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The role of artificial intelligence in the procurement process: State of the art and research agenda

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A R T I C L E I N F O

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A B S T R A C T

Artificial intelligence (AI) is widely adopted in many areas, but it is still in its infancy in procurement, despite its potential. To map the state of the art of both research and practice and identify future research directions, this paper presents a mixed methodology exploratory study of the role of AI in the procurement process. The paper combines a systematic literature review, a mapping of the offerings of providers of AI-based procurement platforms and a focus group with procurement managers. Results map the functionalities of AI-based solutions throughout the procurement process, describe benefits and challenges to their adoption and identify future research directions.

1. Introduction

Increasingly, procurement plays a central role in firm strategy, as companies today spend more than half of their revenues buying goods and services from suppliers (van Weele and van Raaij, 2014; Bienhaus and Haddud, 2018). In this way, procurement has a direct impact on firm profitability. However, procurement not only aims to rationalize spending but also actively contributes to the value generated by the firm in running the business (Schütz et al., 2020). Procurement can lead to quality improvements in finished goods and reduce time to market, building relationships that drive innovation (Luzzini et al., 2015) and sustainability along the supply chain (Giunipero et al., 2012; Marshall et al., 2015). In these ways, procurement contributes to a firm's competitive advantage. Therefore, using all the tools available for procurement provides companies with a strategic benefit (Handfield et al., 2019). Since procurement departments are strongly analytical in nature, receiving and producing large amounts of data, the adoption of artificial intelligence (AI) could be the driving force for further improving the procurement process in various ways (Handfield et al., 2019). Indeed, the promises of AI applied to procurement are remarkable and growing, as new applications, smart platforms and pilot projects are continuously presented to digitize procurement departments.

Scholars and practitioners increasingly recognize the competitive advantage stemming from AI in business processes (Loureiro et al., 2021; Gartner, 2021). The current era generates more data than can be managed, and the potential of available data, still partially untapped, opens up great opportunities thanks to previously unobtainable information from which new business intelligence can be extracted. The applications and benefits of AI are often explored within marketing and sales (e.g. Linoff and Berry, 2011; Tirunillai and Tellis, 2014) or risk management (e.g. Wu et al., 2017; Azan Basallo et al., 2018; Baryannis et al., 2019a,b). Although some authors have discussed its relevance for procurement (Moretto et al., 2017; Handfield et al., 2019; Zair et al., 2019), the academic literature on this topic is still far from blooming.

Artificial intelligence is a branch of computer science that studies the development of hardware and software systems capable of replicating human behaviour, as AI pursues a defined objective in making decisions usually entrusted to human beings (Guo and Wong, 2013). As a result, AI includes a set of technologies that support, inform and augment human decisions based on experience and acquired knowledge, to solve practical problems (Min, 2010; Mugurusi and Oluka, 2021). Due to the profound dynamism of AI technologies, they can be considered general-purpose technologies (Crafts, 2021), i.e. generic technologies, which are recognizable and whose potential grows as the applications and the related infrastructures, systems and skills increase (Åström et al., 2022). In these terms, AI is extremely adaptable since its expertise in a field arises within and is largely based on the context of the application.

When applied to real business problems, the main attributes of AI are automation and smartness, increasing human efficiency and effectiveness, respectively (Boute and Van Mieghem 2021). These attributes strongly apply to the field of procurement, as the actions and decisions

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of humans encompass the procurement process in several instances. Equipping the procurement process with AI-based solutions means replacing the procurement managers in tedious and operational tasks and increasing the power of their decisions. To mention a few applications from the industry, the AI-based negotiation coach described by Schnellbächer et al. (2018) can support the buyer in the preparation of conventional face-to-face negotiations and provide valuable insights for should-cost models used for auctions. AI-powered chatbots can make database querying much more efficient: through natural language processing technology, the buyer can have an assistant making intelligent suggestions about what actions to take in specific situations (Jaggaer, 2019). Nevertheless, evidence suggests that the digital maturity of firms is at an early stage (Wang et al., 2016) and that the potential of AI is untapped in many procurement activities. With that in mind, this research aims to investigate the role of AI in the procurement process, to understand which AI-based functionalities are currently used to assist procurement managers, and to identify the benefits and challenges from a managerial point of view. These research objectives can be formulated in the following research questions.

RQ1. *What AI-based functionalities are applied to the phases of the procurement process?*

RQ2a. *What are the benefits of adopting AI in the procurement process?*

RQ2b. *What are the challenges of adopting AI in the procurement process?*

Building on the results of the research by Moretto et al. (2017), the procurement process described by Spina (2008) is the reference framework, structuring the whole process around three main phases, namely strategic purchasing, sourcing and supply (see Fig. 1), each of which is further divided into activities. This model was chosen because of the granularity of the activities described in the procurement process, which is well suited to a study including the collection of empirical data. Indeed, the procurement activities are described through a practice-oriented perspective. In addition, Spina's procurement process groups the activities into strategic, tactical and operational dimensions, which is useful when synthesizing findings and future research directions.

Addressing the above RQs and given their exploratory nature, this research employs a qualitative multi-step approach, starting with a systematic review of academic literature, followed by an analysis of AI-based procurement platforms and a focus group with procurement managers. The literature review systematizes the current state of scientific knowledge in the field of interest, informing the results from the empirical part of the study.

The screening of procurement platforms investigates the solutions supporting the procurement process. The focus group with procurement managers highlights the user perspective. Combining the two, we show the two sides of the empirical setting of interest.

The ultimate contribution of this paper is therefore to capture the current role of AI in the procurement process and to chart the future trajectories of attention for research and practice in terms of supported functionalities, benefits, and challenges.

The paper is structured as follows. Section two provides the background of the study, and the second section describes the overall research approach. The fourth section provides a detailed explanation of the methodology and describes the findings gathered from the systematic literature review. Section five describes the methodology and the results of the mapping of procurement platforms; the sixth section deals with the focus group, in terms of methodology and outcome. Section seven brings together the findings of the multiple stages of research and charts the trajectories for future investigations. Section eight draws the conclusions.

2. Background

2.1. Artificial intelligence

Artificial intelligence is a multidisciplinary subject that has fascinated researchers in many fields, such as computer science, psychology, neuroscience, mathematics and management. With the rapid development of technology, the definition of AI has had a turbulent evolution and is still far from reaching a consensus. Researchers in computer science are more focused on creating intelligent systems and programs capable of replicating human behaviour; researchers in engineering place greater emphasis on the use of AI as a problem-solving tool (Guo and Wong, 2013). Combining the two perspectives, AI can be considered a branch of computer science that studies the development of hardware and software systems with capabilities typical of humans; it is able to independently pursue a defined objective in making decisions usually entrusted to human beings. In his definition, Min emphasizes more precisely the cognitive aspect of AI and the support provided in solving practical problems: "Artificial Intelligence is referred to as the use of computers for reasoning, recognizing patterns, learning or understanding certain behaviours from experience, acquiring and retaining

Table 1
Definitions of AI applications.

AI application	Definition
Natural language processing (NLP)	"Natural Language Processing is a theoretically motivated range of computational techniques for analyzing and representing naturally occurring texts at one or more levels of linguistic analysis for the purpose of achieving human-like language processing for a range of tasks or applications" (Liddy, E.D. 2001)
Chatbot	"A chatbot system is a software program that interacts with users using natural language" (Shawar et al., 2007, p. 29)
Recommendation system (or recommender system)	"Recommender systems can be defined as programs which attempt to recommend the most suitable items (products or services) to particular users (individuals or businesses) by predicting a user's interest in an item based on related information about the items, the users and the interactions between items and users" (Lu et al., 2015, p. 12)
Robotic process automation (RPA)	Robotic process automation (RPA) is defined as "a preconfigured software instance that uses business rules and predefined activity choreography to complete the autonomous execution of a combination of processes, activities, transactions, and tasks in one or more unrelated software systems to deliver a result or service with human exception management" (IEEE Corporate Advisory Group 2017)

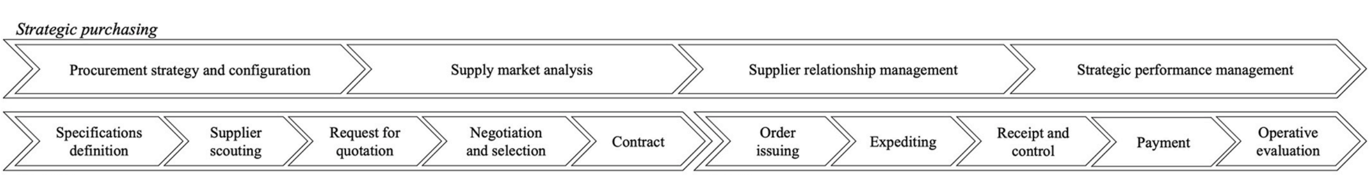

Fig. 1. The procurement process (adapted from Spina, 2008).

knowledge, and developing various forms of inference to solve problems in decision-making situations where optimal or exact solutions are either too expensive or difficult to produce" (Min, 2010, pp. 13–14).

In general, AI aims to imitate intelligent human behaviour: this is a significant challenge, since a computer must be programmed to be able to do many things before being called intelligent (Kok et al., 2009). Trying to narrow down the definition of AI, it has been characterized by the ability to think like humans, act like humans, think rationally and act rationally (Russel and Norvig, 1995). Disregarding the discussion of AI techniques, which is too technical for the aim of this paper, the practical AI applications used in solving common business problems are most interesting. Among these applications, natural language processing, chatbots, recommendation systems and robotic process automation are very relevant for the topic of investigation (see Table 1).

2.2. Digital tools supporting the procurement process

The adoption of digital technologies in procurement has been identified as an engine for transforming the way upstream processes in the supply chain are managed, driving key stakeholders in procurement and supply chain management to develop new technological solutions (Lorentz et al., 2020). As claimed by Bag et al. (2020), the procurement digitalization triggered by new technologies requires the development of new frameworks to rebuild a range of processes within a firm. Eventually, successful implementation will bring the company to new procurement value propositions (Hallikas et al., 2021). However, digital procurement is not limited to the use of new or enhanced technology systems. While digital procurement relates to supporting manual work, smart systems represent one step further, automatically and independently executing certain procurement tasks without any necessary human interference (Glas et al., 2016).

Throughout the years, many steps in the procurement process have been subjected to the influence of digital technologies, streamlining the flow of activities such as the introduction of electronic data interchange (EDI) systems, the extensive use of enterprise resource planning (ERP) for suppliers and purchase order management and the electronic invoice (Kosmol et al., 2019). Today, the amount of data collected is exponentially increasing (Wang et al., 2016), both upstream and downstream. For this reason, advanced analytics should be implemented as the driving force of the procurement evolution, supporting strategic activities. Visibility of spending data and activities is the core of the strategic role of procurement (Barrad et al., 2020), and the impact of analytics and AI in these activities is staggering (Bienhaus and Haddud, 2018; Barrad et al., 2020). Notwithstanding the great power of such technological tools, a study performed by McKinsey Global Institute (2017) observed that most of the ongoing or emerging projects are fostered by AI tool providers; even large firms that are approaching these innovations claim to be in the early development stage. Consequently, actual results are challenging to assess (Lorentz et al., 2020), and the literature lacks examples of successful implementation in the procurement field and quantitative results. In addition, few contributions in the academic literature take a process perspective. Chehbi-Gamoura et al. (2020) developed a literature review regarding big data analytics in supply chain management based on the supply chain operations reference (SCOR) model, thus considering procurement a small instance of a broader process. Moretto et al. (2017) considered the procurement process, focusing on strategic and tactical activities, but missed the operational portion of the process, which is more impacted by AI-enabled automation. Despite these contributions, most of the existing research considers portions of the entire process (e.g. Chowdhary et al., 2011; Baryannis et al., 2019a,b; Zair et al., 2019). In addition, the current literature lacks a solid theoretical framework at the intersection of procurement and AI. To date, only the seminar paper by Waller and Fawcett (2013) has proposed research directions informed by grand theories, crafting potential research questions on the transformation of supply chain management through analytics and recommending the theories to address future research. Therefore, there is a need to systematize the knowledge accumulated to date about AI in the procurement process.

3. Research approach

Our research questions lay the foundation for an exploratory investigation of the phenomenon that targets the basic constructs not yet structured by previous research. The approach in this study reflects the breadth of the research questions by combining multiple methodologies. The authors embrace a multi-step approach, first performing a systematic review of previous literature, then relying on two different sources of information: a mapping of AI-based platforms supporting the procurement process and a focus group with procurement managers.

The triangulation of the results gathered from these methodologies helps address the research questions by combining different

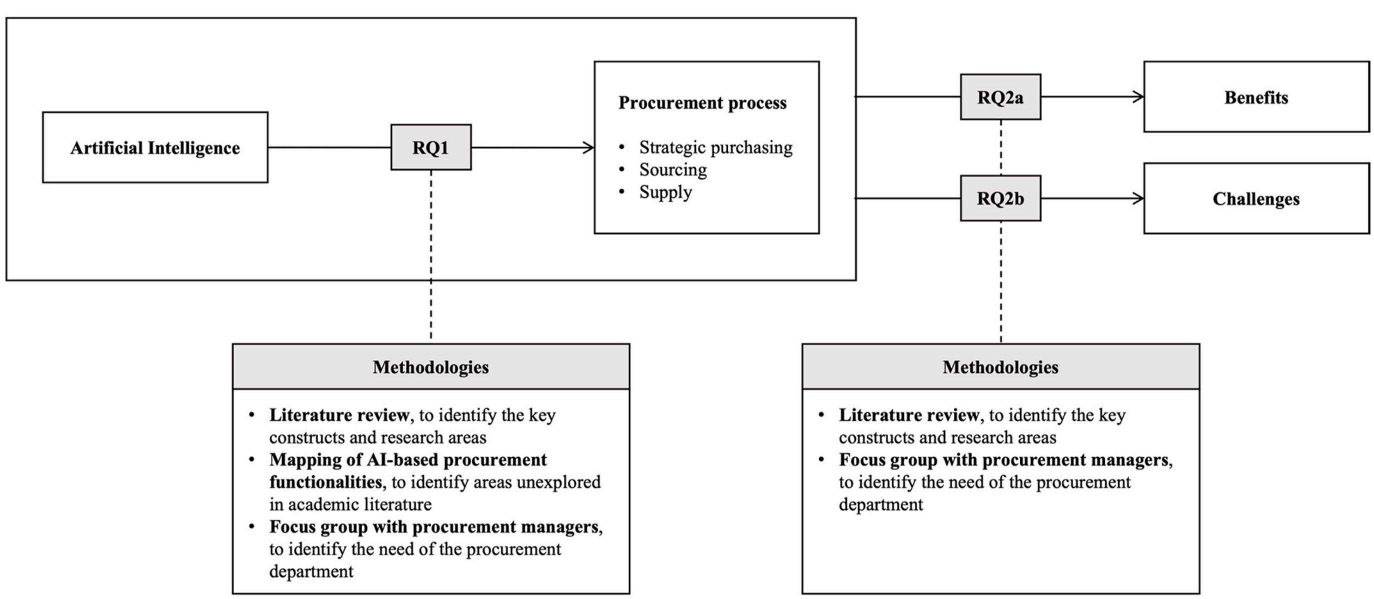

Fig. 2. The research framework.

perspectives. In this way, the study is relevant for the advancement of both research and practice. The major finding from the systematic literature review is the identification of the basic constructs for studying the phenomenon, grouped as functionalities, benefits and challenges. The procurement platforms mapping investigates the match between the available AI-based solutions and the focus of academia in previous research. The focus group sheds light on the firms' perspective when adopting AI in the procurement process. The research questions and adopted methodologies are represented in the research framework in Fig. 2.

The research is designed to reflect the works by Moretto et al. (2017) and Handfield et al. (2019), which are considered seminal papers. They are part of the scoping study (see Section 4.1) and take the whole procurement process as a unit of analysis.

The architecture of the research framework can be recognized in the work of Moretto et al. (2017), who investigated the relationship between the adoption of big data and the procurement process, described in terms of the sequence of strategic purchasing, sourcing and supply. Leveraging a multiple case study and a focus group, Moretto et al. (2017) focused on procurement activities through a qualitative point of view, similar to our investigation of the benefits and challenges of AI in the procurement process. In terms of both structure and combined methodologies, the current study is in line with Handfield et al. (2019), who combined a procurement platform review, a small survey among procurement executives and qualitative interviews with technology experts to study procurement analytics.

4. Systematic literature review

The first part of the research consists of the literature review. The structured literature review studied previous research, combining the systematic technique and snowball sampling for the search phase and using descriptive analysis for the review phase (Hart, 1998; Tranfield et al., 2003). Starting the research with snowball sampling in the scoping study increased prior knowledge about the discipline under investigation in terms of terminology, scope and referenced journals. The scoping study sets the stage for the definition of the query and the systematic search conducted downstream (see Annex A). Narrative and descriptive techniques were used for the literature analysis to focus on the research areas to be addressed in the following stages of the study, as advised by Tranfield et al. (2003). The whole process is described in Fig. 3.

4.1. Planning the review

The scoping study pertains to the initial literature review and aims to study the relevant papers and understand the debate in which the research is positioned. It also includes a brief theoretical, practical and methodological overview, in line with the suggestions from Tranfield et al. (2003). The main output of the scoping study was the definition of the review protocol. The review protocol comprises the search strategy and the criteria for the inclusion and exclusion of sources in the review (Davies and Crombie, 1998). The search strategy consisted of structuring a query to run the systematic search on Scopus by identifying relevant keywords from the preliminary exploration of the literature. Specifically, the review aims to study the intersection between procurement and AI technology, an area where the research is still immature. Due to the novelty of the topic under scrutiny and the vague definition of AI, in the first search, we decided to broaden the scope of the technology and include the wider family of big data analytics (BDA), which encompasses AI. Indeed, even though some papers use the term "analytics" more frequently than "AI" in their titles and keywords, their content is extremely valuable in studying the role of AI in the procurement process (e.g. Brintrup et al., 2020; Dubey et al., 2018).

This approach served two main purposes. First, the authors were able to contextualize their work, even if papers were later discarded from the review. Second, it avoided missing relevant papers that were not tagged with the specific keywords "AI". This second point was the main motivation behind the authors' choice.

The keywords (["big data" OR "artificial intelligence" OR "analytics"] AND ["procurement" OR "purchas*" OR "sourc*" OR "supply" OR "supplier"]) were searched in the title, abstract and author keywords of articles and reviews written in English and published in December 2020 or earlier. The most significant restrictions set by the authors concerned the type of journals. This choice was necessary due to the considerable spread of the keywords "big data" and "artificial intelligence" in academic publications. Indeed, the reference journals were carefully selected among the most important sources in the domain of procurement. The literature reviews by Spina et al. (2013) and Wynstra et al. (2019) and the article by Zheng et al. (2007) were crucial, as they list the most relevant journals in procurement and supply management. More precisely, three groups of journals were selected.

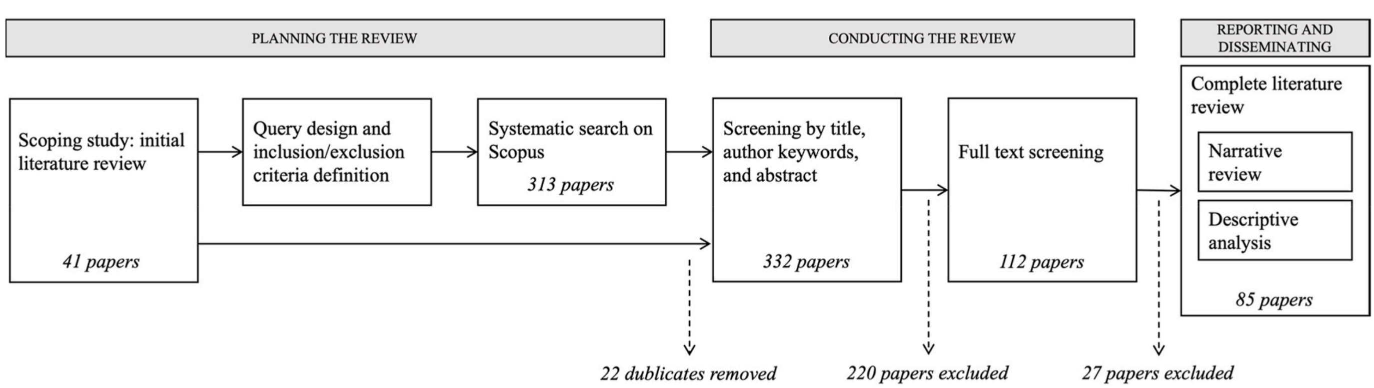

Fig. 3. The literature review process (adapted from Tranfield et al., 2003).

Table 2
Journals included in the Scopus query.

Included journals	Referenced literature review
IEEE Transactions on Engineering Management	Wynstra et al. (2019)
Industrial Management and Data Systems	Zheng et al. (2007)
Industrial Marketing Management	Spina et al. (2013); Wynstra et al. (2019)
International Journal of Production Research	Spina et al. (2013)
International Journal of Operations and Production Management	Zheng et al. (2007); Spina et al. (2013); Wynstra et al. (2019)
International Journal of Physical Distribution and Logistics Management	Zheng et al. (2007)
International Journal of Production Economics	Spina et al. (2013); Wynstra et al. (2019)
Journal of Business Logistics	*none – added by the authors*
Journal of Cleaner Production	*none – added by the authors*
Journal of Marketing Research	Spina et al. (2013)
Journal of Operations Management	Zheng et al. (2007); Spina et al. (2013); Wynstra et al. (2019)
Journal Of Purchasing and Supply Management	Zheng et al. (2007); Spina et al. (2013); Wynstra et al. (2019)
Journal Of Supply Chain Management	Zheng et al. (2007); Spina et al. (2013); Wynstra et al. (2019)
Production and Operations Management	Wynstra et al. (2019)
Production Planning and Control	Spina et al. (2013)
Supply Chain Management: An International Journal	Spina et al. (2013)

- Journals labelled "PSM-related journals" and "Marketing and Operations Management journals" by Spina et al. (2013), neglecting those in the "General Management and Economics journals" category
- Journals in the categories "Operations Management" and "Purchasing and Supply Management" from Wynstra et al. (2019), discarding those grouped under "Marketing" and "Strategy & Organization"
- Journals defined as "Academic Journal Publications" by Zheng et al. (2007), leaving out the two journals related to Public Procurement (i.e. *International Journal of Public Sector Management* and *Journal of Public Procurement*) as they are out of our research scope.

The authors merged these three lists, then broadened them with a few missing journals still relevant to the topic (see Table 2). The inclusion of these additional sources resulted from the insights of the initial literature review and discussion with senior colleagues.

In the review protocol, inclusion and exclusion criteria were defined as well (see Annex B). The criteria were applied to the papers resulting from the systematic search conducted in Scopus, analyzed by title, abstract and author keywords to evaluate whether they should be included in the analysis.

4.2. Conducting the review

The review protocol produced in the previous stage reduced bias in the research, in line with the foundations of the systematic literature review. The output of the search was the complete list of all papers included in the analysis. Since the application of inclusion and exclusion criteria is often difficult and influenced by the personal judgement of the researchers, the review process was conducted by all authors to mitigate bias and resolve any disagreements. The selection of papers to be included in the review comprised several stages. The query, designed through the scoping study, was conducted on Scopus, and the resulting papers were analyzed by title, abstract and author keywords. Then, for all papers deemed relevant based on the abstract, the authors evaluated the full text to determine whether the paper should be included in the database of the whole research. To perform this screening in a systematic way, an Excel database was shared among the authors to track the number of papers included and excluded in each stage of the review. The steps in this process are described in Fig. 3. To be rigorous in the analysis of these sources, all the information in the analyzed papers was reported in the database. The form contained the main bibliographical information of the papers (authors, title, year, source title and author keywords) and some specific fields to support the authors' review (phase and sub-phase of the procurement process, benefits, challenges and additional notes). More than a tool to track the review stage, the database was a valuable support to the authors for the research synthesis, helping them gather and systematize the insights from previous publications.

4.3. Article classification by functionality in the procurement process

One of the main outputs of the systematic literature review was the detailed mapping of papers throughout the procurement process. More precisely, a paper was associated to a phase and a sub-phase of the procurement process if it described a functionality of AI related to that phase. Therefore, a single paper can be associated to more than one phase of the procurement process if it describes different impacts of AI. This matching was only possible for 45 of the 85 papers in the research database. Eighty functionalities described in the papers covered the process in a non-homogeneous pattern (see Fig. 4), 47 of which described functionalities related to strategic purchasing, 32 related to sourcing and only one related to supply. In Fig. 4, encircled numbers are scaled to size of the node.

By examining the distribution of academic papers throughout the procurement process, hotspots in academic interest can be identified in precise portions of the process. Some papers focused on category management, spend analysis, and spend classification, which are considered strategic elements for the proper management of suppliers' relationships. To mention one of these contributions, Abdollahnejadbarough et al. (2020) addressed AI techniques such as text mining and natural language processing to assess suppliers' performances, with the final aim of suppliers' rationalization. Other papers addressed strategic supplier performance analysis through AI, especially focusing on supply risk management. Among them, Baryannis et al. (2019a,b) introduced a supply chain risk prediction framework based on AI techniques in a case study, exploring the trade-off between prediction performance and interpretability. Partly related to supply risk management, the concept of procurement sustainability is also gaining momentum. Gholizadeh et al. (2020) developed a multi-objective model for optimal sustainable procurement and transportation decisions related to cost rationalization, transportation efficiency and information sharing.

Other papers focused on supplier selection solutions, especially for those already in the supply base, using multi-criteria optimization techniques to select the best supplier. Within this research stream, Scott et al. (2015) proposed a method to integrate multiple criteria decision-making techniques and multiple stakeholder requirements in a common optimization algorithm to select appropriate suppliers and allocate orders optimally among them. Upstream of the supplier selection, the literature also mentions negotiation. However, this application is not fully developed yet, often being described generically among many other functionalities potentially enhanced by AI (Liu et al., 2011; Moretto et al., 2017; Wang et al., 2016). In this stream of literature, Zair et al. (2019) described the smart configuration of an agent-based system for supplier selection, where the supplier is selected by the dyad composed of the buyer firm and its customer, so that the supplier is chosen considering the buyer's requirements and the needs of the customer.

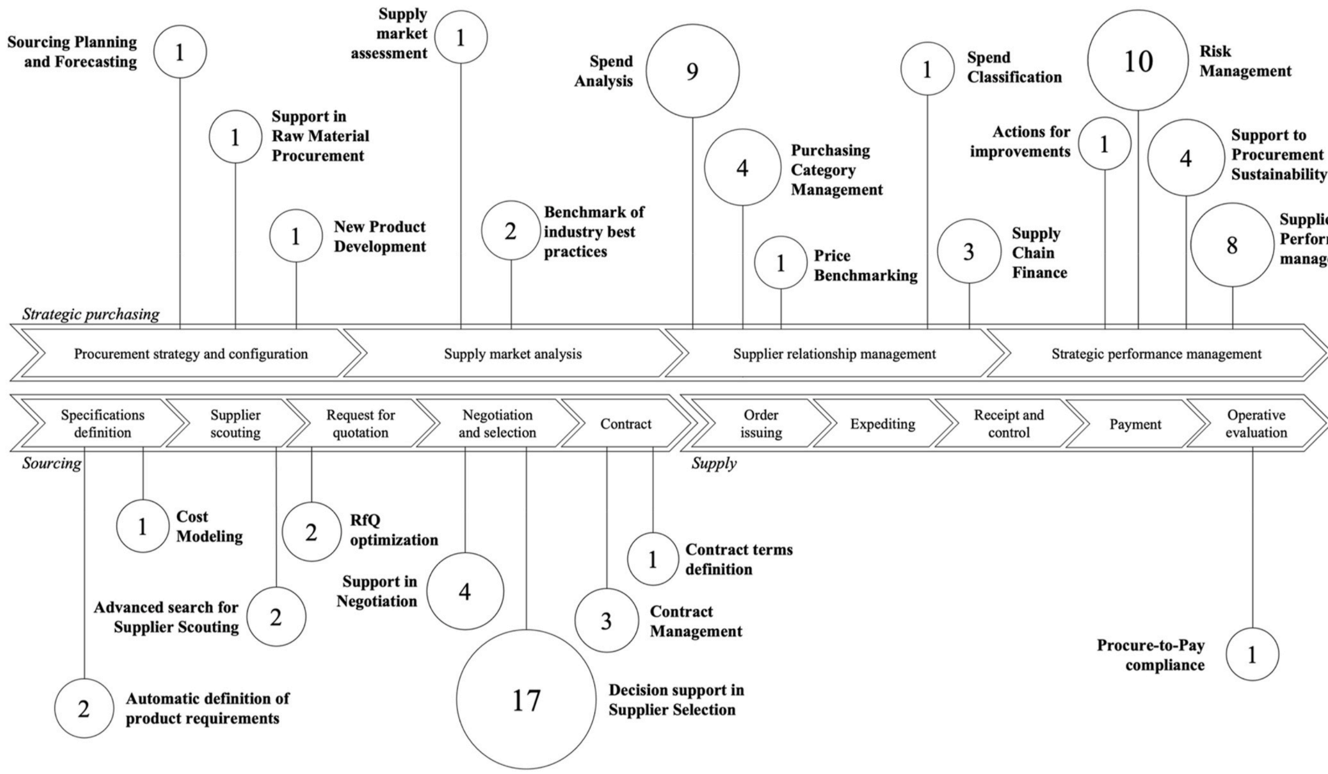

Fig. 4. The functionalities described in the papers.

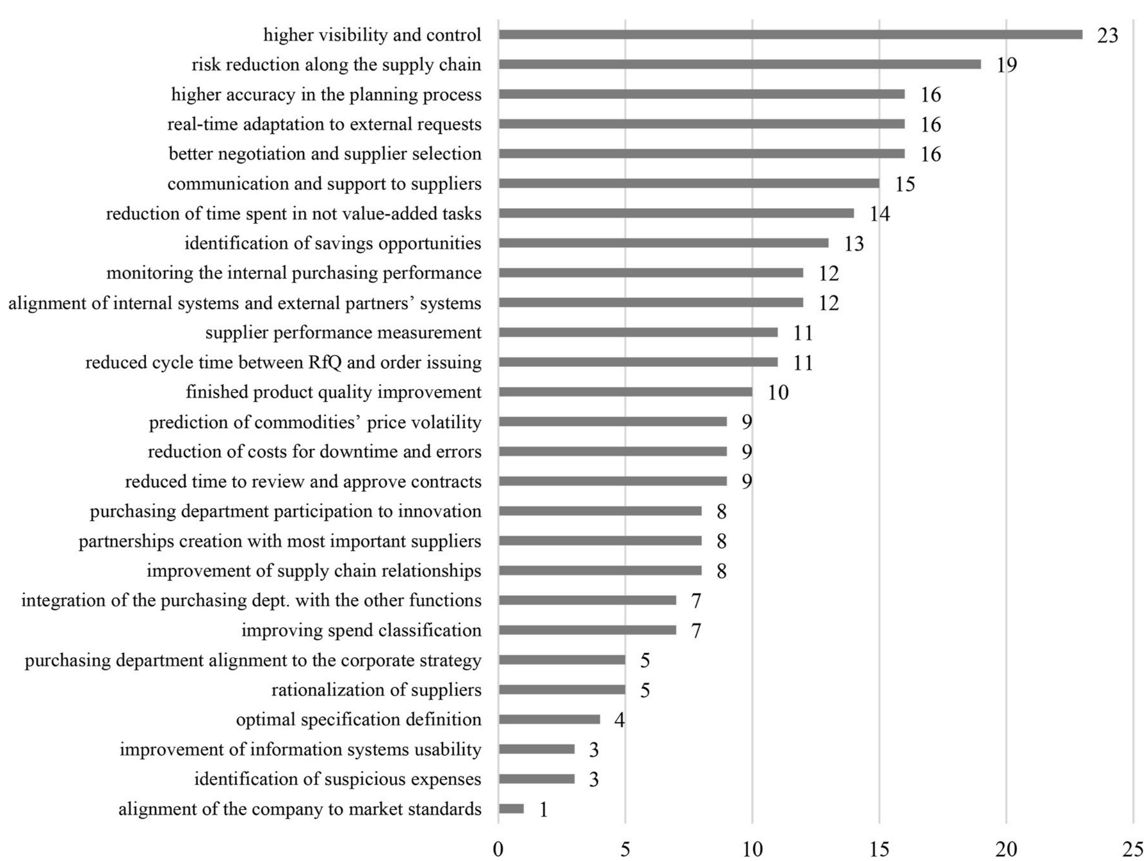

Fig. 5. Benefits described in the papers.

4.4. Article classification by benefits

Looking at the benefits stemming from the adoption of AI throughout the procurement process, 27 different benefits were identified in the literature (Fig. 5). These benefits were mentioned 274 times in total and appeared in 58 out of 85 papers in the research database, meaning that papers were often associated to more than one potential benefit of adopting AI in the procurement process. The detailed match between the papers and the benefits is reported in the online Supplementary data.

The most cited benefits are the increased visibility and control over processes inside and outside the procurement perimeter, as well as the procurement risk mitigation enabled by the predictive power of AI.

Brintrup et al. (2020) analyzed a huge amount of data through advanced analytical techniques, which they trace back to the domain of AI, to predict possible discontinuity events along the supply chain. This kind of application certainly brings considerable benefit to supply risk management and the visibility into supply relationships. Many of the data analyzed by Brintrup et al. pertain to first-tier suppliers, so automatic AI-enabled analysis is crucial to increase visibility and control over certain events in the buyer-supplier relationship.

Kamble and Gunasekaran (2020) underscored the importance of assessing the benefits of a BDA system in terms of decision support for planning and sourcing. The availability and reliability of these systems in planning are a big advantage in many supply chain decisions and in procurement as well.

Although many benefits are envisaged for AI in procurement, these benefits have yet to be systematized. To this end, Moretto et al. (2017) classified benefits in terms of internal or external performance (related to the supplier side). However, a clear understanding of the benefits of AI in procurement processes is still missing and will be difficult to achieve considering the low level of application in the empirical realm and the lack of measurements of impacts (Wang et al., 2016; Lorentz et al., 2020).

4.5. Article classification by challenges

The literature review identified challenges to the adoption of AI in the procurement process. There were 17 different challenges described in 36 papers, with a total occurrence of 99, as many challenges were described by more than one paper. The most common challenge is the availability and systematization of data, which was cited in 23 papers. The poor presence of adequate analytical skills and the lack of a clear understanding of the actual potential of the technology are relevant hurdles as well. A comprehensive description is given in Fig. 6, while the detailed match between the reviewed papers and the identified challenges is reported in the online Supplementary data.

Regarding the lack of data availability and systematization of data, Hazen et al. (2014) deepened the understanding of data quality in supply chain management. According to Schoenherr and Speier-Pero (2015), one of the major barriers is the inability to grasp insights coming from available data. Kache and Seuring (2017) described data availability from a different angle, looking at the issue of cyber security at the company and supply chain level. A major issue addressed in the literature is the lack of appropriate competences in procurement departments.

According to Handfield et al. (2019), the lack of internal skills in procurement departments turns out to be a barrier, as the power of the technology alone is not enough for successful adoption of advanced procurement platforms: data management, cultural change and skills development are fundamental. Based on the results of a survey of procurement professionals, Bienhaus and Haddud (2018) claimed that buyer firms must assess the internal competences before implementing a digital transformation strategy in procurement departments. Some also talk about macrostructural issues related to the CEO's endorsement and prioritization (Bienhaus and Haddud, 2018) or investment cost and budget (Handfield et al., 2019). However, a clear focus on the barriers and, most importantly, possible solutions for these problems is still missing.

5. Mapping of AI-based procurement functionalities offered by IT providers and startups

5.1. Conducting the mapping of AI-based procurement functionalities

The second part of the study increases the reliability of the research, as the triangulation of different sources of information increases the

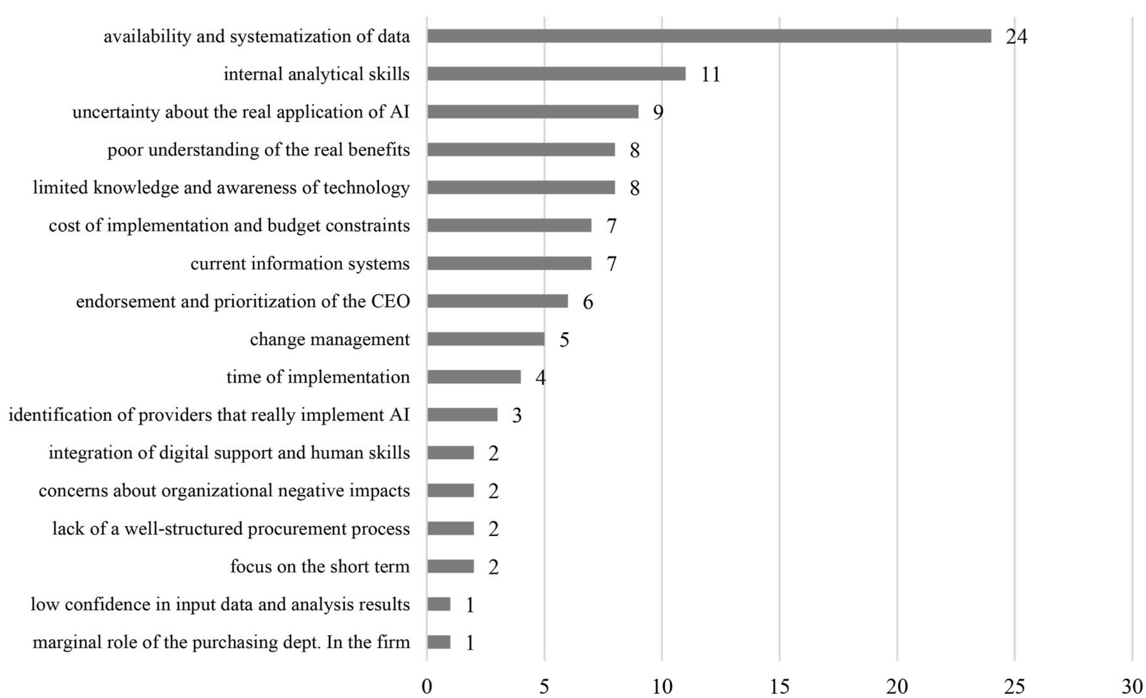

Fig. 6. Challenges described in the papers.

reliability of the study (Flick, 2018a). However, to actively contribute to the overall value of the study, the mapping of the AI-based procurement functionalities must meet the validity requirements. Consistent with Lincoln et al. (2011), the validity of the findings is ensured by providing new insights into innovative solutions and increasing awareness to guide practitioners' actions.

This part of the research takes the solution provider perspective, performing the collection and analysis of data from secondary sources through the mapping of digital procurement functionalities based on AI. More precisely, the screening of procurement platforms refers to the search for players that develop digital solutions for procurement management and offer them to the buyer firms requiring the service. This screening was conducted on the web, using both Google and specialized websites (e.g. Gartner), adopting the same keywords as in the literature search. The search was also repeated on Crunchbase, a worldwide database of information about firms and startups. Two types of players were included in the analysis.

- Established providers in the field of digital procurement offering AI-based solutions. We identified 11 providers supporting innovative technologies (artificial intelligence, big data analytics, etc.) in their solutions.
- Startups offering procurement solutions based on AI. We found 22 startups offering digital procurement functionalities exploiting AI technologies.

After compiling the list of providers and startups, the authors conducted the mapping of functionalities by studying the commercial offers proposed on their websites. Every useful piece of information retrieved on the website was carefully analyzed, including every section or tab of the website, as well as every additional uploaded document such as providers' case studies. When available, a platform demo was also run by one of the authors. All the extracted information was catalogued. This process primarily focused on functionalities offered through the implementation of AI in the procurement process: every functionality was analyzed in detail and categorized according to the phase and sub-phase of the procurement process. The main output of this analysis was the mapping of the AI-based solutions offered by established providers and startups (Fig. 7).

5.2. Mapping of AI-based functionalities throughout the procurement process

Procurement platforms included in the mapping consist of 11 consolidated providers and 22 startups (the complete list is provided in Annex D). The authors classified each of these players according to their offered functionalities, i.e. according to the AI-based functionalities explicitly mentioned on their websites. AI-based functionalities currently offered on the market of digital procurement platforms were thus mapped throughout the procurement process. Procurement platforms often provide several integrated functionalities, so each platform may be associated to different phases of the procurement process. As depicted in Fig. 7, 112 functionalities, grouped into 26 solutions, were recorded in the database and mapped (encircled numbers are scaled to size of the node).

The mapping of AI-based solutions enables an overview of how well currently available functionalities cover the procurement process. Among these functionalities, most of the solutions (54%) support the strategic purchasing phase, where the most strategic activities are carried out. Meanwhile, 31% of the solutions support the activities in the sourcing phase, which are more tactical. Only 4% of current solutions address the more operational activities of the supply phase. In addition, the mapping recognized two solutions developed to support the procurement process. They are *digital assistant* and *automation of non-value-added activities*, counting for 11% of the total.

Among the most common solutions are spend analysis and purchasing category management through category tree design. The websites analyzed describe functionalities such as customized analysis and insights based on AI, cleaning and consolidation of spending data and identification of spending optimization opportunities. For instance, *Suplari* applies AI and machine learning to clean and consolidate spending data, primarily from ERP and supplier accounting systems, as

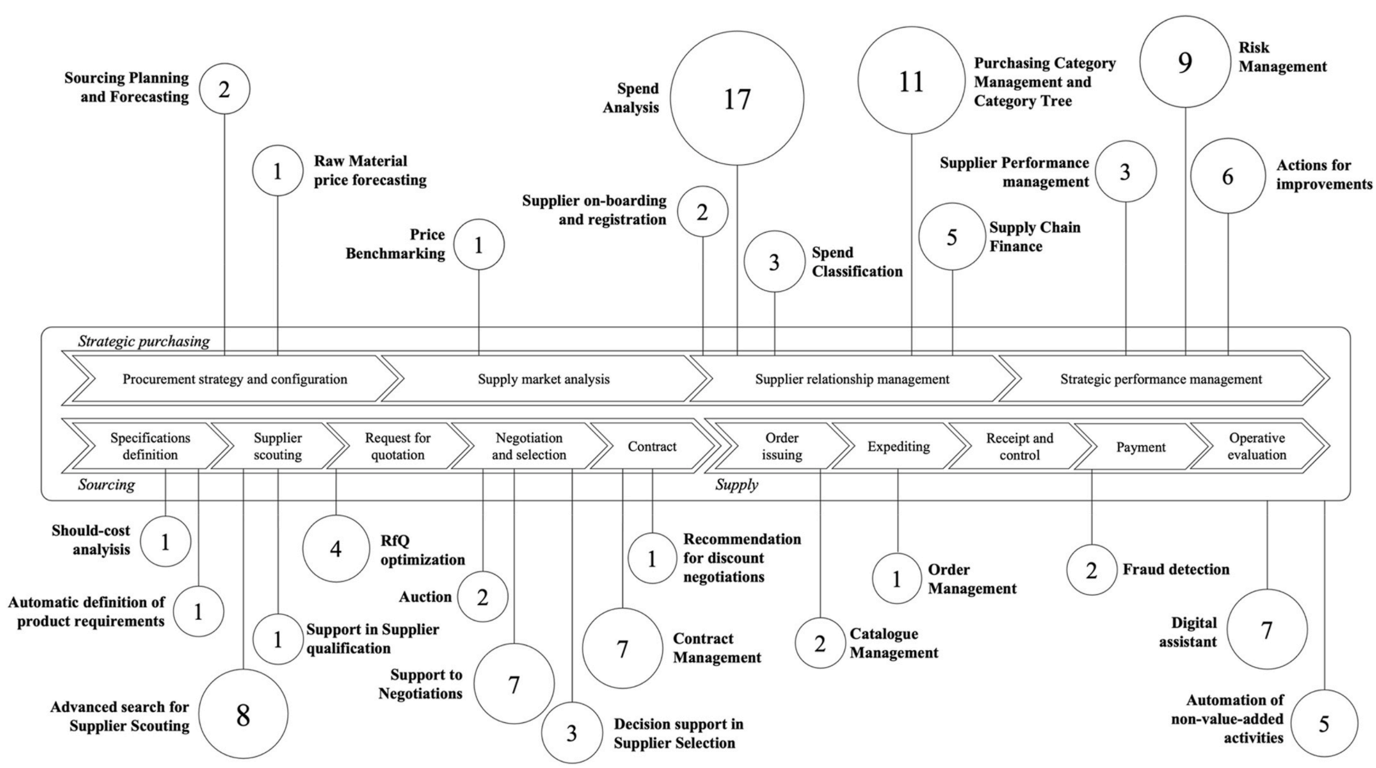

Fig. 7. Mapping of AI-based functionalities offered by IT providers and startups.

well as contracts, travel expenses and purchasing cards repositories. Then, algorithms are run between data sources to spot optimization opportunities. In one of the other cases investigated, *Simfoni*'s platform produces a map of spending data through an automatic classification engine. This solution provides suggestions to improve classification quality and coverage, the ability to slice and dice data using open search and built-in optimization tools to identify opportunities to reduce costs.

Risk management solutions are also relatively common strategic activities addressed by providers in the mapping. For instance, *Coupa* helps companies monitor each supplier through community insights and information from credit ratings, news sentiment and supplier intelligence to proactively identify risks and avoid business disruptions. Similarly, *Jaggaer* provides real-time information about the likelihood of supplier delays in delivery, enabling managers to mitigate risks of disruption to production flows and reduce related costs. The algorithm predicts whether an order will be delivered on time.

There is a growing interest in supply chain finance solutions, with five startups currently offering AI-supported functionalities in this area. One of them, *Gardenia Technologies*, leverages ad hoc algorithms to facilitate short-term financing in the supply chain, systematically reduce risk, identify inefficiencies and propose actions to optimize working capital.

Supplier scouting is also relevant, where AI functionalities connect the buyer with the best suppliers in an efficient way. In *GEP*'s platform, as the AI learns procurement models and behaviours, the buyer firm relates to the best suppliers in a fast and efficient way, saving time in the selection of suppliers, negotiation and evaluation. The *Scoutbee* platform is a search engine for supplier identification and onboarding that finds and evaluates global suppliers of direct or indirect materials. The company claims the process is easy, secure and 75% faster than traditional tools, allowing the digitization of the scout-to-source process. *Scoutbee* allows firms to define requirements rapidly and create a wide network of potential suppliers to get a broad view of the market, thus helping to detect the best suppliers.

In the sourcing phase, negotiation is also well represented. For instance, *Icertis* provides firms with AI-powered suggestions and insights to optimize contract negotiation. It supports the buyer in consistently negotiating the best terms, thus reducing the time otherwise spent manually creating and reviewing long contracts, ensuring compliance for third-party contracts and accelerating the negotiation process.

An important result concerns the operational instances of the procurement process, i.e. the supply stage: only three solutions were identified. However, cross-process solutions, *digital assistant* and *automation of non-value-added activities*, are recognized in many IT providers and startups and are always described as the main agents of operational activities. Among the specific operational activities in supply, more commonly addressed solutions are catalogue management, order management and fraud detection. Among these solutions, *Zycus* provides a complete life-cycle catalogue management functionality with control to ensure the validity of content across different geographical areas and business units. The software uses the *Zycus* AI platform to classify all items into catalogues, enabling automated classification. As far as fraud detection is concerned, a functionality offered within *Coupa* packages uses AI and machine learning techniques to automatically identify errors and fraud to manage fraud risk efficiently and effectively.

6. Focus group with procurement managers

6.1. Conducting the focus group

The third part of the research adopts the buyer firm's perspective, studying the primary data collected through a focus group with procurement managers. The focus group is considered an appropriate methodology to analyze nascent fields and facilitate brainstorming, creating a collaborative discussion among informed stakeholders (Barbour, 2018; Krueger and Casey, 2015). Thirteen respondents were involved from heterogeneous industries with high-level managerial roles in procurement departments (the complete list is provided in Annex C). In line with Morgan David and Hoffman (2018), the number of participants is considered appropriate to ensure fruitful interactions, and the principle of heterogeneous sampling was intentionally chosen. Indeed, heterogeneity generates differing viewpoints appropriately. In our study, heterogeneity is granted by the industry diversity of the participants. However, a certain degree of homogeneity is guaranteed to maintain productive conversations and avoid undue conflict. Homogeneity is driven by two criteria: participants were part of multinational companies in which procurement plays a strategic role, and at the time of the study, they were involved in important projects related to innovating and digitizing the procurement function. This information was retrieved from companies' websites in the institutional communications section and, when possible, through informal conversations between the authors and the target companies. Moreover, respondents were selected based on a convenient sample: they were managers who were known by the authors and who had demonstrated interest in and knowledge about the topic of the paper over the years.

The focus group aimed to augment knowledge about real implementations of AI in the procurement process through the experience of actual users, thereby complementing the insights from the procurement solutions mapping. Indeed, the contribution of procurement managers shed light on AI's potential in supporting procurement department activities, namely the benefits (actual or expected) and the main challenges experienced in real-world business.

The introductory part of the focus group was intended to explain the objectives of the focus group, the session methodology and the general point of view of the study. AI technology and its application solutions were introduced to share the main notions and terminology among all participants to avoid biased results in data collection. For the same reason, AI technology was introduced without any reference to the procurement process to eliminate bias from the participants' responses. In moderating the discussion, the *inverted funnel approach* was pursued (Morgan David and Hoffman, 2018): the questions began with narrower topics and then broadened to a more open-ended discussion. This approach was helpful in our research setting (i.e. the role of AI in the procurement process), as the topic was novel and the participants themselves may not have had an immediately available set of thoughts about it (Morgan David and Hoffman, 2018).

After the introduction, the focus group activities directly involved the experts through individual questionnaires and collective discussions, following the methodology adopted by Moretto et al. (2017). The individual questionnaire had the purpose of triggering the discussion: the questionnaire was quickly completed by participants, and the aggregated results were used to initiate a free and open discussion moderated by the researchers. The focus group lasted approximately two hours and was divided into three sections: *functionalities*, *benefits* and *challenges*. In each round, respondents were asked to individually complete a questionnaire on the specific topic, evaluating a list of propositions from 1 to 5 according to their degree of agreement (where 1: "strongly disagree"; 2: "disagree"; 3: "neutral"; 4: "agree"; 5: "strongly agree"). The authors developed the questionnaires based on the knowledge gathered in the literature review and augmented by the findings from the procurement solutions mapping to align academic notions with industry advancements. Results were collected through an electronic form, and the average of the answers was shown to the participants through a histogram. This was a good catalyst in every round to trigger a lively discussion of the topics. The sequence of individual questionnaires and collective discussion was repeated in the three rounds, dealing respectively with functionalities, benefits and challenges, according to the process in Fig. 8.

The discussion in the focus group was recorded and transcribed at the end of the interaction.

The contributions were first analyzed according to *summary-based reporting* (Morgan and Hoffman, 2018) to determine which topics were

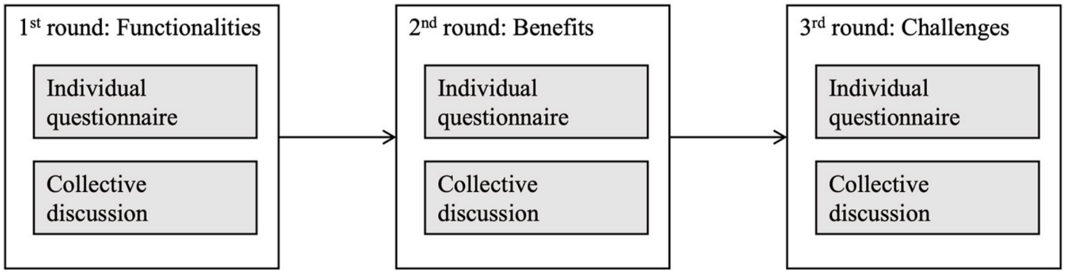

Fig. 8. The focus group process.

most important to the participants through a descriptive account of the primary subjects of the focus group. A simple standard for judging importance is whether a topic arose frequently, as well as the extent to which it engaged the participants when it did arise. Apart from the frequency, we also evaluated the level of significance the procurement managers attached to the topic. This requires a degree of judgement by the authors, but the results of the analyses were then shared with the participants to ensure that their ideas were recorded and perceived properly.

6.2. Procurement managers' opinions about AI-based functionalities in the procurement process

Among the managers involved in the focus group, there was a consensus that AI can impact procurement. According to them, the most beneficial functionalities affect the procurement process crosswise, i.e. the functionalities related to *data consolidation and cleaning* and *automation of non-value-added activities*. According to Manager 2, "*Advanced tools are mostly used to* support *major, strategic decisions. Obviously, they also bring benefits in terms of efficiency in the operating activities, but the real contribution comes for the analysis and the strategic activities of procurement*". However, many of the participants agreed with Manager 11: "*The first approach is to simplify and reduce the workload, which is about automating processes. Firms that have already achieved these goals turn then to more strategic activities in adopting AI*".

Looking at the activities in the strategic purchasing phase, the focus group participants recognized the impact of AI on supply risk management. Indeed, in round two, they described the mitigation of supply risk as one of the main benefits of AI. Manager 9, from the automotive industry, stated, "*The first effort in deploying AI is supply chain mapping. Our supply chain has high depth and complexity, and tracing the relationships from the origin of the material to our contract with the supplier is very hard. This is one of the main issues in the crisis we are going through: supply chain visibility and supply risk management are key, also for the post-pandemic recovery*". Then, diverting the discussion about supply risk management to the narrower topics of working capital financing, some insights arose about the adoption of AI in supporting supply chain finance initiatives: "*When we talk about supply chain finance solutions, it might be helpful for the buyer firm to have support in categorizing the suppliers to engage and selecting the best solutions to support them*" (Manager 8).

Spend analysis and categorization, together with the identification of actions for improvement, were also relevant in the experience of the managers in the focus group: "*We are experimenting with a dynamic categorization solution based on content from open sources or closed sources that are on documents, brochures, descriptions, references, news. This information can give a categorization that changes over time thanks to the natural language processing technology. Non-relevant categories are not classified, but in the future, the procurement department could need to use that category and the related supplier for other works or developments. A lot of interesting vendors are hidden in cluttered databases, so classification is one application where we see value and applicability of this technology*" (Manager 5).

Focusing on the sourcing stage in the procurement process, supplier scouting was perceived as an impacted stage in the procurement process, as explained by Manager 8: "*We are trying to implement an intelligence platform for scouting suppliers that, based on a series of parameters provided by the buyer, make some analyses on external data and information taken from Google and generated very interesting results on potential suppliers available in the market. These solutions would be useful*".

Contributions from the focus group confirm the relevance of AI application in the operative activities carried out in the supply stage as well. In particular, the discussion addressed the issue of fraud detection. As stated by the manager of a fast-moving consumer goods company (Manager 13): "*A promising area of application is fraud detection, with algorithms to check if a buyer is doing something wrong. We are a multinational company, with many offices across Europe, hundreds of people buying something every day. Having alerts to monitor internal fraud would be very valuable because we currently go by trial and error to look for fraud, which unfortunately exists*".

6.3. Procurement managers' opinions about the benefits of AI in the procurement process

Regarding the benefits of AI in the procurement process, the most discussed benefit was *reduction of time spent in non-value-added tasks*. This benefit found consensus among all participants, consistent with the functionalities described above. According to the managers in the focus group, another key gain from adopting AI in the procurement process lies in *risk reduction along the supply chain*. The improvements made possible by *identification of suspicious expenses* and *identification of saving opportunities* were considered highly relevant as well.

Some managers also agreed on the benefit of AI in better adapting the procurement department to external situations and requests: AI comes to support the buyer when timely decisions are required to deal with unforeseen contingencies, such as the pandemic emergency. In many cases, the advantage of AI is real-time scenario analysis, creating predictive and synthetic reports to increase the awareness of decisions, even if they must be made fast. Manager 11 stated, "*The benefit I see in AI is the adaptation to external situations. Especially in the last few months, I have had to make decisions very quickly: a few months ago, we were asked to understand what the impact of a likely shutdown in China might be. So, a tool that could make a data synthesis would certainly have helped me save the hours we spent to build Excel files*".

Apart from the main benefits specifically perceived by managers, important insights were raised in the discussion. According to Manager 1, "*The real benefits of AI in procurement are not clearly communicable, because there are not solutions established through successful cases in companies. Understanding the real benefits of AI-based procurement solutions is critical because investments in the procurement function are not as frequent as in other departments*". In other words, the benefits from AI are not perceived by the procurement managers and are not communicated within the company. This perception is missing because of the low knowledge about the technicalities of AI-based solutions and how they support firms' specific activities in the procurement process.

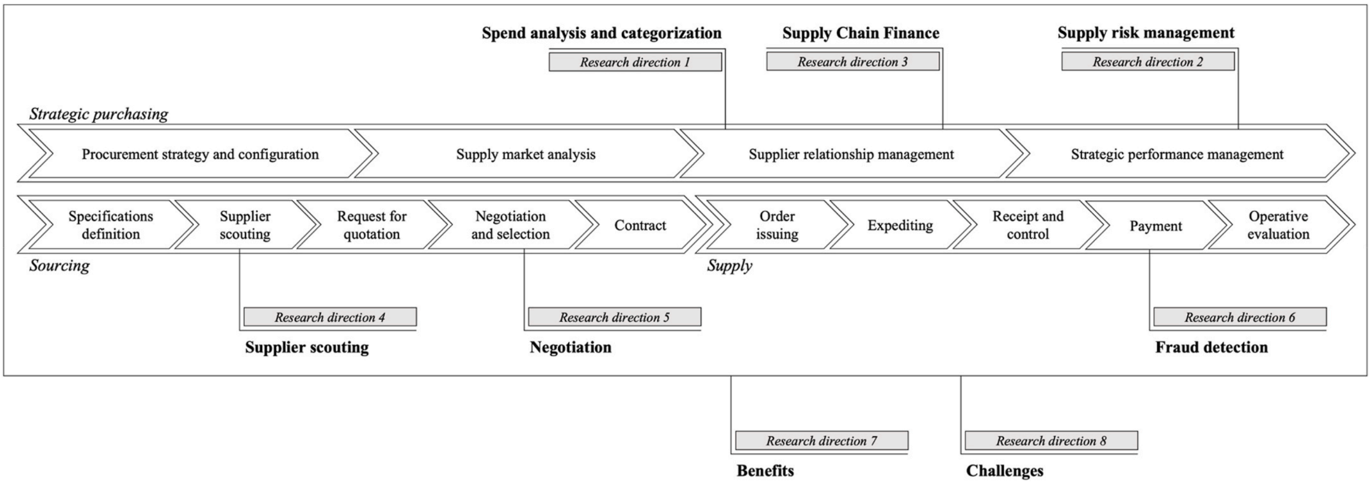

Fig. 9. Proposed research framework.

6.4. Procurement managers' opinions about the challenges of AI in the procurement process

Finally, the managers discussed the reasons preventing the proper implementation of AI in the procurement process. The most recurrent challenges were *focus on the short term, limited knowledge and awareness of technology* and *cost of implementation and budget constraints*.

Looking at the challenges stemming from the proper adoption of AI in the procurement process, managers provided interesting opinions. According to Manager 2, "*A significant problem is the general maturity of the procurement function in the face of innovative solutions: often the procurement department equips itself with new systems or innovative solutions but continues to use the previous solutions, either for convenience or because people do not understand the value of the new solution. In this way, different systems and disorganized databases overlap, preventing the achievement of expected benefits and indeed worsening the situation*".

Moreover, the hurdle related to skills and culture still harms the procurement department. According to a manager from the engineering industry, "*The culture of procurement people is often rooted in practices, procedures, traditions and soft knowledge that are not easily transferable to an algorithm in order to augment the technology contribution to the human activities*" (Manager 11).

The managers also recognized other challenges outside the procurement department: "*The barrier is often external to the procurement department and comes from the company. Investments are generally directed to other business functions, more closely linked to sales, so there is not the sensitivity to the impact of these projects in procurement*" (Manager 12). Moreover, from the perspective of Manager 5, "*AI solutions applied to procurement are not plug-and-play; they must be somehow developed based on the industrial context and the company. Now, they are very costly in terms of implementation time and customization of the solution based on the needs of each procurement department*".

This situation exacerbates one of the perennial procurement challenges: the perception of its impact. In some organizations, the role of procurement is still perceived as operative, merely tied to savings. This prevents investments in procurement departments, including technology updates, since they are not considered strategic and profitable.

7. Discussion and future research directions

Aiming to probe a new and continuously evolving research field, this paper combined different methodologies to triangulate information from multiple sources. The systematic literature review laid the foundation of the study and defined the main research areas. The mapping of procurement solutions offered by IT providers and startups collected insights from the industry. Finally, the focus group contributions from the managers shed light on the direct user experience in terms of future perspectives and needs. By combining the collected contributions into a complete result, the authors could identify the areas uncovered by academic research and practitioner knowledge and the topics already investigated but still in need of further research. The answer to the research questions is illustrated in this section and synthesized in Fig. 9, representing the proposed research directions and their relationships with the overarching research framework.

7.1. The role of AI in the procurement process: functionalities

The first research question (RQ1) is approached through a process perspective, considering the role of AI in the activities of the procurement process and the functionalities enabled.

The first phase of the procurement process is strategic purchasing, in which the main strategic decisions and actions are taken, laying the foundations for the next stages. According to the present research, strategic purchasing is the most interesting portion of the process for academics and practitioners when it comes to the implementation of AI (Moretto et al., 2017).

Among the strategic activities, spend classification is defined as the design of the category tree and the spend analysis. The key activity in spend classification is spend analysis, which is run according to the category tree of the buyer firm (Monczka et al., 2016).

Chowdhary et al. (2011) developed a new analytical solution enabling scenario analyses for those spending categories resulting as non-compliant, besides other analyses on orders and invoices. Zou et al. (2020) described advancements pertaining to product categorization based on AI. The system described by Zou et al. (2020) retrieves information about the product by processing pictures and defining a category tree based on clustering algorithms that identify similarities between commodities. However, in academic literature, there is a lack of practical examples or case studies that operationalize data collection and identify the analytical capabilities invoked by AI in spend analysis and categorization.

Among the solutions offered by IT providers and startups, spend analysis is the most common, recurring in several functionalities. Consolidation and automatic cleaning of spend data (*Lexi Solutions*), analytics for normalizing and tagging suppliers (*Suplari*), examination of purchasing patterns with different suppliers and recommendation of actions for improvement (*GEP*) are just a few examples.

In the focus group, Manager 5 described a trial of a dynamic purchasing category classification solution based on structured and unstructured data analyzed by means of *natural language processing* algorithms. However, according to Managers 1 and 12 in the focus group, AI-based data analysis solutions for spend classification are still inefficient, mainly due to the complexity of this activity and the underlying information requirements. The different classifications used by the procurement functions confirm this issue: CPV,[1] UNSPSC[2] and eCl@ss[3] often overlap in the same buyer firm. On top of that, other proprietary classifications of the IT providers exacerbate the issue, making it impossible to harmonize the data, design and maintain the category tree and run a proper spend analysis. Managers are looking for practical support from AI in the category tree design and the spend analysis, still feeling the lack of a solution to deal with the significant information requirements underlying spend classification.

Thus, AI is an enabler for the capabilities required to cope with the information processing needs in spend classification. In line with this objective, the *information processing theory* (Galbraith, 1974) is suggested as a theoretical lens when studying the support of AI in spend classification, addressing the information processing needs of the purchasing department when dealing with the category tree and the spend analysis, and the information processing capabilities enabled by AI to fit these requirements.

The information processing theory is the favoured lens to study the change in the organization triggered by a technological innovation (Galbraith, 1974). Therefore, analyzing the role of information and the contribution of AI through the constructs of information processing needs and capabilities provides a solid architecture to frame the support of AI in spend classification. In addition, this theory is part of relevant studies about the buyer-supplier relationship (Bensaou and Venkatraman, 1995), so it is well fitted with constructs valid in the context of purchasing. Thus, to summarize the finding about the role of AI in spend classification:

Research direction 1: Future research should study the support given by AI to spend analysis and categorization (i.e. spend classification), addressing the specific AI techniques and their role in reducing the mismatch of information processing needs and capabilities in spend classification.

Supply risk management was the functionality most described in the reviewed papers (Baryannis et al., 2019a,b; Singh and Singh, 2019; Ivanov and Dolgui, 2021; Chu et al., 2020). Among these papers, Ivanov and Dolgui (2021) described a data-driven approach to spot the interrelations of risk data and model disruptive events. Baryannis et al. (2019a,b) introduced an AI-based framework for supply chain risk prediction, testing its reliability and interpretability in a case study.

Increasingly, supply risk management relies on AI. According to Ding et al. (2019), this is happening especially in businesses characterized by global supply chains which span multiple countries. Indeed, when dealing with highly integrated markets, even minor disruptions in a supply chain may severely affect entire supply chain performances, as integrated markets react to disruptions and negative shocks faster and with enhanced volatility.

Enhancing risk management through AI is even more relevant in the wake of recent events (e.g. COVID-19, global chip shortage, raw material scarcity, war in Ukraine). In this complex downturn, risk management is a priority for the purchasing department. In the experience of Manager 9, AI is leveraged in mapping the suppliers coping with the depth and complexity of a global supply chain. Supply chain visibility and supply risk management are key for all the procurement managers in the focus group, even if some of them struggle to find an optimal solution for their business and industry needs, with supply risk management being rooted in the specificities of the buyer firm (Manager 2).

The needs of the buyer firms in managing supply risk are reflected in the solutions offered by providers and startups included in the solutions mapping. Many IT players are increasing their offering of tools and solutions to assess and mitigate the risk coming from supply chain disruptive events. In the most successful cases, these solutions are customized, being industry-specific and built upon integration with many information providers (as in the solution by *Jaggaer*).

Although AI-based risk management solutions are gaining ground, a complete understanding of the issue in the industry is still lacking. Procurement managers in the focus group state they cannot find an IT solution that fully meets their risk management requirements. On the other hand, IT providers and startups cannot leverage enough case studies and implementation stories to improve their solutions. For this reason, scientific research should support the formalization of key constructs to explain the phenomenon, which has many unexplored and ever-changing facets. Indeed, supply risk management moves in an evolutionary pattern in response to or in anticipation of disruptive phenomena, and its dynamism must necessarily be considered. For this reason, the *dynamic capabilities theory* (Teece et al., 1997) is an appropriate theoretical lens to study AI support in supply risk management.

In our research domain, dynamic capabilities are intended as the buyer firm's ability to integrate, build, and reconfigure internal and external resources to address and rapidly shape the changes in the supply chain and the risky events plaguing the business continuity (Teece et al., 1997). This theoretical lens is suggested, as it is in line with the dynamism required by risk management and the evolution of the AI technology. Indeed, the theory fits well with the two facets of the phenomenon under scrutiny (i.e. AI supporting supply risk management). In the work of Gani et al. (2022), collaboration capability is recognized as a *sensing* dimension to recognize the mutual benefit of collaboration between the actors involved. Supply chain alignment is a *seizing* dimension where supply chain actors share their action and commitment by balancing risk. Lastly, supply chain risk management is the actual *reconfiguring* dimension. Alternatively, Chirumalla (2021) uses the same theory to define a framework for building digitally enabled process innovation using dynamic capabilities, following an approach well tied with the adoption of AI in supply risk management.

The above results lead to the following future research direction:

Research direction 2: Future research should further study supply risk management and the role of AI, investigating the type of data and AI techniques supporting the ability to dynamically reconfigure the resources of the buyer firm in dealing with supply risk management.

The research findings highlight the topics of risk management and strategic supplier relationships, especially when dealing with supply chain finance. Recently, this topic has also been presented as a possible way to deal with the crisis triggered by the COVID-19 pandemic (Moretto and Caniato, 2021), and the research describing the support of analytics and AI in supply chain finance is gaining momentum. Badakhshan et al. (2020) studied how to reduce the cash flow bullwhip effect, i.e. the inefficiency in the distribution of cash along the supply chain, through a simulation-based optimization approach that integrates genetic algorithms and system dynamics simulation. The most widespread adoption of AI in the SCF domain is related to the credit risk assessment process (Khashman 2011; Zhu et al. 2016, 2017, 2019). To forecast credit risk, AI-based solutions do not need to assume *a priori* data distributions and may achieve acceptable forecasting accuracy, even when the dataset is small (Khashman, 2011; Zhu et al., 2019; Chen

[1] Common procurement vocabulary (CPV) is "a single classification system for public procurement aimed at standardizing the references used by contracting authorities and entities to describe procurement contracts" (European Commission, https://ec.europa.eu/growth/single-market/public-procurement/digital/common-vocabulary_en).

[2] "The United Nations Standard Products and Services Code® (UNSPSC®), managed by GS1 US™ for the UN Development Programme (UNDP), is an open, global, multi-sector standard for efficient, accurate classification of products and services" (UNSPC, https://www.unspsc.org/).

[3] eCl@ss. is "the only worldwide ISO/IEC-compliant data standard for goods and services. eCl@ss contains tens of thousands of product classes and unique properties" (eCl@ss, https://www.eclass.eu/en/index.html).

et al., 2022). Mentioning recent research, Song et al. (2021) conceive AI techniques as a support for financial service providers in assessing the supply chain credit of small and medium enterprises and defining the most appropriate SCF solutions. Other applications of AI have been poorly discussed in the SCF-related literature so far, leaving a considerable gap in the scientific and practitioners' knowledge.

The managers involved in the focus group consider the support offered by AI to supply chain finance to be substantial. The buyer firms require AI support for categorizing suppliers based on their creditworthiness and operational performance and a recommendation of the best solutions to support them (Manager 8). Manager 11 emphasized the advantages of AI in supporting the paperwork related to supplier evaluation and onboarding on the SCF solution platform, as these activities are repetitive and easily automated, making the SCF solution easier for the buyer and more attractive for small suppliers.

This growing interest is also confirmed on the solution providers' side, as five startups included in the mapping currently offer supply chain finance solutions with the support of AI. Among them, there is a growing interest in supply chain finance solutions, with five startups currently offering AI-supported functionalities in this area. The startup called *Gardenia Technologies* manages the approval for short-term financing in the supply chain thanks to ad hoc algorithms, reducing risk and inefficiencies. *Finturi* leverages data from several sources, such as the Chamber of Commerce or accounting systems, to assess with certainty whether the invoice financing to suppliers is secure for the buyer firm.

In this direction, future research should focus on decision-making gates in the SCF adoption process to understand the contribution of AI. This is crucial since the novelty component in this phenomenon is twofold: the adoption of SCF solutions is often a new choice for companies, and so is the adoption of AI. Therefore, the theoretical model suggested is the *innovation process* developed by Rogers (2003) to understand how companies introduce the innovation brought by SCF solutions and how AI can boost the potential of SCF.

This theory has already proven its validity in the SCF domain in the past. Moving from the innovation process framework proposed by Rogers (2003), Wuttke et al. (2013) first attempted to shed light on the steps of the SCF innovation process, which was intended as the sequence of several decision-making steps leading to the adoption of an SCF programme. Our suggestion is to take a further leap in research, studying the role of AI in the SCF innovation process, possibly through the innovation adoption framework by Rogers (2003).

The above reasonings point out the following future research direction:

Research direction 3: Future research should explore how AI supports supply chain finance, analyzing the support of AI in the stages of the innovation process initiated by the adoption of a supply chain finance solution and investigating the benefits and challenges for all actors involved.

According to our research, there are also significant benefits from AI in the sourcing stage. Looking at the mapping of papers related to sourcing activities, supplier selection is the most recurring functionality (Pitchipoo et al., 2013; Kannan, 2018; Allaoui et al., 2019; Brintrup et al., 2020). These papers involve a context with a lower degree of complexity, as the suppliers are already known to the buyer. Indeed, many applications of AI are described as a support to the selection of the best supplier, often designed as multi-criteria decision models (Ho et al., 2010). Pitchipoo et al. (2013) introduce a hybrid decision-making model to evaluate and select the supplier based on a multi-criteria approach. Scott et al. (2015) propose an integrated method to deal with multi-criteria and multi-stakeholder supplier selection using a combined analytic hierarchy process/quality function deployment. More recently, Lorentz et al. (2020) described supply market intelligence and identification of possible new partners in the external and unknown environment as one of the current developments in procurement analytics with great potential for the future.

However, most of the applications identified in the literature review perform the selection of the best supplier from a list of potential partners already known rather than scouting new suppliers. AI-related research neglects supplier scouting, which is certainly relevant to practice. Indeed, the solutions identified in the mapping of procurement platforms address the increased complexity of supplier scouting, where semantic search and web data crawling are applied in market intelligence to scout for new suppliers and alternative ways to obtain the required resource (for instance, *GEP*, *Scoutbee*, *Tealbook*).

According to the managers in the focus group, AI is a powerful technology for scanning a complex network of players in a structured and thorough way. Manager 8 described a pilot project where internal and external data are integrated with buyer requirements to run an intelligent search for potential suppliers. According to other managers, an AI solution supporting the search for new suppliers would be very useful, but they have faced issues in identifying a platform running the scouting process in a structured manner. In supplier scouting, there is a strong need for information. At the same time, the appropriate capabilities to process information, adjust processes and leverage technology are imperative.

Supplier scouting activities, involving several decision-making variables and stakeholders, generate uncertainty in the buyer firm, leading to information processing needs. Coping with the information processing needs in supplier scouting, the buyer firms can resort to AI-based solutions to achieve a high level of information processing capabilities. This suggests adopting the *information processing theory* to study the support of AI in supplier scouting. Confirming our suggestion of information processing theory as the foundation of the research, many studies in the supply chain domain have been designed based on information processing theory constructs, including: Cegielski et al. (2012) to study cloud computing in supply chains; Busse et al. (2017) for sustainable supply chain management; and Lorentz et al. (2020) for supply market intelligence.

The above findings are encapsulated in the following future research direction:

Research direction 4: Future research should focus on studying the support of AI to supplier scouting activities, investigating the role of AI in achieving the fit between the information processing needs of the supplier scouting activities and the required information processing capabilities.

Negotiation and the possible support gained from digitalization and information availability are highly debated and tackled from different angles by academics and practitioners. However, in the presented literature review, there were few papers related to negotiation (Liu et al., 2011; Moretto et al., 2017; Wang et al., 2016), and none of the papers conducted a thorough analysis of negotiation. Zair et al. (2019) describe an agent-based algorithm in which negotiation and supplier selection are conducted by a purchasing dyad, i.e. the buyer and the buyer's customer.

Although academic interest is still nascent, the negotiation functionalities identified in the solutions mapping are numerous as well as increasingly sophisticated: some of the IT providers claim a futuristic vision in which negotiations between buyers and suppliers will be managed by bots able to interact and maximize their own objective function. From a more functional standpoint, the main support described by IT providers and startups in preparing and leading the negotiation consists of the retrieval of data from internal and external sources, the profiling of suppliers, and real-time recommendations and strategies provided to the human buyer conducting the negotiation (some examples are *Pactum, Levadata, Oracle, Icertis*). However, procurement managers in the focus group are mostly sceptical, believing that the typical skills of the human buyer are strictly related to negotiation and that this knowledge, often tacit and not formalized, cannot be transferred to autonomous agents or systems.

Thus, dedicating a research effort in the study of AI in buyer-supplier negotiation could bring advancements to both scientific knowledge and managerial practice. In this direction, *transaction cost economics* (Coase, 1937; Williamson, 2008) provides a good basis for the research framework. Transaction cost economics is an appropriate lens to explore the benefits of AI in capturing the information needed to prepare for the negotiation and learn more about the supplier (Tate and Ellram, 2022), thus reducing the transaction costs stemming from information asymmetry and uncertainty. Indeed, AI-enabled functionalities, such as semantic information search or web crawling, make the search for supplier information more efficient, lowering the costs of search and information gathering (Heide and Stump, 1995). The increased spectrum of information in the buyer's decisions addresses the issue of bounded rationality, inherent in human nature (Rindfleisch and Heide, 1997). Through the augmented information and recommendations in the decision-making process enabled by AI, the human buyer can more appropriately evaluate possible alternatives and set negotiation strategies more consciously. Afterwards, AI also has a strong impact on bargaining costs (Rindfleisch and Heide, 1997; Tate et al., 2011), i.e. the costs of negotiating, documenting and enforcing agreements, especially when considering the more advanced solutions of automating negotiation activities or even the total autonomy of the negotiating bot.

To summarize, the following research direction can be proposed:

Research direction 5: Future research should investigate the impact of AI in supporting the negotiation with suppliers, in terms of applicability and implementation paradigms, to understand the extent to which AI can reduce the transaction costs related to information gathering and bargaining activities.

In the study conducted by Moretto et al. (2017), the operational supply phase was found to be irrelevant in the adoption of analytics. In contrast, Handfield et al. (2019) were the first to see a possible contribution of analytics in supply, referring to the procure-to-pay (P2P) process. This process has long been supported by other digital tools that are not AI-based. However, according to Handfield et al. (2019), the P2P process can be further improved through captured transactional data, reduced paperwork and improved process efficiency enabled by analytics.

In fact, according to the mapping of procurement platforms, the supply phase (concerning operational activities) is less involved in the adoption of AI. The most frequent features are catalogue management, order management and fraud detection. Among these, the managers in the focus group placed great emphasis on fraud detection, considering this functionality quite urgent and the support of AI very promising. In the experience of Managers 12 and 13, the procurement department is affected to a large extent by internal frauds, i.e. frauds from individual buyers or category managers within the company. This finding is in line with recent practitioner studies: according to PwC's 2022 Global Economic Crime and Fraud Survey, procurement fraud comprises 19% of all frauds.

Especially in multinational companies, where complex procurement processes are carried out by offices in different geographical areas, the problem of fraudulent behaviour exists and can cause significant damage to a firm. To give a few examples, an individual defrauds the buyer firm because he/she has a personal connection to the supplier, is a silent partner of the supplier or receives bribes and kickbacks from the supplier. In this case, the buyer makes personal decisions at odds with the goals of the enterprise. This type of fraud is expressed in specifications tailored to target specific contractors, statements or agreements written in collaboration with a preferred supplier or intentional exclusion of some qualified contractors. Frauds may also originate from outside, i.e. directly from the supplier, such as a mismatch in material and labour costs or the delivery of defective materials or missing volumes.

In this vein, the *agency theory* (Eisenhardt, 1989) can contribute to studying how AI supports procurement fraud detection in two ways. If we consider internal fraud, agency theory could be exploited to understand how AI can support the procurement department (i.e. the principal) in the detection of fraud by the individual buyer (i.e. the agent), applying the theory to a new unit of analysis as suggested by Zsidisin (2022).

The theory names several factors influencing the relationship between the individual buyer and the procurement department. Information systems (Eisenhardt, 1989) play a key role when fraud is detected through AI-based solutions. For instance, appropriate algorithms can identify patterns in behaviour or suspicious communications, highlighting unethical buyer conduct. Similarly, AI-based solutions can be designed to pursue greater programmability (Goodale et al., 2008; Stroh et al., 1996), i.e. an appropriate specification of the buyer's conduct, to follow behaviour-based approaches instead of an outcome-based reward for the buyer (Eisenhardt, 1989), with the intention of eliminating fraudulent actions.

Considering external fraud, the unit of analysis would be the most conventional one: the buyer-supplier dyad (Norrman, 2008; Zsidisin and Ellram, 2003). Information systems are the main factor to describe the support provided by AI in the detection of fraudulent behaviour by the supplier, mainly facilitating the accumulation and processing of information (Eisenhardt, 1989). Web crawling, advanced analysis of supplier information through analytics and natural language processing aim to reduce information asymmetries, mitigate adverse selection (as in the case of mischarging of materials and labour) and moral hazard (as in the case of non-delivery of agreed volumes; Logan, 2000).

The authors thus envision a promising research direction with a strong practical impact:

Research direction 6: Future research should investigate the impact of AI in the detection of procurement fraud, both internal and external, investigating how AI-based information systems can pursue the programmability of human buyer activities (*internal fraud*) and the reduction of information asymmetries with the supplier (*external fraud*).

7.2. The role of AI in the procurement process: benefits

Regarding RQ2 and the benefits stemming from AI, it is difficult to reconcile the results from the focus group with the insights from the literature review. Indeed, several benefits were identified that academics and practitioners judged differently.

In the academic literature, the main benefits are higher visibility and control (e.g. Hazen et al., 2014), the reduction of risk along the supply chain (e.g. Brintrup et al., 2020), the improvement in negotiation and supplier selection (e.g. Zair et al., 2019), higher accuracy in the planning process (e.g. Fawcett and Waller, 2014) and real-time adaptation to external requests (e.g. Kache and Seuring, 2017). These benefits all have an effectiveness-oriented and strongly strategic nature.

The benefits most expected, or wished for, by managers are in line with the most impacted functionalities. Indeed, the most recognized advantage lies in the speed of data preparation and analysis, conducted mainly in the spend analysis phase. The perception of many managers conceives AI as a purely operative support to foster efficiency in analytical and routine activities, leaving control over strategic decisions to the human buyer. For the same reason, procurement managers did not believe that AI brings a consistent benefit in improving relations with strategic suppliers, managed by the direct experience of the buyer.

Thus, a dichotomy exists between the academic literature and the opinions of procurement professionals: the former focuses mainly on strategic and effectiveness-oriented gains while the latter are more concerned with efficiency benefits. Summarizing the main findings, we produced a systematization of the benefits expected from AI, while an empirical understanding of the efficiency and effectiveness gains coming from AI is still required. A structured framework is needed to calculate the benefit of AI-based procurement solutions and examine the potential return on investment (ROI) the buyer firm might achieve by deploying an AI-based platform. In this direction, future studies are invited to leverage the well-established body of knowledge, called *value assessment* (Farbey et al., 1993; Farbey and Finkelstein, 2000). Although there are some studies on the value assessment of e-procurement (e.g. Brun et al., 2004; Ronchi et al., 2010), the research to date has not devoted much attention to the value generated by AI in the procurement process.

At a higher level, the study of the benefits coming from AI in the procurement process could be addressed through the concept of *absorptive capacity*, intended as the "ability to identify, assimilate, and exploit knowledge from the environment" (Cohen and Levinthal, 1989, p. 589). Knowledge and absorptive capacity are at the core of creation and maintenance of competitive advantage (McEvily and Chakravarthy 2002), and this also applies in procurement, considering the capabilities generated or increased by AI.

Adopting this theoretical lens, future studies on the benefits derived from AI in procurement should analyze the absorptive capacity process to investigate how the new learning is acquired, assimilated, transformed and exploited (Arcidiacono et al., 2022). Afterwards, the benefits could be described according to their contribution to competitive advantage (Cohen and Levinthal 1989), innovation (Stock et al., 2001), exploitation/exploration orientation (Lewin and Volberda, 1999) and firm performance, i.e. according to the constructs of absorptive capacity outcomes.

Because of this gap in the academic literature – which, if filled, would be valuable for enterprises – the following research direction can be formulated:

Research direction 7: Future research should focus more on quantifying the benefits of AI in the procurement process to understand how the purchasing department can absorb the capabilities generated or increased by AI, as well as assessing the benefits of AI in the specific activities of the procurement process.

7.3. The role of AI in the procurement process: challenges

From the literature review, the main obstacle to the adoption of AI in procurement is still the availability and quality of the data to be processed (Chehbi-Gamoura et al., 2020; Kache and Seuring, 2017; Hazen et al., 2014). Some other barriers can be grouped under the definition of cultural barriers, as they describe a lack of internal analytical skills and digital maturity (Zhu et al., 2016; Kosmol et al., 2019), uncertainty about the real applications of AI (Bienhaus and Haddud, 2018) and low awareness of the technology (Schoenherr and Speier-Pero, 2015). Although many of the papers about procurement identified these limitations, they described only general conditions that prevent the full exploitation of AI, without entering into the specificities of the procurement process.

The challenges perceived by the managers in the focus group were numerous and significant. Many hurdles are generalized in the firm, while others are specific to the procurement department. According to managers, the main obstacle is internal to the procurement department. This comes from three original causes. First, the procurement department faces significant difficulties in converging towards a standardization of processes and decisions (this is in line with the research by Frank et al., 2019). Second, there is little awareness of the real impact and benefits of AI, as it is hard to understand which functionalities can be attributed to AI. Third, there is a cultural reason: although the procurement department is open to the introduction of new tools to support decisions, the old systems in place are never completely dismantled; instead, they are kept and continue to be used, creating an overlapping of IT systems that generates problems with data consistency and consolidation (in line with what is described in the paper by Kosmol et al., 2019 about procurement digital maturity).

A considerable challenge to overcome lies in the current organizational and technological structure (Xu et al., 2018). In fact, there is a lack of skills, resources and tools to ensure that change happens and is sustained over time. This barrier is further worsened by the fact that the current offerings of AI-based solutions are characterized by a low degree of customization. In this situation, the required commitment of managers and key decision makers is weak, and poor investment prevents the full exploitation of the potential of AI (Frank et al., 2019).

Since AI is a new technological development in the procurement realm, the *technology acceptance model* (Davis, 1989; Davis et al., 1989) could be adopted to frame the dynamics triggered in procurement professionals when faced with the new technology. Indeed, the technology acceptance model is well proven by past research investigating the user acceptance of new information systems (Venkatesh and Davis, 2000).

According to the theory, the intention of the individual buyer to use new AI-based procurement solutions is driven by two beliefs: the perceived usefulness and the perceived ease of use. The technology acceptance model theorizes that the perceived usefulness and perceived ease of use mediate the effect of external variables (e.g. system characteristics, development process, training) on the intention to use (Venkatesh and Davis, 2000).

Thus, the technology acceptance model presents a well-rounded set of constructs to describe the challenges in the implementation of AI in procurement. It addresses the cultural and perceptual barriers related to the human buyer, also related to the digital maturity and training of people, including the more technical characteristics of the solutions and the development process.

Summarizing the key findings, the research direction below is envisioned:

Research direction 8: Further research should investigate the challenges for AI adoption in procurement departments. Skills, competences, culture and maturity must be analyzed to better understand existing implementation challenges and the user acceptance of the technology.

8. Conclusions

8.1. Theoretical contribution

This paper contributes to the debate at the intersection of technology and procurement in several ways. It explores a frontier topic, namely the impact of AI in the procurement process, which is under-investigated in existing literature.

The authors decided to adopt an overarching framework to ensure consistency in the collection of data from different sources: the procurement process model described by Spina (2008). This process-oriented approach is not common in previous studies.

For instance, Chehbi-Gamoura et al. (2020) designed a literature review about big data analytics in supply chain management based on the SCOR model. Moretto et al. (2017) scrutinized the procurement process, focusing on strategic and tactical activities. The majority of the extant research addresses single instances of the procurement process (e.g. Chowdhary et al., 2011; Baryannis et al., 2019a,b; Zair et al., 2019). Therefore, a literature review taking the procurement process as the focal point is a valuable contribution to the current knowledge about AI and procurement. The structured approach is fundamental to compile current knowledge, producing a synthetic mapping of AI-based solutions throughout the procurement process. Indeed, the mapping of papers throughout the procurement process helps identify the areas where research has mostly focused, as well as the blank areas where research efforts could be devoted in the future. In addition, by combining this analysis with the mapping of solutions currently offered by IT providers and startups, the present research highlights the mismatch between solutions studied in the literature and those actually developed, thus suggesting new directions for research that are oriented to a practical impact.

The present research also considers the benefits of adopting AI in the procurement process, as described in the literature and expected by procurement managers. As actual results of AI in procurement are still hard to assess (Lorentz et al., 2020), the identification of expected benefits provides insight into the main triggers for the evolution of AI in procurement, and projecting future developments in this evolution is a driving force for research. Similar reasoning applies to the challenges studied in the literature compared with those faced by procurement managers. Highlighting barriers points to critical issues for research to investigate so future studies can support overcoming existing challenges.

The main findings of the present research are therefore the formulation of clear directions for future research, making a structured contribution to stimulating new investigations in the field. Such directions cover AI functionalities, benefits, challenges as well as the theoretical perspective.

8.2. Managerial implications

Over time, procurement has incrementally benefited from a greater degree of digitization (Steward et al., 2019) and a substantial access to data, thanks to multiple internal and external interfaces. A possible prediction about this phenomenon is that the adoption of AI in the procurement process will continue to grow in terms of diffusion and impact, triggering great interest both in the business world and in research.

This paper outlines many relevant consequences for practitioners. Indeed, this state of the art starts from the literature, augmenting the results through the practical perspective of technology providers and business users.

From the point of view of firms adopting AI-based procurement solutions, i.e. buyer firms, the overview of currently offered solutions provides tangible insight into the possibilities for procurement departments. This view is then augmented by identifying benefits, giving procurement managers the necessary tools to understand the benefits of adopting AI in procurement, stimulating interest and knowledge in the phenomenon. Similarly, the description of the challenges can support practitioners, informing managerial decisions with the main issues to be addressed before adopting AI in the procurement process.

This paper also offers value for solution providers in many respects. The solutions mapping is the first valuable outcome. By comparing the distribution of solutions throughout the procurement process with the same distribution in the academic literature, it is possible to compare the current state of the market with the solutions explained by scholars. For instance, the functionalities identified in the literature review and labelled *supplier performance management* and *decision* support *in supplier selection*, are missing in the solutions mapping. In turn, it helps to understand whether solutions formalized in scientific knowledge are translated into practice and to identify potential areas of interest proposed in the papers. The mapping could also be read as a self-assessment or benchmarking tool in which IT providers or startups can compare their solutions with the ones offered in the market, identify areas of the procurement process currently under-covered and potentially invest in the development of innovative solutions. At the same time, an extensive understanding of the benefits and challenges perceived by buyer firms is an important insight for technology providers in defining, or adjusting, their value proposition.

8.3. Limitations and further research directions

Given the goal of exploring a current phenomenon and projecting it into future research, the study adopts multiple methodologies. In this way, it is extremely difficult to combine all the results of heterogeneous methodologies into future research directions.

The literature review bears limitations: although systematically conducted, it is affected by intrinsic subjectivity in the review and classification of the papers, which is typical of such studies. Moreover, the papers included are published until December 2020, neglecting more recent valuable publications. Bridging this gap, future research should continue with the analysis of academic publications to monitor the evolution of AI in the procurement research domain.

As far as the collection and elaboration of empirical data is concerned, there are limits as well. The mapping of AI-based procurement platforms was conducted on the websites of well-established providers and startups. It is highly probable that some information is unclear, misleading or biased for commercial purposes. Deeper research should be performed, perhaps through direct interviews. In addition, it is possible that some players relevant to the phenomenon escaped the mapping of procurement platforms. For this reason, the present study should be updated over time to continuously analyze new solutions offered and to identify the possible entry of innovative players.

The focus group may be partially biased as well. The focus group provides the point of view of only 13 managers at the time they were involved in the research. For this reason, the focus group should be replicated in a similar way involving other significant respondents, also in a repeated manner over time to monitor progress in the field.

Finally, looking at the nature of previous literature review in the procurement and supply management domain (e.g. Spina et al., 2016), our research misses a classification of the papers reviewed according to the theories applied to the phenomenon. This is mainly because the papers in the presented review often lack a theoretical architecture. However, we expect that future studies will increasingly frame the role of AI in procurement through a theoretical lens.

Supplementary data.

Supplementary data to this article can be found online at https://doi.org/10.1016/j.pursup.2023.100823.

Annex A – *Scoping study*

Area	Aim of the scoping study	Reference papers
Procurement *	It provided methodological information on previous literature reviews in the procurement discipline and shed light on the relevance of procurement in research It has been useful also for the definition of the journals to be included in the query run on Scopus.	Spina et al. (2013); Wynstra et al. (2019); Zheng et al. (2007)
BDA and AI	It served to frame the definition of Artificial Intelligence, also in relation to the wider domain of BDA and specific applications. It has been useful also for the definition of the keywords in the query run on Scopus.	Guo and Wong (2013); Russel and Norvig (1995); Kok et al. (2009); Sun and Huo (2021); Trunk et al. (2020)
Methodology	It was used to gather preliminary insights into the methodology implemented in the research.	Johnson and Onwuegbuzie (2004); Tranfield et al. (2003); Durach et al. (2017)
AI (or BDA) in procurement *	In general, it served to explore the research to date at the intersection of Artificial Intelligence and procurement. It has been useful also for the definition of the keywords in the query run on Scopus.	Abdollahnejadbarough et al. (2020); Abels and Hahn (2006); Baryannis et al. (2019a); Bienhaus and Haddud (2018); Brinch, (2018); Brintrup et al. (2020); Chehbi-Gamoura et al. (2020); Chen et al. (2022); Chowdhary et al. (2011); Chu et al. (2020); De Mauro et al. (2016); Fosso Wamba and Akter (2019); Handfield et al. (2019); Hazen et al. (2014); Hofmann (2017); Huang and Handfield (2015); Kache and Seuring (2017); Kara et al. (2020); Kaur and Singh (2018); Liu et al. (2011); Min (2010); Mišić and Perakis (2020); Moretto et al. (2017); Nguyen et al. (2018); Pitchipoo et al. (2013); Pournader et al. (2019); Roberts et al. (2014); Sanders and Ganeshan (2018); Schoenherr and Speier-Pero (2015); Scott et al. (2015); Shore and Venkatachalam (2003); Singh et al. (2005); Singh and Singh (2019); Singh et al. (2018); Sodero et al. (2019); Tan et al. (2015); Waller and Fawcett (2013); Zou et al. (2020)

* These papers are included in the counting in Fig. 3.

Annex B – *Data extraction form in the review protocol*

Review protocol field	Description
ID. number	Identification number of the paper, defined by the authors
Authors	Name and surname of the authors of the paper
Journal	Name of the publishing journal
Research domain	Research domain of the paper according to the categories of the Association of Business Schools (ABS)
Title	Title of the paper
Authors' keywords	Keywords defined by the authors of the paper
Link to Scopus	Link to the Scopus page of the paper
Reference to the inclusion/ exclusion criteria	Reference code to the inclusion/exclusion criteria. The inclusion criteria codes are: [1]: papers that contribute to the evolution of BDA and AI in procurement [2]: papers describing the evolution of BDA and AI in Supply Chain Management [3]: papers describing the evolution of BDA and AI technologies in PSM from a managerial point of view, i.e. managerial implications, drivers and challenges, costs and benefits, analyzed in general through a managerial perspective The exclusion criteria codes are: [4]: papers in which the presence of the keywords is misleading (e.g. "purchase" in the B2C marketing context, sentences like "in the Artificial Intelligence era …") [5]: papers in which BDA and AI technologies are described only as possible future implications in research
Methodology	Methodology used in the research
Industry focus	Possible focus on a specific industry
Country focus	Possible focus on a specific country
Actors involved	Type actors involved/described in the study
Number of tiers involved	Number of supply chain tiers involved/described in the study
Phase in the procurement process	Phase in the procurement process according to the reference model (Strategic purchasing, Sourcing, Supply) described in the research
Sub-phase in the procurement process	Sub-phase in the procurement process according to the reference model described in the research (they are the sub-phases of Strategic purchasing, Sourcing, Supply)
Type of technology	Type of technology investigated in the research
Type of data	Possible description of the data used by the technology investigated (structured/unstructured, source of data, etc.)
Type of algorithm/technique	Possible description of the AI algorithm or technique
Benefits	Possible benefits described or assessed in the study, related to the adoption of AI in the procurement process
Challenges	Possible challenges described or assessed in the study, related to the adoption of AI in the procurement process
Main gaps identified	Description of the main gap identified by the authors in the research
Additional notes	Additional notes and comments useful for the authors

Annex C – *Participants to the focus group with procurement managers*

	Industry	Job title	Contact mode
Manager 1	Food	Procurement Director	Contact by phone
Manager 2	Electronics	Procurement Director	Contact by phone
Manager 3	Capital goods	Global Head of Chemical Commodity - Agriculture Purchasing	Contact by email
Manager 4	Energy	Procurement Manager Corporate - Head of ICT & General Goods/Services categories	Contact by email
Manager 5	Oil and gas	Digital & Innovation Strategic Sourcing - Manager	Contact by email
Manager 6	Oil and gas	Procurement Systems Client Management	Contact by email
Manager 7	Automation	Chief Procurement Officer	Contact by email
Manager 8	Fashion	Senior Fashion Operation Manager	Contact by phone
Manager 9	Automotive	Supply-Chain Sustainability Manager	Contact by email
Manager 10	Energy and infrastructure	Head of Milan Hub - Engineering and Procurement	Contact by email
Manager 11	Engineering	Head of Procurement and Logistics	Contact by email
Manager 12	Fast-moving consumer goods	Global Commodity Manager	Contact by phone
Manager 13	Fast-moving consumer goods	Procurement Senior Manager	Contact by phone

Annex D – *IT providers and startups included in the mapping of AI-based procurement solutions*

	Name	Web site	Country
Consolidated IT providers	Basware	https://www.basware.com/en-en/home/	Finland
	Coupa	https://www.coupa.com/	U.S.A.
	GEP	https://www.gep.com/	U.S.A.
	Icertis	https://www.icertis.com/	U.S.A.
	Jaggaer	https://www.jaggaer.com/	U.S.A.
	Oracle	https://www.oracle.com/index.html	U.S.A.
	SAP Ariba	https://www.ariba.com/	U.S.A.
	SupplHI	https://www.supplhi.com/	Italy
	Synertrade	https://synertrade.com/en/	U.S.A.
	Xchanging	http://www.xchanging.com/glance	U.K.
	Zycus	https://www.zycus.com/	U.S.A.
Startups	Archlet	https://www.archlet.io/	Switzerland
	ChAI	https://chaipredict.com/	U.K.
	Evisort	https://www.evisort.com/	U.S.A.
	Fairmarkit	https://www.fairmarkit.com/	U.S.A.
	Finturi	https://www.finturi.com/	The Netherlands
	Gardenia Technologies	https://www.gardeniatech.com/	U.K.
	Globality	https://www.globality.com/en-us	U.S.A.
	INHUBBER	https://inhubber.com/en/	Germany
	Keelvar	https://www.keelvar.com/	Ireland
	Levadata	https://levadata.com/	U.S.A.
	Lexi Solutions	https://www.lexisolution.com/	Sweden
	Liberatrade	http://www.liberatrade.ai	Hong Kong
	Linklogis	https://www.linklogis.com/	China
	Pactum	https://pactum.com/	U.S.A.
	Part Analytics	https://partanalytics.com/	U.S.A.
	ProcessBolt	https://processbolt.com/	U.S.A.
	ScoutBee	https://scoutbee.com/	Germany
	Simfoni	https://simfoni.com/	U.S.A.
	Suplari	https://www.suplari.com/	U.S.A.
	Supplean	https://supplean.it/	Italy
	Supplier.ai	https://www.supplier.ai/	U.S.A.
	tacto	https://tacto.ai/	Germany
	Tallyx	https://tallyx.com	U.S.A.
	Tealbook	https://www.tealbook.com/	Canada
	WeAreBrain	https://www.wearebrain.com/	Netherlands
	Xeeva	https://www.xeeva.com/	U.S.A.
	Yaydoo	https://www.yaydoo.com/en/	Mexico

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