgaria or Luxembourg. AI adoption is estimated to contribute to a $15.7 trillion global GDP increase, making it the greatest commercial opportunity in today's fast-changing economy [2]. Firms no longer consider AI as an innovation but as a core entity of their decision-making models [3].

Opportunities to leverage data via AI techniques and business intelligence (BI) technologies have revolutionized the ways in which firms manage their operations, rethink their products and services, and create new business models [4]. This in turn has spurred the notion of platforms specifically designed for developing and operationalizing AI models. Such examples include Anaconda and RStudio, which are widely used by firms with knowledge of the entire data pipeline, from ingestion to operationalization of the model and its maintenance. Moreover, other off-the-shelf solutions, such as Google AI, SAS, Alteryx, and Dataiku—amongst a vast number of AI as a Service (AI-aaS) and AI as a Product (AI-aaP) providers—allow companies without knowledge of the entire data pipeline to leverage their data easily and challenge competitors who have managed to set up an internal data science team [5].

With the rapid development of AI, enterprise resource planning (ERP) providers are aware that the main challenge they face is embedding "intelligence" in their products [6]. Companies nowadays are looking for ways to discover new revenue streams as well as improve existing ones, as this is how their strategy imposes growth through newly available technologies [7]. The major advantage of ERP implementation is cost reduction as a result of low-level data analysis and optimization. ERP providers understand this trend, and indeed players such as SAP, Salesforce, and Oracle now make their AI platforms core or add-on packages.

However, despite the rapidly growing number of AI service providers [8], it has been demonstrated that the majority of firms either do not trust AI service providers or do not believe AI solutions can meet their specific needs [9]. It has been found that 47% of all AI projects deployed fail in production [10], and according to Gartner, AI projects culminating in successful outcomes have barely crossed the 50% threshold [10]. A survey by Bain & Company reveals that nearly 90% of executives mention AI initiatives as a priority, albeit 87% of them are not satisfied with their current usage [9].

Over the past few years, an increasing number of studies have investigated the challenges companies face when implementing AI solutions. They examine barriers to AI adoption in different industries such as healthcare, construction, education, banking, etc.; however, the extant literature on this topic focuses on a user perspective. For example, [11] studies in-house issues related to technology, skill gaps, employee fear and distrust in AI regulatory measures, and so on. It is interesting to note that around 80% of companies involved in AI activities buy at least 50% of their capabilities from vendors, and only 8% build in-house capabilities [12]. However, the viewpoint from AI service providers is hardly known in relation to the mitigation of AI diffusion challenges. It is not clear if challenges either result from or can be resolved by AI service providers.

In this study, we explore the role of service providers in maturing AI implementation. Specifically, we focus on enterprise artificial intelligence (EAI), which is defined as 'the ability to embed a methodology into the very core of an organization's data strategy' [13]. It is a category of enterprise software that incorporates AI techniques. We aim to understand the emergence of EAI and how it can improve performance across the whole enterprise. In this regard, we seek to answer the following research questions:

What challenges do firms face when scaling AI throughout their enterprise, and how can AI service providers address them?

We collect secondary data from 66 white papers1 issued by the world's leading AI service providers in the past five years (e.g., the top 10 AI service providers according to Gartner Magic Quadrant [3], namely, Amazon, McKinsey, Microsoft, Deloitte, Alteryx, IDC, Gartner, IBM, SAS, and KPMG.) White papers are usually drawn up based on specific capabilities and expertise, and they follow similar formats, which allows for pooling the results across all chosen AI providers. Since EAI is a rather modern topic, we only focus on white papers published in the previous five years. In order to synergize the large database for knowledge, we analyze the data by using a topic modeling technique, specifically the latent Dirichlet allocation (LDA) algorithm.

After that, we explain the challenges found from topic modeling the through the lens of the using the classical Technology-Organization-Environment (TOE) framework. According to this theory, technology adoption is influenced by technological, organizational, and environmental contexts [14, 15]. This framework allows us to classify and clarify the factors obtained from topic modeling, and to further understand the key challenges in enterprise-wide EAI adoption. We identify a key challenge of EAI implementation that spans over TOE contexts, namely, the gap between the features demanded by end-users and the skills possessed and focused on by AI service providers. The gap can be explained from technological, organizational and environmental perspectives. In this regard, AI service providers should apply a holistic TOE framework to guide firms comprehensively in the journey to AI maturity.

The remainder of this paper is structured as follows. We review related literature in section 2 and present our methodology in section 3. After that, we present and discuss our results in section 4 and conclude the paper in section 5.

2 Related Literature

2.1 Artificial Intelligence

The term "artificial intelligence" was first used in 1955 by academics at Dartmouth University, USA, with the idea being that 'every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it' [16]. In simpler terms, the underlying idea was that a machine could imitate the thought processes of humans, but it had not been put into practice at that point, due to the inability to write and store programs to carry out these tasks [17]. Fast forward to today, and we see AI being used to diagnose lung cancer [18], reduce food waste [19], optimize transport schedules [20], etc.

The last 70 years have seen various definitions [21] provided by both academics and businesses alike. A widely accepted framework from the academic side is presented by [22], which highlights how one sees the goal of AI (Table 1). Most companies with an

[1] A list of the white papers is presented in the Appendix.

AI-related product or service will have a page dedicated to AI, alongside their preferred definition. Gartner defines AI as the '[…] advanced analysis and logic-based techniques, including machine learning, to interpret events, support and automate decisions, and take actions' [23], which falls into the 'systems that act rationally' category. Analytics provider SAS maintains that 'Artificial intelligence makes it possible for machines to learn from experience, adjust to new inputs and perform human-like tasks'. In this instance, the emphasis is placed on 'acting as a human'.

Table 1. Goals of AI [22]

	Human-Based	**Ideal Rationality**
Reasoning-based	Systems that think like humans	Systems that think rationally
Behavior-based	Systems that act like humans	Systems that act rationally

AI is an umbrella term for a family of techniques [24, 25]. In a formal definition, 'artificial intelligence is a set of advanced computer software applicable to classes of non-deterministic problems such as natural language understanding, image understanding, expert systems, knowledge acquisition and representation, heuristics search, deductive reasoning, and planning' [25]. According to research, the three main fields in AI are cognitive analytics, machine learning, and robotics. This is not an exhaustive list, but it does comprise present-day techniques and algorithms used in business. Each of these fields has its own subfields, which will be explained in the following. For more details on the AI family of techniques, see [25].

The key to understanding the commonality between AI subfields is the word "intelligence". As per the definitions given in [22],, the terms "think", "act", "rational", and "human" are provided as goals of AI. Hence, it is somewhat implied that a human who thinks or acts rationally is indeed "intelligent." Machine learning focuses on thinking, robotics uses sight and motion (two key actions defining humans), and, lastly, cognitive analytics uses thinking and, partly, sight. The secondary aspect connecting these fields is their heavy reliance on similar statistical methodologies [26], albeit this requires a disclaimer: there are several representations of the AI family, and sometimes cognitive analytics and robotics are included as part of machine learning, as they use similar statistical techniques.

One last topic in terms of AI as a whole is the concept of narrow and general AI. General AI—also known as "singularity"—is the idea that a machine can act and think beyond the ability of a single human across several aspects of human life [27]. Hence, only narrow AI systems are considered herein.

2.2 Enterprise Systems

ERP systems became prominent in the business environment in the late 1990s. ERP can be defined as '[…] a framework for organizing, defining, and standardizing the business processes necessary to effectively plan and control an organization […]'. The key here is the organization as a whole. ERPs can be considered an evolution of material resource planning (MRP) systems, which focused solely on complex materials production [28] but missed the overall journey of a product (from ordering materials all the way to invoicing to the final client). There seems to be some consensus in defining the nature of an ERP, as Gartner [29] also provides a similar definition, focusing on data models and cross-functional, end-to-end processes.

The main driver of early ERP implementations was cost-cutting (mainly in the supply chain), the need for a system where information could be trusted and relied upon, and, generally speaking, leaner processes [30]. Requests came from the supply chain and, mainly, management. [31] point out the apparent need for firms to integrate inventory data with financial, sales, and HR data, in order to price products accurately, automatically draw up financial statements, and effectively manage resources such as employees and materials. This definition is particularly important, as it highlights the main asset on which enterprise systems focus, namely, data.

In order to achieve leaner processes, there is a need to share accurate information with suppliers and customers [32]. According to [30], the two main benefits of ERP implementations are 1) a unified enterprise view of the business that encompasses all functions and departments and 2) an enterprise database in which all business transactions are entered, recorded, processed, monitored, and reported. The above definition highlights the importance of a centralized database for the effective functioning of a business. Another definition provided by [33] focuses on the tangible and intangible benefits of ERP implementation. Tangible benefits are cost reductions or improvements in cash-flow management, whereas intangible benefits are the increased visibility of corporate data and new or improved business processes, among others. [34] identified benefits primarily from an accounting perspective, in that firms implementing an ERP see benefits in inventory turnover, fixed asset turnover, and accounts payable management, leading to an increase in profitability within 2 years of implementation. [35] focuses primarily on strategic and management benefits, or so-called "intangible" benefits, concluding that ERP implementation has an undeniable impact on internal processes, and is driven by automated transactions and an integrated database.

2.3 Enterprise Artificial Intelligence

Enterprise artificial intelligence (EAI) is mostly crafted by firms that provide AI-related products and services, i.e., mostly traditional consulting firms. Perhaps the most acknowledged definition is provided by Gartner Magic Quadrants [36].

The term "EAI" is rather recent, so formal definitions are not abundant. Indeed, only six papers containing the term "enterprise artificial intelligence" in their title were found on Google Scholar, and none of them was published in a renowned academic journal. Players in the EAI market tend to define the term on their websites. For instance, C3.ai defines it as 'applying AI at scale across an organization's entire value chain' [37]. Dataiku defines EAI as 'the ability to embed a methodology into the very core of an organization's data strategy' [13], while Teradata focuses on the outcomes of EAI, asserting that '[it] will provide us with a never-before-seen scale' [38]. Databricks asserts that EAI is about collaboration across the full data and analytics lifecycle

[39]. In addition, major consulting firms have recently shifted focus towards AI and specifically towards leveraging it throughout organizations. Professionals at McKinsey & Company, for instance, assert that enterprise AI involves integrating advanced analytics throughout the entire business [40], and KPMG states that companies who will thrive in the near future will 'use AI for the full range of benefits, from back and middle office productivity to front office product innovations and customer engagement' [41].

2.4 Barriers to AI Usage

One study, amongst others, has recognized several barriers and their associations with each other, each negatively impacting the enterprise-wide scaling of AI [42]. It suggests that challenges, such as a lack of reusable models, reside on the first level, followed by a lack of usable data and trust in AI on the second level. The threat of job security, poor infrastructure for AI model deployment, and a paucity of the AI talent and skills required are some other barriers to AI scalability [42]. In a quantitative study [43], the main obstacle is identified as a lack of adequate AI skills and talent to deploy AI models successfully [43]. In another survey, [44] suggests that negative emotions of employees toward AI, cost, uncertainty surrounding the advantages of AI, insecurity, and a lack of AI skills are barriers to small and medium organizations adopting it. However, a study by Gartner shows that insufficient AI skills/talent is not a challenge in scalability across an organization [23]. Another study examining resistance to AI identifies obstacles such as the fear of job losses, managers rejecting machine recommendations, and concerns about being made obsolete by firms [11].

3 Methodology

The main objective of this paper is to identify the challenges faced by firms when scaling AI throughout their enterprise, and to provide insights into how AI service providers can address these questions. Accordingly, this study applies an explorative qualitative approach by analyzing secondary data collected from white papers published by leading companies in the field. In the following, we first explain the data collected and then present the topic modeling algorithm we have implemented in order to answer the research questions mentioned above.

3.1 Data

The data chosen for this paper comprise white papers from top AI service providers, including the top 10 vendors according to the Gartner Magic Quadrant [3] in the past five years. The rationale behind using them is that they usually address the specific capabilities and expertise of a firm, which is the aim of this thesis, and, more specifically, of the research question. A wide variety of content is produced consistently by these providers, ranging from blog posts or user-generated content through webinars and case studies. Additionally, white papers are constant across all chosen providers, which allows for results pooling.

The retrieval process was manual, as all firms required credentials to log in and download their content. Once all white papers had been retrieved, they were manually investigated, with case studies or industry-specific use cases discarded. This ensured that only content on the general knowledge of AI service providers would be analyzed, in order to preserve the results' generalizability. Finally, a total of 66 white papers were retrieved from 15 firms, with a maximum of 10 per company.

The white papers in ."pdf" files were then converted into ."txt" files via the python package PDFminer [45]. Subsequently, text cleaning took place using a python package called Tmtoolkit that offers text preprocessing and mining options. Numbers, punctuation, and characters not forming English words were removed. Subsequently, lemmatization was applied to the text, thereby normalizing words to their root forms [46]. Lastly, empty tokens and common stop words [46] shorter than two letters were removed, because using only lemmatized nouns is believed to increase semantic coherence [47]. Various iterations of the analysis were carried out, and the results demonstrated a need to also include verbs and adjectives, to retrieve meaningful topics from the texts. Furthermore, the list of stop words was extended by excluding common words such as "data" and "computer," organization names such as "Amazon" and "McKinsey," and industry-based terms such as "food" and "bank." These words were high in occurrence and did not contribute to meaningful insights, in which case they were removed from the vocabulary destined for further analysis.

Additionally, we also identified and joined collocations (tokens that co-occur frequently in the corpus) to form a single token/word, using the thresholds measured by pointwise mutual information (NPMI) and the minimum number of times they occur together (five in our case). This resulted in 16 collocations, the most meaningful of which were "artificial_intelligence," "machine_learning," "use_case" and "supply_chain." Moreover, we also filtered our corpus based on the keywords "PROBLEM," "skill," "talent," "barrier," "knowledge," "challenge," "gap," and "skill gap." The criteria for choosing keywords were based on congruence with answering the research question. This resulted in the removal of four white papers. The final data preparation step involved "aggressive" cleaning, whereby we removed common and uncommon tokens based on the document frequency threshold. The final corpus for analysis consisted of 62 documents and 3,410 words.

Since the Tmtoolkit does not provide a library for latent semantic analysis (LSA), we used the Genism and NLTK packages in python for data preparation and the analysis of LSA. Initial data preparation was exactly the same, including the removal of numbers, punctuation, and an extended stop word list almost similar to the one mentioned above. No joined collocations were applied. Documents were filtered based on the absolute word and document frequency of tokens. The final corpus for LSA consisted of 66 documents and 2,500 words/tokens.

3.2 Topic Modeling

Topic modeling is a machine learning technique used for extracting underlying themes/concepts—called "topics"—from a collection of text documents [48-50]. Exponential growth in the generation of digital text data in the form of online blogs, company reports, and online consumer reviews has led to the development of automated methods such as topic modeling to provide efficient ways to discover patterns in such types of text data [51, 52].

Furthermore, the framework is utilized to summarize the contents of a large collection of text documents (as in this paper), which would otherwise be difficult and inefficient to perform by manual text analysis. Therefore, topic modeling seemed to be the most appropriate text analysis method as compared to manual content analysis for our dataset consisting of 66 industrial reports. Being an automated process, it is also able to detect patterns in the dataset which might be missed in an otherwise manual content analysis approach [51, 52].

To create robust results, different techniques were trialed for the analysis, following which the results were evaluated and compared. The paper synthesizes the unsupervised topic modeling approach, namely LDA, which is believed to generate better results in our analysis, in that 1) the average number of words per document is greater than 50 and 2) complex topic relationships are of interest (for a more detailed comparison among topic modeling algorithms, please see [48]).

LDA input is a “corpus” (a collection of documents, i.e., all 66 white papers collected by us). A “document” is an ordered collection of words. A “vocabulary” is the set of unique words or terms in a corpus, and a “word” is the basic unit of a corpus, defined as an item from the vocabulary set. A “topic” represents an underlying semantic theme/concept [53, 54].

Documents are functions of topics, and topics are functions of words [53]. Each document can be assigned to more than one topic. It is therefore considered a “soft clustering” way of grouping documents according to their underlying themes. It is called soft clustering because a document need not be strictly assigned to only one cluster (topic) [54]. The essence of a topic modeling algorithm such as LDA is to represent posteriorly a document on several topics with some probabilities.

By running LDA, the number of topics is assigned a so-called “coherence score,” i.e., an evaluation metric for examining the quality of the themes, or “topics,” which have been derived from topic modeling techniques [51, 55]. The quality of the themes is indicative of the extent of the human-interpretability of the themes generated from the topic modeling technique. For instance, topic “AI” can be defined as a set {machine learning, predictive, data, analysis, architecture}.

It is important for the domain experts that the topics generated are of good quality, meaning that they should contain words that are strongly semantically related to each other [55]. Poor topic quality reduces the confidence of users in statistical automated topic generation methodologies [55]. The coherence score metric is developed to evaluate semantic coherence in a topic and a topic set [56-58]. The coherence score has been found to be consistent with the human interpretability of topics. The closer the coherence score to zero, the higher the topic quality and topic interpretability [51, 57]. In our analysis, we identified the appropriate number of topics by examining average semantic coherence using coherence scores provided by [55] and [59] for different topic models, ranging from two to 40 topics. Upper and lower bounds of this range (Fig. 1) were motivated by the aforementioned Tmtoolkit package.

4 Results

In this section, we present the various topics identified from the topic modeling algorithm. In a next step, we discuss these results through the lens of the classical TOE framework, and finally we highlight our findings. TOE is the choice of framework in this paper, as it provides a comprehensive view regarding the various factors that firms face when scaling AI throughout their enterprise. Moreover, it helps to shape the AI service provider landscape.

4.1 Topics Identified

Figure 1 shows the scores for the semantic coherence of topics, which increased in line with an increase in the number of topics. The reading of the graphs suggests that one may opt for a topic number greater than ten, since these yield good statistical measures as the number of topics increases. However, it is also observed that the coherence score remains relatively constant when the topic number is over 20.

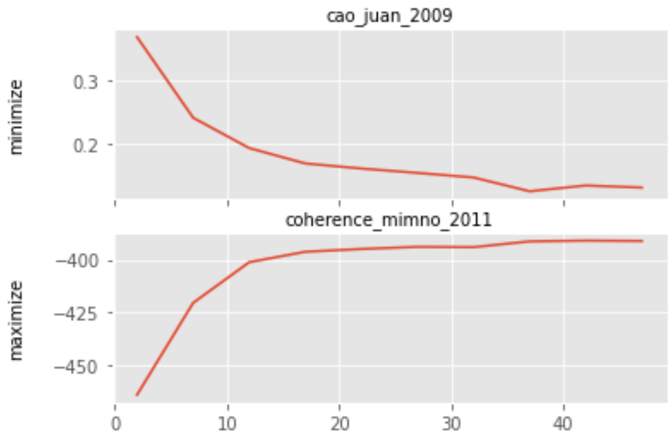

Fig. 1. Cao Juan topic evaluation metric for the LDA topic model (above), and coherence score developed using LDA topic modeling (below).

To decide on the appropriate number of topics, and to complement our statistical approach, we performed qualitative analysis to examine the interpretability of different models. The small topic models (fewer than 15 topics) were discarded, since they merged similar topics and were not able to distinguish between different concepts. Further large topic models (topics over 25) produced duplicate themes with a high amount of overlapping. Hence, we settled on 17 topics as the best option, as the values for semantic coherence did not substantially improve for larger topic models, and the qualitative analysis of the 17 topics model revealed clearly interpretable topics.

Table 2. Topics obtained from LDA topic modeling

Topic number	Word Distribution
1_artificial_intelligence	artificial intelligence, machine, digital, firm, global, machine learning
3_skill	skill, help, research, develop, create, adoption, value, strategic, management, challenge
4_services	services, incumbent, organization, firm, market, investment, implementation, Regulation
5_vision	vision, transformation, strategy, digital, ecosystem, employee, leader, change, People, create, future, enterprise, world, build
6_use_case	use case, analytic, potential, impact, industry, technique, sale, management, global, product, learning
7_scale	scale, organization, initiative, build, enable, leader, executive, strategy
9_state	state, enterprise, global, software, market, revenue, adopter
11_worker	worker, employee, role, maker, human, power, impact, knowledge, positive, believe, analytics, ml, question, change
12_erp	erp, cloud, sap, application, solution, capitalize, system, hybrid, create, intelligent, future, organization, system
13_algorithm	machine learning, decision, deep, learning, prediction, problem, model, train
14_organizational	organization, impact, change, organization, significant, strategy, management, consulting

To generate labels for the topics, we used the "generate_topic_labels_from_top_words" function in the Tmtoolkit package, which generated labels based on the most "relevant" words in each topic. The next step involved the determination of topics relevant to our research question. We performed individual examinations of 17 topics and excluded those that did not provide meaningful insights into our research question. Themes labeled "algorithms," "use_case," and "artificial intelligence" are some of the topics associated with AI technologies. Keywords for these topics were as follows: "machine learning," "model," "application," "prediction," "artificial intelligence," "system," "analytic," "technique," "industry," "train," and so on. We also found topics representing factors associated with enterprises, such as their vision to scale AI diffusion, or the state of AI integration in ERP systems. Additional topics also pointed towards challenges in AI scaling across organizations which were not related to enterprises. They included topics such as the skills or capabilities of AI service providers, consisting of words like "skills," "services," "worker," "profession," and "knowledge."

Additionally, some themes were generated that did not reveal meaningful insights; for instance, topics relating to data collection methods (containing terms such as "survey," "respondents," and so on) were excluded. We realized from the further analysis that six topics were irrelevant to our research purposes. Following this examination, we focused on 11 topics, which allowed us to address our research question. Table 2 illustrates the topic labels and term distribution of each of the final 11 topics, and Figure 2 illustrates the word clouds around the 11 topics.

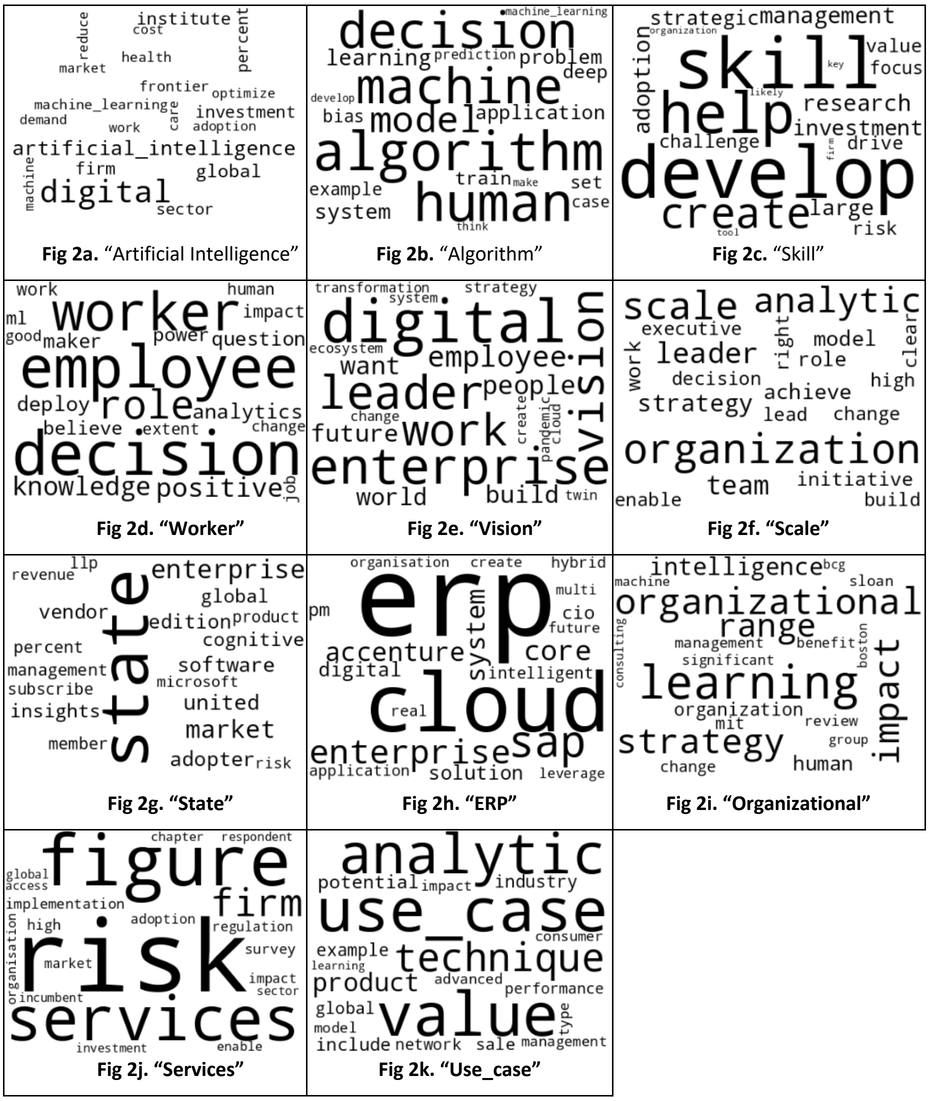

Fig 2a. "Artificial Intelligence" Fig 2b. "Algorithm" Fig 2c. "Skill" Fig 2d. "Worker" Fig 2e. "Vision" Fig 2f. "Scale" Fig 2g. "State" Fig 2h. "ERP" Fig 2i. "Organizational" Fig 2j. "Services" Fig 2k. "Use_case"

Fig. 2. Topic clouds for the 11 topics obtained from the LDA model

On investigating the topic clouds obtained from the LDA, it is evident that skills, talent, and knowledge in AI technologies are of imperative importance for AI scaling in firms. Word clouds for the topics "artificial intelligence" and "algorithm" (Fig. 2a and 2b) indicate that AI and its related technologies, such as machine learning, complicated machine algorithms, and system integrations, should be at the center of the offerings supplied by AI service providers. It can thus be inferred that proficiency in implementing AI and its technologies should be one of the central focus areas for service providers.

Another category of challenges described by LDA topics is the capabilities of AI service providers, depicted by the topics labeled “skill” and “worker.” From Fig. 2c and Fig. 2d, it can be deduced that AI service providers face challenges in terms of building, creating, and developing AI models which can be attributed to the skills, knowledge, and learning potential of employees/workers. It can also be reasoned that even though there is investment and research in AI/ML, the slow adoption of AI can still be attributed to the “human” factor, which in turn can potentially involve questioning AI’s results, the struggle to believe in AI, along with the fear of change with respect to skills and job losses. These factors therefore create issues relating to the enterprise adoption of AI, due to a potential gap in their capabilities, skills, and offers.

Fig 2e shows that leadership has the vision to transform/change the world via the digital ecosystem, and potentially by AI integration into ERP. Fig. 2f seems to be pointing towards a goal in order to scale AI adoption by implementing initiatives and strategies that enable organizations to effect digital change. The word cloud for the topics “state,” “ERP” and “organizational” depicts the current state of digital ERP technologies such as cloud, SAP, or hybrid models in global organizations. The business dimensions of implementing AI in ERP are revenue generation, the risks involved in adopting AI, and organizational management challenges. The slow adoption rate of AI in enterprises can be due to challenges in strategy, leadership, and management, thereby resulting in the poor implementation of a clear business vision—as inferred from Figs. 2e to 2i.

AI implementation and adoption issues also occur due to a lack of focus on regulatory, security, and privacy concerns, as observed in Fig. 2j. Hence, the services provided by AI service providers are deemed to pose a risk to the security and privacy of the consumers. Lastly, from Fig. 2k, technical issues in the product and system might result from the complexity behind hardware integration, as well as insufficient skills possessed by AI service providers to resolve this issue efficiently.

4.2 Challenges Explained in the TOE Framework

The technology-organization-environment (TOE) framework explains how firms adopt technology innovations [60]. The key elements of the framework are, naturally, the technological, organizational, and environmental contexts. Using a TOE framework as a theoretical lens, we categorize and explain themes obtained from the previous topic modeling algorithm.

The technology context includes not only technologies to be used (in this case, EAI), but also those that are already in use by firms. Concerns are raised on the compatibility and accountability of EAI with other installed technologies, whilst implemented AI platforms need to be able to coexist with legacy systems when they cannot replace them [61].

Regarding AI itself, its benefit mainly lies in two areas: saving time and saving costs [62-64]. In value-generating activities such as marketing, sales, and product/service development, vast numbers of respondents report increases in revenue, whereas in areas where the main KPIs are cost-related, such as supply chain and manufacturing, the vast majority describe cost reductions.

It seems that the technology has still not fully uncovered its potential. Studies show that technology competence, such as advanced reinforcement learning techniques, can be increased to enhance further the value provided to firms [65]. Companies should thus implement a continuous process improvement methodology that can be applied to the algorithms developed [11].

The most significant concern relating to the technology itself might originate from data; for instance, data issues (e.g., privacy, accessing) were deemed the “top challenge” in a McKinsey survey [65]. Another survey revealed that only 17% of respondents asserted their company had a clear strategy to acquire the data needed for AI to work [66]. Data needs to be mapped, and data ontology and master data models need to be created. Moreover, it is suggested to focus on data when it is needed, rather than from the very beginning of the project, to avoid unnecessary and unavoidable bottlenecks.

The organizational context in this study specifically refers to descriptive measures about the organization such management, financial investment, and structural issues. It is important to mention how AI adoption has affected the workforce in terms of numbers across industries in the past year. As of 2019, more companies have increased their workforce instead of decreasing it, and aside from a few cases in the technology or professional services industries, this trend will change [67]. However, the same study then proceeds to highlight that 83% of companies are planning to retrain parts of their workforce, to reuse them in AI-related roles. More companies foresee a decrease in their workforce rather than an increase, due to AI adoption.

Financial resources in the organization have been a popular antecedent to technology diffusion [68]. Financial investment in technology has significant paths leading to its adoption [69]. Our topic modeling reveals that firms hesitate to implement AI because they are not sure about its added value and return of investment (ROI). Moreover, some projects that would improve processes are deemed too expensive, as they have no direct impact on the bottom line, whereas others are viewed as potentially lucrative, but given a degree of uncertainty, they are usually overlooked [70].

A lack of AI talent in firms is widely reported. Staff without qualified skills, as well as executives short on commitment, are both found in the data. Teams are suggested to work cross-functionally and in an agile manner to allow subject matter experts and analytics talent to be accountable for the impact of projects, while engineers in charge of analytics efforts are suggested to coach executives and top-level management, in order to clarify any misconceptions about what AI can and cannot do [61].

Another organization issue is a lack of enterprise-wide strategy and vision [41]. There is a fundamental need for an all-encompassing strategy and capabilities, including talent, infrastructure, new processes, and governance, around AI [41]. Companies should thus have a master data model across functions with clear ownership [11].

The environmental context generally refers to factors related to competition [71], regulation [69], and suppliers [72]. A major concern regarding this particular context is a lack of support (or support is not appreciated) provided by AI service providers, who are often regarded as untrustworthy and overly expensive by a large proportion of potential clients [9]. In addition, AI is regarded as a threat to competitive advantage. In 2018, for instance, 45% of survey respondents recognized the risk of lagging behind direct and indirect competitors who had implemented AI [73]. Suggestions have already been made, i.e., a risk management program team should be established to work alongside legal and ethics experts to minimize the potential backlash of AI and data on the company [61].

The topics labeled “service” and “state” capture the environmental context. “State” reveals an association between support from AI vendors and the state of AI adoption in the global market, as well as the cost-effectiveness of AI solutions. “Service” suggests that AI service adoption in organizations might pose a risk in terms of negative social impacts, and therefore regulations have been implemented to keep privacy and security concerns in check. Both topics clearly illustrate the global market trend across firms in terms of regulatory measures and vendor support.

Table 3. Challenges in EAI implementation, analyzed using the TOE framework

Context	**Topics**	**Challenges**
Technology	Artificial intelligence, Algorithm, ERP	Complexity of software functionality
		Complexity of integrating systems
		Potential bias in algorithms
		Performance measures are not adapted to ensure changes
		Challenges in measuring and proving business value
		Analytics roles are poorly defined
		Data accuracy is not ensured
		Explainability of models and outputs is not clear
		Lack of relevant data
		Security and privacy concerns
		Technical difficulties, such as bugs, hardware connectivity, or interfaces with older systems
		Data privacy and integrating issues
Organization	Worker, skill, organizational, vision, scale	Lack of top management commitment and support
		An implementation team is not properly selected
		Integrating AI into the company's roles and functions
		Uncertainty regarding the added value of AI
		Uncertain ROI for AI
		Inadequate training of users
		Inadequacy of qualified staff
		Executives lack a clear vision
		Lack of skills in AI
		Organizational structure
Environment	State, service	Lagging behind direct and indirect competitors who have already implemented AI
		Difficulty in aligning AI solutions with the firm's vision
		Lack of/poor support provided by vendors
		Ethical, social, and regulatory implications
		Lack of availability from implementation partners
		Data strategy and governance

4.3 Major Findings and Interpretations

FINDING 1: There exists a gap between the features demanded by end-users and the skills possessed by and focused on by AI service providers.

Even though, at an overarching industrial level, AI has already been successfully adopted by a wide range of firms, not all specific requests made by individual users can be fully addressed by AI service providers. Previous studies have identified a lack of skills on the user side as a barrier to AI adoption [43], especially for small- and medium-sized firms [44], while other studies claim that AI models should be further improved, in order to expand their scalability [42].

We find the co-existence of barriers on both the vendor and the user sides. For example, whereas vendors believe their AI applications and functions are already sufficiently complex, users still think the explainability of AI models is questionable. Table 4 provides a list of such problems identified by both parties.

Table 4. Vendors and users have different opinions on the challenges of AI implementation

Vendor's perspective	User's perspective
AI software is already comprehensive	The output of AI software cannot explain real problems
There is a lack of relevant data to implement AI	There are concerns about the security and privacy of data
The user has not properly selected an implementation team	The vendor has not provided sufficient support for AI implementation
Firms have a slow AI adoption rate	Managers are uncertain about the added value and ROI of AI adoption
Executives do not have a clear vision on AI adoption	It is difficult to align AI solutions with the company vision

Such a mismatch reveals a gap between the vendor and the user, and in general terms it is observed in almost every industry. However, perhaps because of the complexity of AI and its rapid development, the gap is especially obvious here. This disparity between supply and demand should be mitigated by both sides; for example, end users may need more training on AI, and vendors could make their products more user-friendly and user-oriented.

FINDING 2: Such a gap is driven by technological, organizational, and environmental factors, and it should be addressed from all three perspectives.

In the classical TOE framework, influencing factors are split into three categories, namely, technology, organization, and environment [60]. Interestingly, the gap between the AI vendor and AI user can be explained by these three contexts. From a technological perspective, this mismatch lowers the competencies of AI, because users have not required the correct technology required. Such insufficiency can also be examined as an organizational problem because of a lack of management support and staff training.

This could also be explained as an environmental issue, since vendors and users have not sufficiently communicated during the implementation process.

Our result coincides with previous studies. For example, [11] talks about resistance to change with respect to the culture, management, and leadership that becomes a bigger barrier than the lack of AI skills. The paper suggests that failure to reflect organizational and employee fears about becoming obsolete and losing jobs, as well as management's rejection of machine-based recommendations, offers some obstacles to AI integration [11]. By analyzing AI service providers' white papers, we find that the technological, organizational and environmental contexts are inter-correlated, and a holistic review of the TOE framework is needed in order to guide firms comprehensively on the journey to AI maturity.

5 Conclusion and Future Works

This paper has the overarching goal of understanding the role of enterprise AI (EAI) service providers on the journey to AI maturity and enterprise-wide implementation. The value of this work lies in the multiplicity of potentially interested stakeholders, including both EAI practitioners and researchers. Vendors may find the value in a systematic assessment of their offerings and capabilities set against the most commonly mentioned issues in scaling AI solutions. Furthermore, academics studying information systems, management, and analytics may find in this work a scholarly assessment that is essentially the first of its kind. Indeed, the academic literature on this topic is extremely scarce, if not non-existent.

Our research paper provides a structural categorization of challenges to scaling AI from the perspective of AI service providers. These factors are obtained by collecting secondary data from white papers and further analyzed by topic modeling algorithms. This thus helps in mitigating the issue of a lack of consensus in the previous literature with respect to barriers faced by AI service providers in scaling AI in enterprises.

Our result reveals that, generally speaking, there exists a gap between the demand for specific skills and those possessed by AI service providers. However, the results tend to highlight the fact that providers are aware of this gap, and they are devoting a—not yet significant—part of their focus to bridging this gap. The insights herein could be of vital importance for future players in this environment. The result encourages knowledge exchange between researchers and practitioners.

One of the limitations of this research is the unsupervised learning algorithm used to uncover topics from the corpus. Additionally, the themes were only a function of words (and not sentences or phrases), which are subjective in the interpretations of domain experts. Perhaps more powerful tools can be developed that will feed topics to the model and cluster documents based on these topics. Additionally, they may also produce not just word clouds but phrases, thereby improving output interpretability. Furthermore, to improve the results of this study, it would be interesting to analyze the full breadth of content produced by AI service providers by collecting more data from interviews, case studies, webinars, or even end-user-generated content. Other theories, besides the TOE framework, can be used or extended to interpret the results.

Appendix

Table 5. A list of data collected

No.	Year	Organization	Title
1	2017	Ocado Technology	Experimenting with robots for grocery picking and packing
2	2017	ERP Software Blog Writer	What Is the Cost of a Typical ERP Implementation?
3	2017	McKinsey & Company	Artificial Intelligence: The Next Digital Frontier?
4	2017	The Boston Consulting Group	Reshaping Business with Artificial Intelligence: Closing The Gap Between Ambition and Action
5	2017	Deloitte	The Internet of Things: Moving from cost savings to revenue generation
6	2018	Ernst & Young	The growing impact of AI on business
7	2018	Accenture	Unleashing exponential evolution
8	2018	McKinsey & Company	Breaking away: The secrets to scaling analytic
9	2018	McKinsey & Company	Crossing the frontier: How to apply AI for impact: How to apply AI for impact
10	2018	Deloitte	State of AI in the Enterprise, 2nd Edition
11	2018	McKinsey & Company	Notes from the AI frontier: AI adoption advances, but foundational barriers remain
12	2018	McKinsey & Company	Notes from the AI frontier: Insights from hundreds of use cases
13	2018	McKinsey & Company	Ten red flags signaling your analytics program will fail
14	2018	McKinsey & Company	What AI can and cannot do (yet) for your business
15	2018	Teradata	Why Enterprise AI Will Be Highly Differentiating
16	2018	SAS, Accenture, Intel and Forbes	AI Momentum, maturity & models for success: based on findings from a global executive survey
17	2019	KPMG	AI transforming the enterprise, 8 key AI adoption trends
18	2019	Bain & Company	AI Is Lifting Service-Center Performance

19	2019	Bain & Company	From Hype to Hero: A Look at Artificial Intelligence in the Consumer Packaged Goods Industry
20	2019	McKinsey & Company	Global AI Survey: AI provides its worth, but few scale impact
21	2019	Forbes	How AI can Transform the Transportation Industry
22	2019	McKinsey & Company	How AI can unlock a $127B opportunity by reducing food waste
23	2019	Teradata	How Reinforcement Learning is Changing Customer Engagement
24	2019	Forbes	Rethinking Weak Vs. Strong AI
25	2019	Accenture	AI built to scale: from experimental to exponential
26	2020	The Boston Consulting Group	The rise of the AI-powered company in the post-crisis world
27	2020	Deloitte	State of AI in the Enterprise, 3rd Edition
28	2020	Deloitte	Thriving in the era of pervasive AI
29	2020	Gartner	Gartner's 2020 Magic Quadrant For Data Science And Machine Learning Platforms Has Many Surprises
30	2020	C3.ai	10 Core Principles of Enterprise AI
31	2020	Alteryx	Using Alteryx to help get employees back to work post Covid-19
32	2020	Bain & Company	Will the Pandemic Accelerate Adoption of Artificial Intelligence?
33	2020	Capgemini	The AI-powered enterprise: Unlocking the potential of AI at scale
34	2020	Ernst & Young, Invesco	Transforming Paradigms: A Global AI in Financial Services Survey
35	2020	Gartner	The Reset: Re-examining AI Investment Strategies
36	2020	Gartner	Drive Strategic Mandates for AI in the Enterprise
37	2020	Accenture SAP Business Group	Turning intelligence into value
38	2020	The Boston Consulting Group and MIT	Expanding AI's Impact with Organizational Learning

39	2020	Microsoft	Empowering Your Organization with Responsible AI
40	2020	IBM	Proven concepts for scaling AI. From experimentation to engineering discipline
41	2020	Gartner	The AI Crunch Demands Practical Responses: A Gartner Trend Insight Report
42	2021	Apps Run The World	Top 10 ERP Software Vendors, Market Size and Market Forecast 2020-2025
43	2021	Accenture	Leaders Wanted Technology Vision 2021 Experts at Change at a Moment of Truth
44	2021	Deloitte	Scaling AI in government: How to reach the heights of enterprise-wide adoption of AI
45	2021	Cloudera	Limitless: The positive power of AI
46	2021	Gartner	The Gartner Hype Cycle for AI: Prioritize & Accelerate Innovation Investments
47	2021	Gartner	The Gartner 2021 Data Science & Machine Learning Magic Quadrant Highlights
48	2021	Deloitte	Becoming an AI-fueled organization: Deloitte's State of AI in the Enterprise, 4th Edition
49	2021	McKinsey & Company	The state of AI in 2021
50	2021	Gartner	Gartner Predicts the Future and Impacts of AI Beyond 2021
51	2021	Deloitte	Artificial Intelligence & Data: Welcome to The Age of With TM
52	2021	IDC	IDC Forecasts Improved Growth for Global AI Marketing 2021
53	2021	Accenture	Scaling AI: Giving data its due
54	2021	IDC	IDC Market scape: Asia/Pacific (Excluding Japan) Vision Artificial Intelligence Software Platform 2021 Vendor Assessment
55	2021	McKinsey & Company	Winning with AI is a state of mind
56	2022	Alteryx	7,736 Hours Saved with Alteryx

57	2022	Microsoft	Announcing automated ML capability in Azure Machine Learning
58	2022	Gartner	Definition of Enterprise Resource Planning (ERP) – Gartner Information Technology Glossary
59	2022	TEC Team	ERP Software Facts and Lessons Learned: Expert Advice on Avoiding ERP Failure
60	2022	Dataiku	GE Aviation: From Data Silos to Self-Service
61	2022	Dataiku	Making Enterprise AI an Organizational Asset
62	2022	SAS	Manufacturing smarter, safer vehicles with analytics
63	2022	Cloudera	The Future Is Hybrid Data, Embrace It
64	2022	IBM corporation	IBM Global AI Adoption Index 2022
65	2022	Gartner	The Gartner Top AI Predictions for 2022 and Beyond
66	2022	Amazon	Banking Trends 2022: Transforming Customer Experience

References

1. Statista: Global total corporate artificial intelligence (AI) investment from 2015 to 2021. (2022). https://www.statista.com/statistics/941137/ai-investment-and-funding-worldwide/, last accessed 24 October 2022.
2. PWC: Sizing the prize What's the real value of AI for your business and how can you capitalise? (2017). https://www.pwc.com/gx/en/issues/analytics/assets/pwc-ai-analysis-sizing-the-prize-report.pdf, last accessed 24 October 2022.
3. Janakiram, M.: Gartner's 2020 Magic Quadrant for data science and machine learning platforms has many surprises. Forbes (2020, February 20). https://www.forbes.com/sites/janakirammsv/2020/02/20/gartners-2020-magic-quadrant-for-data-science-and-machine-learning-platforms-has-many-surprises/?sh=6a08bd0b3f55, last accessed 5 September 2021.
4. EY: The growing impact of AI on business. (2018, April 30). https://www.technologyreview.com/2018/04/30/143136/the-growing-impact-of-ai-on-business, last accessed 5 September 2021.
5. Sharma, M.: Navigating the new landscape of AI platforms. Harvard Business Review (2020, March 10). https://hbr.org/2020/03/navigating-the-new-landscape-of-ai-platforms, last accessed 5 September 2021.
6. Accenture: Unleashing exponential evolution - 2019 ERP Trends. Accenture (2019). https://www.accenture.com/_acnmedia/PDF-90/Accenture-Unleashing-Exponential-Evolution-PDF.pdf, last accessed 5 September 2021.

7. Odusote, A., Tiwari, A., Arora, G.: The Internet of Things: Moving from cost savings to revenue generation. (2020). https://www2.deloitte.com/us/en/pages/finance/articles/cfo-insights-internet-of-things-cost-savings-revenue-generation.html, last accessed 5 September 2021.
8. Allied Analytics LLP: Enterprise artificial intelligence market: Global opportunity analysis and industry forecast, 2019-2026. Allied Analytics LLP (2019). https://www.researchandmarkets.com/reports/4989422/enterprise-artificial-intelligence-market-global, last accessed 5 September 2021.
9. Renno, P., Sinha, V.: Will the pandemic accelerate adoption of artificial intelligence? Bain & Company (2020, May 26). https://www.bain.com/insights/will-the-pandemic-accelerate-adoption-of-artificial-intelligence/, last accessed 5 September 2021.
10. Gartner, I.: Drive Strategic Mandates for AI in the Enterprise. (2020). https://www.gartner.com/en/webinars/3988416/drive-strategic-mandates-for-ai-in-the-enterprise, last accessed 25 October 2022.
11. Fountaine, T., McCarthy, B., Saleh, T.: Building the AI-powered organization. Harvard Business Review **July–August**, 62–73 (2019).
12. Ammanath, B., Hupfer, S., Jarvis, D.: Thriving in the era of pervasive AI. Deloitte's State of AI in the Enterprise, 3rd Edition. (2020). https://www2.deloitte.com/content/dam/Deloitte/cn/Documents/about-deloitte/deloitte-cn-dtt-thriving-in-the-era-of-persuasive-ai-en-200819.pdf, last accessed 5 September 2021.
13. Dataiku: Making enterprise AI an organizational asset. (2021). https://www.dataiku.com/stories/enterprise-ai/, last accessed 5 September 2021.
14. Nkhoma, M., Dang, D.: Contributing factors of cloud computing adoption: A technology-organization-environment framework approach. International Journal of Information Systems and Engineering **1**(1), 38–49 (2013).
15. Awa, H.O., Ukoha, O., Igwe, S.R.: Revisiting technology-organization-environment (T-O-E) theory for enriched applicability. The Bottom Line **30**(1), 2–22 (2017). doi: 10.1108/BL-12-2016-0044.
16. McCarthy, J., Minsky, M., Rochester, N., Shannon, C.: A proposal for the dartmouth summer research project on artificial intelligence. (1955, August 31). http://jmc.stanford.edu/articles/dartmouth/dartmouth.pdf, last accessed 5 September 2021.
17. Buchanan, B.G.: A (very) brief history of artificial intelligence. AI Magazine **26**(4), 53 (2005). doi: 10.1609/aimag.v26i4.1848.
18. Ardila, D., Kiraly, A.P., Bharadwaj, S., Choi, B., Reicher, J.J., Peng, L., et al.: End-to-end lung cancer screening with three-dimensional deep learning on low-dose chest computed tomography. Nature Medicine **25**(6), 954–961 (2019). doi: 10.1038/s41591-019-0447-x.
19. Magnin, C.: How AI can unlock a $127B opportunity by reducing food waste. McKinsey Sustainability. McKinsey (2019, March 27). https://www.mckinsey.com/business-functions/sustainability/our-insights/sustainability-blog/how-ai-can-unlock-a-127b-opportunity-by-reducing-food-waste#, last accessed 5 September 2021.
20. Joshi, N.: How AI can transform the transportation industry. Forbes (2019, July 26). https://www.forbes.com/sites/cognitiveworld/2019/07/26/how-ai-can-transform-the-transportation-industry/#205087e74964, last accessed 5 September 2021.
21. Hand, D.: Introduction. In: Hand D, (ed.). Artificial intelligence and psychiatry. p. 1–20. Cambridge University Press, Cambridge (1985).

22. Russell, S., Norvig, P., (eds.): Artificial intelligence: A modern approach. Prentice Hall, Englewood Cliffs (1994).
23. Gartner, I.: Artificial intelligence (AI). (2021). https://www.gartner.com/en/information-technology/glossary/artificial-intelligence, last accessed 5 September 2021.
24. Agrawal, A., Gans, J., Goldfarb, A.: Prediction machines: The simple economics of artificial intelligence. Harvard Business Review Press, Boston, MA, United States (2018).
25. Brady, M., Gerhardt, L.A., Davidson, H.F., (eds.): Robotics and artificial intelligence. NATO ASI Series F: Computer and System Sciences. Springer-Verlag, Berlin (1983).
26. Liu, J., Kong, X., Xia, F., Bai, X., Lei, W., Qing, Q., et al.: Artificial intelligence in the 21st century. IEEE Access **6**, 34403–34421 (2018). doi: 10.1109/ACCESS.2018.2819688.
27. Walch, K.: Rethinking weak vs. strong AI. Forbes (2019, October 04). https://www.forbes.com/sites/cognitiveworld/2019/10/04/rethinking-weak-vs-strong-ai/#60ad4b796da3, last accessed 5 September 2021.
28. Robert Jacobs, F., Weston, F.C.: Enterprise resource planning (ERP)—A brief history. Journal of Operations Management **25**(2), 357–363 (2007). doi: 10.1016/j.jom.2006.11.005.
29. Gartner, I.: Enterprise resource planning (ERP). (2021). https://www.gartner.com/en/information-technology/glossary/enterprise-resource-planning-erp, last accessed 5 September 2021.
30. Umble, E.J., Haft, R.R., Umble, M.M.: Enterprise resource planning: Implementation procedures and critical success factors. European Journal of Operational Research **146**(2), 241–257 (2003). doi: 10.1016/S0377-2217(02)00547-7.
31. Lynne, M., Tanis, C., van Fenema, P.: Enterprise resource planning: Multisite ERP implementations. Communications of the ACM **43**(4), 42–46 (2000). doi: 10.1145/332051.332068.
32. Loizos, C.: ERP: Is it the ultimate software solution. Industry Week **7**(33), 33–48 (1998).
33. Al-Mashari, M., Al-Mudimigh, A., Zairi, M.: Enterprise resource planning: A taxonomy of critical factors. European Journal of Operational Research **146**(2), 352–364 (2003). doi: 10.1016/S0377-2217(02)00554-4.
34. Matolcsy, Z.P., Booth, P., Wieder, B.: Economic benefits of enterprise resource planning systems: Some empirical evidence. Accounting & Finance **45**(3), 439–456 (2005). doi: 10.1111/j.1467-629X.2005.00149.x.
35. Stratman, J.K.: Realizing benefits from enterprise resource planning: Does strategic focus matter? Production and Operations Management **16**(2), 203–216 (2007). doi: 10.1111/j.1937-5956.2007.tb00176.x.
36. Gartner, I.: Gartner Magic Quadrant & critical capabilities. (2021). https://www.gartner.com/en/research/magic-quadrant?utm_expid=.KduDEZhhQCu-BkCJKlBIqg.0&utm_referrer=https%3A%2F%2Fwww.google.com%2F, last accessed 5 September 2021.
37. C3.ai: 10 core principles of enterprise AI. C3.ai (2020). https://c3.ai/wp-content/uploads/2020/12/Principles-of-Enterprise-AI.pdf, last accessed 5 September 2021.
38. Kureishy, A.: Why enterprise AI will be highly differentiating. Teradata (2018, January 24). https://www.teradata.com/Blogs/Why-Enterprise-AI-Will-Be-Highly-Differentiating, last accessed 5 September 2021.
39. Databricks: Unified data analytics platform. (2021). https://databricks.com/product/unified-data-analytics-platform, last accessed 5 September 2021.

40. Bisson, P., Hall, B., McCarthy, B., Rifai, K.: Breaking away: The secrets to scaling analytics. (2018, May 22). https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/breaking-away-the-secrets-to-scaling-analytics#, last accessed 5 September 2021.
41. Hill, S., Evans, P., Don, R., Zaman, N., Congalton, A.: AI transforming the enterprise—Eight key AI adoption trends. (2019). https://advisory.kpmg.us/articles/2019/ai-transforming-enterprise.html, last accessed 5 September 2021.
42. Kar, S., Kar, A.K., Gupta, M.P.: Modeling Drivers and Barriers of Artificial Intelligence Adoption: Insights from a Strategic Management Perspective. Intelligent Systems in Accounting, Finance and Management **28**(4), 217–238 (2021). doi: 10.1002/isaf.1503.
43. Alsheiabni, S., Cheung, Y., Messom, C.: Factors inhibiting the adoption of artificial intelligence at organizational-level: A preliminary investigation. AMCIS 2019 Proceedings **2**, (2019). doi: https://aisel.aisnet.org/amcis2019/adoption_diffusion_IT/adoption_diffusion_IT/2/.
44. Kushwaha, A.K., Kar, A.K.: Micro-foundations of Artificial Intelligence Adoption in Business: Making the Shift. In: Sharma SK, Dwivedi YK, Metri B, Rana NP, (eds.) Re-imagining Diffusion and Adoption of Information Technology and Systems: A Continuing Conversation. p. 249–260. Springer International, Cham, CH (2020).
45. Shinyama, Y.: PDFminer. Python Software Foundation (2019, November 25). https://pypi.org/project/pdfminer/, last accessed 5 September 2021.
46. Manning, C.D., Raghavan, P., Schütze, H.: Introduction to information retrieval. Cambridge University Press, Cambridge (2012).
47. Martin, F., Johnson, M.: More efficient topic modelling through a noun only approach. Proceedings of Australasian Language Technology Association Workshop. p. 111–115. ALTA, Parramatta (2015).
48. Vayansky, I., Kumar, S.A.: A review of topic modeling methods. Information Systems **94**(101582), (2020). doi: 10.1016/j.is.2020.101582.
49. Aggarwal, C.C., Zhai, C.: Mining Text Data. Springer US, Boston, MA (2012).
50. Blei, D.M.: Probabilistic topic models. Communications of the ACM **55**(4), 77–84 (2012). doi: 10.1145/2133806.2133826.
51. Pietsch, A.-S., Lessmann, S.: Topic modeling for analyzing open-ended survey responses. Journal of Business Analytics **1**(2), 93–116 (2018). doi: 10.1080/2573234X.2019.1590131.
52. ten Kleij, F., Musters, P.A.: Text analysis of open-ended survey responses: A complementary method to preference mapping. Food Quality and Preference **14**(1), 43–52 (2003). doi: 10.1016/S0950-3293(02)00011-3.
53. Blei, D.M., Ng, A.Y., Jordan, M.I.: Latent dirichlet allocation. Journal of Machine Learning Research **3**, 993–1022 (2003).
54. Blei, D., Mcauliffe, J.: Supervised Topic Models. Neural Information Processing Systems, (2007).
55. Mimno, D., Wallach, H.M., Talley, E., Leenders, M., McCallum, A.: Optimizing Semantic Coherence in Topic Models. Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing. p. 262–272. Association for Computational Linguistics, Edinburgh, UK (2011).
56. Lau, J.H., Newman, D., Baldwin, T.: Machine Reading Tea Leaves: Automatically Evaluating Topic Coherence and Topic Model Quality. Proceedings of the 14th Conference of the European Chapter of the Association for Computational Linguistics. p. 530–539. Association for Computational Linguistics, Gothenburg, Sweden (2014).

57. Zuo, Y., Zhao, J., Xu, K.: Word Network Topic Model: A Simple but General Solution for Short and Imbalanced Texts. arXiv arXiv:1412.5404v1, (2014, December 17). doi: 10.48550/arXiv.1412.5404.
58. Schwabe, D.: Proceedings of the 22nd International Conference on World Wide Web. Association for Computing Machinery, New York, NY (2013).
59. Cao, J., Xia, T., Li, J., Zhang, Y., Tang, S.: A density-based method for adaptive LDA model selection. Neurocomputing **72**(7-9), 1775–1781 (2009). doi: 10.1016/j.neucom.2008.06.011.
60. Tornatzky, L.G.: Processes of technological innovation. Lexington Books, Lexington, MA (1990).
61. Fleming, O., Fountaine, T., Henke, N., Saleh, T.: Ten red flags signaling your analytics program will fail. (2018, May 14). https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/ten-red-flags-signaling-your-analytics-program-will-fail, last accessed 5 September 2021.
62. Allas, T., Bughin, J., Chui, M., Dahlström, P., Hazan, E., Henke, N., et al.: Artificial intelligence is getting ready for business, but are businesses ready for AI? In: McKinsey & Company, (ed.). Crossing the frontier: How to apply AI for impact. p. 7–22. McKinsey Analytics, (2018). https://www.mckinsey.com/~/media/McKinsey/Business%20Functions/McKinsey%20Analytics/Our%20Insights/Crossing%20the%20frontier%20How%20to%20apply%20AI%20for%20impact/Crossing-the-frontier-collection.ashx, last accessed 25 October 2022.
63. Cloudera: Limitless: The positive power of AI. (2021). https://www.cloudera.com/content/dam/www/marketing/resources/whitepapers/cloudera-global-ai-report.pdf?daqp=true, last accessed 15 July 2022.
64. McKinsey: The state of AI in 2021. (2021). https://www.McKinsey.com/~/media/McKinsey/Business%20Functions/McKinsey%20Analytics/Our%20Insights/Global%20survey%20The%20state%20of%20AI%20in%202021/Global-survey-The-state-of-AI-in-2021.pdf, last accessed
65. Loucks, J., Davenport, T., Schatsky, D.: State of AI in the enterprise. Deloitte (2018). https://www2.deloitte.com/content/dam/Deloitte/de/Documents/technology-media-telecommunications/DELO-6418_State%20of%20AI%202020_KS4.pdf, last accessed 5 September 2021.
66. McKinsey: AI adoption advances, but foundational barriers remain. (2018, November 13). https://www.mckinsey.com/featured-insights/artificial-intelligence/ai-adoption-advances-but-foundational-barriers-remain#, last accessed 5 September 2021.
67. Cam, A., Chui, M., Hall, B.: Global AI Survey: AI proves its worth, but few scale impact. McKinsey (2019, November 22). https://www.mckinsey.com/featured-insights/artificial-intelligence/global-ai-survey-ai-proves-its-worth-but-few-scale-impact#, last accessed 5 September 2021.
68. Lacovou, C.L., Benbasat, I., Dexter, A.S.: Electronic Data Interchange and Small Organizations: Adoption and Impact of Technology. MIS Quarterly 19, 465–485 (1995).
69. Zhu, K., Kraemer, K.L.: Post-Adoption Variations in Usage and Value of E-Business by Organizations: Cross-Country Evidence from the Retail Industry. Information Systems Research, 1661–1684 (2005).
70. Chui, M., Manyika, J., Miremadi, M., Henke, N., Chung, R., Nel, P., et al.: Notes from the AI frontier insights from hundreds of use cases. Discussion paper. McKinsey Global Institute

(2018, April). https://www.mckinsey.com/~/media/mckinsey/featured%20insights/artificial%20intelligence/notes%20from%20the%20ai%20frontier%20applications%20and%20value%20of%20deep%20learning/notes-from-the-ai-frontier-insights-from-hundreds-of-use-cases-discussion-paper, last accessed 5 September 2021.

71. Porter, M.: Strategy and the Internet. Harvard Business Review **79**, 63-78 (2001).

72. Hart, P.J., Saunders, C.S.: Emerging Electronic Partnerships: Antecedents and Dimensions of EDI Use from the Supplier's Perspective. Journal of Management Information Systems **14**(4), 87–111 (1998). doi: 10.1080/07421222.1998.11518187.

73. Ransbotham, S., Khodabandeh, S., Fehling, R., Lafountain, B., Kiron, D.: Winning with AI — Pioneers combine strategy, organizational behavior, and technology. MITSloan (2019, October 15). https://sloanreview.mit.edu/projects/winning-with-ai/, last accessed 5 September 2021.