ARTICLE IN PRESS

Journal of Purchasing & Supply Management xxx (xxxx) xxx

Contents lists available at ScienceDirect

Journal of Purchasing and Supply Management

journal homepage: www.elsevier.com/locate/pursup

AI meets spend classification: A new frontier in information processing

Michela Guida *, Federico Caniato, Antonella Moretto

School of Management, Politecnico di Milano, Via Lambruschini 4/b, 20156, Milano, Italy

ARTICLE INFO

Keywords:
Spend classification
Spend analysis
Purchasing category management
Artificial intelligence
Organizational information processing theory

ABSTRACT

This paper investigates the impact of artificial intelligence (AI) on spend classification in buyer firms, using the organizational information processing theory (OIPT) as a reference framework. Existing research on the use of AI in procurement lacks a holistic approach that effectively integrates human oversight. This gap is particularly evident in procurement activities beyond automating repetitive tasks, especially in advanced analyses supporting strategic purchasing decisions, such as spend classification. Through a case study approach focusing on providers of AI-based spend classification solutions, this research highlights how AI addresses the substantial information processing needs that exceed the internal capabilities of buyer firms. By aligning these needs with the capabilities enabled by the adoption of AI, the study demonstrates a significant advancement in spend classification practices. This research applies the theoretical constructs of the OIPT at the intersection of two relatively unexplored domains—spend classification and AI and aims to translate these constructs into actionable insights for professionals, thereby making a significant contribution to the field.

"Computers make excellent and efficient servants, but I have no wish to serve under them"

Star Trek, season 2, episode 24 (1968)

1. Introduction

The aim of this paper is to investigate the support that AI provides to spend classification conducted by a buyer firm, focusing on the functionalities enabled by this technology.

The literature on the use of AI in the procurement process highlights several key concepts, including the benefits, challenges, and evolving roles within procurement departments. AI's ability to efficiently process vast amounts of data is a significant advantage, enabling the automation and optimization of various procurement stages such as spend analysis, contract management, and quality control. This leads to immediate cost and time savings as well as long-term qualitative value (Allal-Cherif et al., 2021). The integration of AI in procurement is also seen as a way to enhance performance through ongoing learning and adaptation, thereby improving business agility and productivity (Durach and Gutierrez, 2024).

However, the literature also identifies several challenges, such as data availability and quality, lack of internal analytical skills, and cultural barriers, which hinder the full exploitation of AI's potential in procurement (van Hoek, 2024). Hybrid intelligence models, which combine human and AI capabilities, are proposed to address these challenges by leveraging human expertise for tasks like validating AI outputs and making necessary adjustments, thus ensuring more accurate and reliable outcomes (Burger et al., 2023). Despite these advancements, the literature cautions against over-reliance on AI, highlighting the need for a balanced approach that incorporates human oversight to maintain ethical standards and prevent potential biases (Richey et al., 2023). This is particularly true in procurement activities that go beyond automating repetitive tasks, especially in specific analyses that inform strategic purchasing decisions, such as spend classification (Guida et al., 2023a).

In general, the literature underscores AI's transformative potential in procurement, and specifically in spend classification performed by buyer firms, while advocating for strategic implementation and continuous improvement to overcome existing barriers and maximize benefits (Durach and Gutierrez, 2024; Hendriksen, 2023). For this reason, our paper focuses on understanding the impact of AI on spend classification, encompassing the design of the category tree and spend analysis.

In pursuit of this objective, the theoretical framework is the organizational information processing theory (OIPT). OIPT serves as a valuable lens for examining organizational transformations induced by

* Corresponding author.
E-mail addresses: michela.guida@polimi.it (M. Guida), federico.caniato@polimi.it (F. Caniato), antonella.moretto@polimi.it (A. Moretto).

https://doi.org/10.1016/j.pursup.2025.100993
Received 6 January 2024; Received in revised form 16 December 2024; Accepted 31 January 2025
Available online 10 February 2025

technological advancements (Galbraith, 1974). Indeed, the contribution of our research lies in the detailed compilation of information processing needs underlying spend classification and the identification of capabilities enabled by the adoption of AI to support this activity. This includes not only the technological capabilities attributed to AI but also those related to processes and structures that integrate human contributions with technological advancements. This integration ensures that AI-based spend classification solutions are effective allies without the human *serving under them*.

To achieve the research objective outcome, our paper is based on ten case studies involving information technology (IT) providers and start-ups currently offering AI-based spend classification solutions. These case studies contribute to understanding the support of AI in spend classification, addressing the following exploratory research question.

RQ: *How does artificial intelligence affect the fit between information processing needs and capabilities in spend classification?*

The paper is structured as follows: first, the theoretical background section defines the relevant research domains and their intersections, positioning our work within this context. Next, we present the definition of the research framework, followed by the methodology. This is followed by a description of the empirical results obtained. Finally, the paper includes a discussion of the results and a short conclusion.

2. Theoretical background

2.1. Artificial intelligence

Artificial Intelligence (AI) is an interdisciplinary field that captivates researchers across various domains, including computer science, psychology, neuroscience, mathematics, and management. With the swift advancements in technology and the growing complexity of AI, its definition remains fluid and far from settled. According to Samoili et al. (2020), AI systems encompass both software and hardware designed by humans, and operate in physical or digital environments to achieve complex objectives. AI systems perceive their environment through data acquisition, interpret both structured and unstructured data, reason based on this knowledge, and decide on the best actions to accomplish the given goals. These systems can also adapt their behavior by analysing the impact of their previous actions on the environment.

AI incorporates a variety of technologies that enhance human decision-making through accumulated knowledge and experience, thus qualifying as a general-purpose technology (Crafts, 2021). This means AI is a versatile and recognizable technology whose potential grows with increased applications and related infrastructures, systems, and skills (Åström et al., 2022). AI enables machines to perform cognitive functions similar to those of the human mind, such as learning, problem-solving, and interaction. As noted by Raisch and Krakowski (2021), organizations can utilize AI through two primary paradigms: automation and augmentation.

In the automation paradigm, tasks are entirely delegated to machines, minimizing human involvement and enhancing process efficiency. Conversely, the augmentation approach fosters close collaboration between humans and machines, leveraging the unique capabilities of both to achieve better outcomes. Complementing this definition and applying it to the domain of procurement, Burger et al. (2023) expand on the augmentation vs. automation paradox by introducing the concept of hybrid intelligence, which aligns more closely with our study on AI supporting spend classification. Hybrid intelligence can be defined as a human-centred AI enhanced by continuous mutual human-AI learning, based on the management field. Hybrid intelligence refers to the integration of human and artificial intelligence to achieve complex objectives that neither could accomplish independently. By combining the strengths of both, it seeks to deliver superior results through continuous mutual learning. This approach creates a reinforcing feedback loop between human and machine elements, enhancing AI tools and leading to better outcomes (Burger et al., 2023). It encompasses various methods, such as *human-in-the-loop* (where humans assist in planning, execution, or evaluation) and *human-on-the-loop* (where humans oversee and verify final outcomes). In our study, we assume significant involvement from human decision-makers in utilizing technology to support spend classification. Our objective is to understand how AI capabilities enhance those specifically possessed by the organization, and therefore the human involved in the process, to address the

Table 1
AI solutions.

AI domain	AI subdomain	Definition
Reasoning	Intelligent data processing	Intelligent data processing involves a set of techniques applied to both structured and unstructured data to transform it into knowledge or to infer facts. Several classifications within the field of AI address knowledge representation and automated reasoning, describing the process of justifying (reasoning) the available data and information, providing solutions, and representing them efficiently based on a set of symbolic rules (McCarthy, 2007; Samoili et al., 2020)
Communication	Natural language processing	"Natural Language Processing is a theoretically motivated range of computational techniques for analysing 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, 2001)
	Virtual assistant/ chatbot	"A chatbot system is a software program that interacts with users using natural language" (Shawar and Atwell, 2007, p. 29)
Learning	Recommendation systems	"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)
	Supervised/ unsupervised learning	"Supervised learning employs a training set to train models. This training dataset comprises proper inputs and outputs to help the model learn. The algorithm adjusts its loss function to reduce errors" (Jhaveri et al., 2022) Unsupervised learning is a technique of pattern detection that employs artificial intelligence (AI) algorithms to examine data sets that do not contain categorized or labelled data points. These algorithms uncover hidden relationships between datasets without the guidance of a human user ((Mishra and Gupta, 2017)
	Neural network	"A neural network is an interconnected assembly of simple processing elements, *units* or *nodes*, whose functionality is loosely based on the neuron. The processing ability of the network is stored in the inter-unit connection strengths, or *weights*, obtained through a process of adaptation to, or *learning* from, a set of training patterns" (Gurney, 1997)

multiple sources of uncertainty present in the specific domain of interest, namely procurement.

To gain a more specific and technical view, albeit through a managerial approach, the main AI solutions useful for understanding the phenomenon under inquiry are described here following the reference framework introduced by Samoili et al. (2020). The AI domains involved in supporting spend classification activities include reasoning, learning, and communication. The solutions relevant to this paper are described in Table 1.

2.2. Spend classification

Spend classification refers to the systematic categorization of an organization's spending to enhance procurement strategies, optimize supplier relationships, and improve cost management. This process involves grouping similar types of spend into categories, which can be analyzed to identify cost-saving opportunities, streamline procurement processes, and enhance supplier performance. Spend classification is crucial for effective supplier development, as it helps in identifying areas where cost, quality, and delivery improvements can be made (Mandl, 2023).

The primary task in spend classification entails *spend analysis*, which involves examining the category tree of the buyer firm (Monczka et al., 2016). Spend analysis is the quantification of the economic value and volume of expenditures that an organization performs to support operations. Spend analysis aims to determine what goods and services are purchased and from which suppliers, and who triggers the demand within the organization (Monczka et al., 2016). Spend analysis can utilize various data mining techniques to predict future spending patterns and discover hidden relationships between the purchasing categories (Tapkan et al., 2016). Additionally, spend analysis can benefit from numerical taxonomic analysis to identify distinctive buyer groups and their information-gathering behaviors.

Spend analysis is the input for the definition of category strategies; therefore, the level of aggregation in the analysis is the purchasing category. At the basis of an effective spend analysis there is a correct taxonomy of purchasing categories. Practically, a *category tree* is a structured set of names and descriptions used to organize information consistently; it enables an efficient retrieval and sharing of knowledge, information, and data across organizations (Pellini and Jones, 2011). The heterogeneity of electronic formats, transactional codes and commodity names make the correct aggregation of data and the communication between buyer and supplier a challenge. To cope with this, product classification schemes such as CPV,[1] UNSPSC[2] and eCl@ss[3] have attempted the creation of standards taxonomies intended to create a reliable and efficient exchange of information between firms (Mehrbod et al., 2017).

Notwithstanding the effort made by these organizations, lots of firms have developed proprietary commodity taxonomies: SAP Ariba, eBay and Amazon are just some examples. Most of the buyer firms design their classification internally, without any reference to standardized classifications. In this way, the current multiplicity of standards creates an environment. In addition to such complexity, organizations are confronted with a vast array of categories, i.e. the branches stemming from the taxonomy, which can sometimes complicate the identification of the accurate placement for a product.

2.3. Spend classification and the support of AI

In the recent research, several comprehensive reviews pointed out the power of AI in procurement (Burger et al., 2023; Guida et al., 2023a; Spreitzenbarth et al., 2024). Indeed, spend classification, comprising the definition of the category tree and the spend analysis, is a complex task that benefits significantly from analytics due to several key characteristics. Firstly, the procurement process involves handling vast amounts of transactional data from various sources such as invoices, purchase orders, and account ledgers, which are often heterogeneous and unstructured. AI techniques, particularly those from information retrieval and machine learning, can automate the cleansing and normalization of this data, creating a homogeneous repository that is crucial for accurate spend analysis (Shaham et al., 2021). Additionally, AI's ability to model behavior dynamics and detect anomalies, such as maverick spends, enhances the precision of spend analysis by identifying non-compliant procurement activities and recommending alternative options (Chaugule and Natu, 2021). AI also facilitates the aggregation of procurement demands, which can lead to significant cost savings through bulk purchasing and better vendor negotiations, as demonstrated by the implementation of an AI solution described in (Hoffman and Elm, 2006), which resulted in substantial annual savings. Furthermore, AI's capability to anticipate demand and optimize procurement strategies through advanced forecasting models, such as support vector machines, helps in reducing storage and handling costs by aligning procurement with actual demand patterns (Singh et al., 2005). Moreover, AI's explainable models, like the multi-criteria ABC classification, provide transparency and managerial insights into inventory management, making the decision-making process more informed and efficient (Cui et al., 2022; Qaffas et al., 2023). Lastly, AI's dual abilities of automation and smartness can influence suppliers' pricing strategies, ensuring that buyers receive competitive quotes, thereby maximizing procurement value (Burger et al., 2023). These characteristics collectively underscore the transformative impact of AI on spend classification and analysis in procurement.

While acknowledging AI's transformative potential in procurement, particularly in spend classification, the literature advocates for strategic use and continuous improvement to overcome barriers and maximize benefits (Durach and Gutierrez, 2024; Guida et al., 2023a). Accordingly, our paper examines the impact of AI on spend classification, focusing on category tree design and spend analysis.

2.4. Organizational information processing theory

In exploring the impact of AI on spend classification, the organizational information processing theory (OIPT) serves as the theoretical framework, aligning with the research direction advocated by Guida et al. (2023a). As highlighted the seminal papers by Galbraith (1974) and (Roßmann et al., 2018), this theory offers valuable insights, particularly in the context of technological-induced organizational changes. Furthermore, delineating the information needs and avenues for enhancing information is pivotal in intricate processes like spend classification. Notably, the constructs of OIPT closely correspond to procurement dynamics and AI adoption (Bensaou and Venkatraman, 1995; Guida et al., 2023b).

When dealing with uncertainty, a firm can either act upon reducing information processing needs (IPN) or increase the capability of processing such information (Galbraith, 1974). In this regard, the reduction of needs can be performed by introducing redundant resources to unload the interdependence between units. The firm capabilities can be enhanced by investing in vertical systems which can streamline the

[1] CPV stands for Common Procurement Vocabulary; it 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).

communication process or by creating lateral relationship, informal processes that evolve with the uncertainty degree and integrate the subunits in a simpler way. Bensaou and Venkatraman (1995) formally structured the information processing capabilities (IPC) classifying their intrinsic mechanisms under three categories: structural mechanisms, process mechanisms and information technology mechanisms. Tushman and Nadler (1978) provided the first conceptualization of fit between needs and capabilities: a firm's effectiveness can be seen as the capacity of matching them, providing proper answers to uncertainties by leveraging internal resources. Conversely, fewer IPN will require lower IPC from companies. Then, companies showing the fit conditions proved to have higher organizational achievements.

Leveraging normative contracts and improving information quality are crucial factors in enhancing interfirm IPC in supply chain relationships (Zhou, 2011; Wang et al., 2016). Furthermore, utilizing technology-enabled supply chain management systems can act as a mediator in the relationship between supply chain integration activities and operational performance, improving planning comprehensiveness and overall IPC within organizations (Swink and Schoenherr, 2015).

Indeed, technology plays a crucial role in enhancing IPC within organizations. According to Trautmann et al. (2009), technological uncertainty and complexity have a direct negative impact on IPC. However, other research highlights the integration of technology in supply chain management as a key factor in improving operational performance, with information sharing among supply chain partners aiding in reducing IPN and enhancing coordination across the supply chain (Fan et al., 2017).

Technology has significantly revolutionized information processing methods by enhancing firms' IPC (Zhou, 2011; Jilke, 2020). This is especially true in the realm of global supply chains, where technology plays a crucial role in managing the increasing complexity of IPN, as evidenced by measures such as insourcing, product standardization, and modularization, product life cycle prolongation, product redesign, and reshoring and nearshoring, all of which are influenced by technological advancements (Busse et al., 2017). These technological innovations enable firms to align their IPC with their IPN more effectively, resulting in streamlined processes, increased efficiency, and ultimately, superior performance outcomes. The integration of technology in information processing has not only optimized internal operations but has also facilitated better decision-making and strategic planning in the increasingly complex and interconnected global business environment (Riedl et al., 2013; Fan et al., 2017; Cao et al., 2015).

Confirming the validity of OIPT in this research, previous studies in the supply chain domain have leveraged the OIPT constructs. Through the lens of OIPT, Cegielski et al. (2012) investigates cloud computing in supply chains, Busse et al. (2017) studies sustainable supply chain management, Lorentz et al. (2021) digs into supply market intelligence and Guida et al. (2023b) applies the theory in studying the support of AI in scouting new suppliers.

3. Research framework

The choice of OIPT as the focal lens of this research is inevitably derived from the proximity between the constructs of the theory itself and the elements describing the empirical phenomenon under study, namely the use of AI in spend classification.

As explained in the theoretical background section, procurement activities – particularly *spend analysis* and the definition of the *category tree* – are data-intensive activities that require processing large amounts of data (Monczka et al., 2016). These activities are affected by several sources of uncertainty that trigger considerable IPN (Dubey et al., 2022; Nair et al., 2016; Lorentz et al., 2021). On the other side, within the scope of the phenomenon under scrutiny, the analytical and technology management capabilities enabled by the adoption of AI are investigated. This aligns with our definition of technology as hybrid AI, which combines the capabilities of automation and augmentation, and is further reinforced by the taxonomy of AI solutions (Samoili et al., 2020; see Table 1), where the main AI techniques are clustered in terms of capabilities (*reasoning*, *communication*, *learning*).

For this reason, the focus of our research lies in studying the IPN intrinsic to spend classification, linked to the very nature of the analyses performed and the interfaces to which procurement is exposed, especially in the collection and analysis of data from numerous sources (Pandit and Marmanis, 2008). In this context, our interest is directed towards the capabilities augmented by AI, while keeping the human decision-maker in the loop. Indeed, the capabilities provided by AI allow for meeting the IPN underlying spend classification (Guida et al., 2023b; Patrucco et al., 2023).

Consequently, the case studies presented in this research explore the IPN of the procurement department in navigating the category tree and conducting spend analysis, as well as the IPC enabled by AI to meet these needs. The variables under scrutiny in this paper are detailed in Table 2, aligning with the definitions established in seminal works on OIPT. Each variable is then applied within the context of procurement management discourse, particularly focusing on AI adoption in spend classification. These objectives can be visualized through the research framework in Fig. 1.

4. Methodology

4.1. Sample description

Our research embraces the IT provider perspective, consistently with the research conducted by Handfield et al. (2019), Guida et al. (2023b), Ronchini et al. (2024), in similar context of investigation. IT providers enhance the orchestration of multifunctional teams, both internal and external, through AI, thereby fostering collaboration and achieving defined objectives (Jarrahi et al., 2023). Additionally, the quality and timeliness of data, as well as integration with ERP systems, are crucial factors contributed by IT providers in these implementations, ensuring the success of AI applications in procurement processes (Allal-Cherif et al., 2021; Swink and Schoenherr, 2015).

The choice of the sample in the presented research was driven by several rationales. First, the implementation of advanced digital technologies, such as AI, presumes the capability of the adopting firm to fully embrace and use the technological asset (Hallikas et al., 2021; Dubey et al., 2022) and IT infrastructure is the most important element in digital procurement (Viale and Zouari, 2020; Patrucco et al., 2023). Second, IT providers are the first in approaching customer's requirements by applying their know-how to generate value for the final user (Urbinati et al., 2019). Third, IT providers own a heterogeneous experience spanning across different industries, size, product-type, countries, being able to provide a complete view on real requirements of the buyer firms. Fourth, IT providers are also aware about the analytical processes behind spend analysis and category tree definition, hence, they know where AI can provide higher value for the buyer.

So, due to their expertise in new implementation processes and specific knowledge of the procurement domain, IT providers understand the technological structure behind the solution and the benefits of spend classification for the buyer firm. This is especially relevant for AI, as user companies often lack sufficient knowledge in this area. Both the buyer firm and the suppliers view AI as a general-purpose technology (Crafts, 2021), perceiving it as a black box capable of achieving desired business objectives, regardless of the underlying mechanisms (Priore et al., 2018).

Designing the sample, we selected actors who could provide their experience on the deployment of AI for spend classification, considering established IT providers and startups. The respondents selected for this study were chosen through purposive sampling (Schreier, 2018), based on the list of procurement IT providers and startups in Guida et al. (2023a). The selection was further refined by reviewing the solutions these providers currently offer on their websites. The details are

Table 2
IPT variables included in the research framework.

	Reference from the seminal work	Findings from procurement management discourse
Environmental Uncertainty		
Socio-political component	The socio-political component encompasses governmental regulatory oversight of the industry, public perceptions of the industry and its specific products, and interactions with relevant trade unions within the organization (Duncan, 1972).	Buyer firms are influenced by both international regulations and pressures from various stakeholders, including customers and non-governmental organizations (Nair et al., 2016). Macro-level shifts in a buyer firm's environment entail changes in government policies, regulatory standards, cultural values, and social and political landscapes (Dubey et al., 2022). Institutional pressures, such as coercive data regulations or normative expectations for excellence, prompt interventions in information processing for automated data storage and management in procurement processes (Lorentz et al., 2021).
Environmental dynamism	Environmental dynamism underscores the necessity for organizational design to adapt to external dynamics. It is notably influenced by the maturity of the underlying technologies, among other factors. This is also impacted by the product technical complexity, related to the changes in product, ranging from technically simple to technically complex (Bensaou and Venkatraman, 1995).	Within the realm of digital procurement, the maturity of underlying technology pertains to a company's capacity to adopt and utilize new technological resources. Technological readiness encompasses the information technology (IT) infrastructure that facilitates digital procurement (Kosmol et al., 2019).
Environmental complexity	Environmental complexity denotes the heterogeneity and scope of an organization's operations. From a resource-dependence standpoint, environmental complexity reflects industry competition that necessitates a wide array of inputs or outputs (Bensaou and Venkatraman, 1995).	Running the spend analysis across all purchasing categories requires a one-on-one attention to the specificities of each good/service purchased. For this reason, a significant degree of customization is required in the spend analyses and the supporting software, collaborating with the IT provider to tailor the user interface or implement improvements in subsequent releases to address identified gaps (Pandit and Marmanis, 2008).
Environmental capacity	Environmental capacity is the extent to which the environment can or does support growth (Bensaou and Venkatraman, 1995).	Most strategic sourcing and spend analysis initiatives begin when executive management makes a decision to establish procurement excellence as a core value in order to sustain high performance and support the enterprise growth (Pandit and Marmanis, 2008).
Task Uncertainty		
Organizational personnel component	This component pertains to factors such as educational and technological background and skills, prior technological and managerial experience, individual members' commitment to achieving system goals, interpersonal behavior styles, and the availability of manpower for system utilization (Duncan, 1972).	This component encompasses human resources possessing the necessary knowledge and skills to implement digital technologies in the digital procurement domain (Bals et al., 2019; Kosmol et al., 2019). Top management support signifies the extent to which top managers comprehend and value the potential of digital procurement, as well as their advocacy for and promotion of digital technologies and practices in procurement (Kosmol et al., 2019).
Organizational functional and staff units component	This component encompasses the technological attributes of organizational units, the interdependence of these units in achieving their objectives, intra-unit and inter-unit conflicts among organizational functional and staff units (Duncan, 1972).	In the digital procurement realm, this component refers to the roles, responsibilities, and interfaces for coordinating and integrating digital procurement both within the company and with external partners. Coordination and integration can be achieved through vertical mechanisms (e.g., centralized under a chief digital officer) or through lateral mechanisms (e.g., decentralized across cross-functional teams); (Kosmol et al., 2019).
Partnership Uncertainty		
Supplier's assets specificity	This denotes the extent to which the supply of a good/service necessitates capabilities and skills unique to a particular supplier (Bensaou and Venkatraman, 1995).	Significant supplier asset specificity results in high switching and search costs for buyer firms. Conversely, the supplier's offering is relatively unique, enhancing the supplier's power in the supply relationship (Cox, 2015).
Focal firm's asset specificity	The focal firm's asset specificity represents investments highly tailored to the relationship, potentially granting the buyer leverage over the supplier (Bensaou and Venkatraman, 1995).	Buyer power relative to the supplier is a consequence of the latter's dependence on the former, often due to highly specific buyer requirements and significant cumulative transaction value between the parties (Cox, 2001).
Level of mutual trust	Mutual trust can mitigate uncertainty regarding opportunistic behavior by the other partner (Bensaou and Venkatraman, 1995).	In cases where both buyer and supplier can trust each other objectively, fostering mutual trust and collaborative information sharing is crucial for relationship success. However, in other scenarios - which are believed to be more common in business exchanges - such approaches may pose challenges (Cox, 2001).
Overall supply chain uncertainty	The overall supply chain arises from multiple factors, including the quantity of suppliers per sourced item (horizontal complexity), the number of tiers involved (vertical complexity), and the geographical distance separating the buying and supplying entities (spatial complexity) (Busse et al., 2017).	In a centralized spend analysis tool, the analysis encompasses both direct and indirect expenditures across all business sectors, considering all the purchasing categories purchased from many different suppliers. Both supply chain and internal data are insightful for the spend analysis to cope with the supply chain uncertainty (Pandit and Marmanis, 2008).
Structural Mechanisms		
Data-driven Environment	A data-driven environment is characterized by the development of explicit strategies and policies, as well as the design of structures and processes that facilitate analytical activities (Cao et al., 2015).	Within the data-driven environment, a significant focus is placed on collaboration between the core purchasing team and the IT department, particularly concerning spend classification. While the responsibility of IT lies in data extraction, it's crucial for the sourcing team to identify and address any data gaps or inconsistencies prior to loading the data into the spend cube. The proper approach to data management in spend analysis should be a structural feature of the environment (Pandit and Marmanis, 2008; Culot et al., 2024).
Process Mechanisms		
Conflict Resolution	Conflict resolution processes reflect the socio-political dynamics within relationships, spanning a continuum from cooperation to conflict, and directly influencing the exchange of information between the parties involved (Bensaou and Venkatraman, 1995).	At its core, all buyer-supplier relationships entail some level of inherent conflict. The critical decision for each party revolves around the extent of conflict over value appropriation and the degree of collaboration needed to achieve their individual objectives (Cox, 2001).

(*continued on next page*)

Table 2 (*continued*)

	Reference from the seminal work	Findings from procurement management discourse
Commitment	Commitment is measured by the extent to which risks, burdens, and benefits are equally shared between the two firms (Bensaou and Venkatraman, 1995).	In digital procurement, commitment extends to broader value creation through knowledge sharing, market intelligence, collaboration, and integration. In this research, the commitment involves not only the buyer firm and suppliers but also the IT provider delivering the spend classification solution (Lorentz et al., 2021).
Joint action	Joint action refers to the level of cooperation and collaborative effort between companies in various areas such as long-range planning, product and process engineering, tooling development, and training/education (Bensaou and Venkatraman, 1995).	Procurement departments often have unique workflows and requirements that may not be fully addressed by standard spend classification solutions. The extent to which IT providers adapt their solutions to meet these specific needs and are open to new ideas from the buyer firm determines the effectiveness of joint action (Pandit and Marmanis, 2008).
Technological Mechanisms		
Use of Information Technology	The utilization of information technologies enables organizations to capture, integrate, and analyze data for informed decision-making processes (Cao et al., 2015).	In the spend classification, leveraging information technology encompasses various mechanisms, including analyses of commercial databases, ERP-based supplier scorecards, Internet-based reports, and collaborative platforms. Integration of ERP systems into procurement processes is also instrumental in adopting Procurement 4.0 systems (Huang and Handfield, 2015; Lorentz et al., 2021).
Information Quality	Information quality encompasses aspects such as accuracy, availability, timeliness, internal and external connectivity, completeness, relevance, accessibility, and update frequency. The demand for high-quality information systems intensifies with increasing business environment uncertainty (Zhou, 2011).	In digital procurement, ensuring information quality involves managing high volumes of diverse and rapidly changing data from both internal and external sources. This includes sharing data with external stakeholders, organizing data to ensure accessibility and usability, and maintaining data integrity throughout its lifecycle (Lorentz et al., 2021).

presented in Table 3.

4.2. Data collection and analysis

Data collection was conducted from multiple data sources, triangulating information to consolidate an accurate and comprehensive snapshot of the phenomenon under investigation: the website of the IT providers, the whitepapers and case studies disseminated by the IT provider, referring to previous success stories. When available, a demo of the solution has been run online. For all the IT providers and startups in the sample, specialized technical evaluation reports produced by external companies were accessible, as well as official webinars and presentations. This information was the basis for the semi-structured interviews. In the interview track (available upon request), each question is conceptually linked to construct of the research framework.

The unit of analysis is the AI-based spend classification solution offered by the IT vendor and the resulting relationship between the IT provider delivering the solution and the buyer firm implementing it. The variables identified in the research framework (Table 2) were taken as the architecture to draw a coding tree (see Annex A) with a deductive approach (Boyatzis, 1998). In this way, we probed the case based on codes developed from the literature. Additionally, to avoid limiting our analysis to elements already known in academic literature, ‘in-vivo’ codes were created to capture concepts not previously formalized in the literature, so with an inductive approach.

A within-case analysis was first conducted for each of the case studies, to understand the variables of interest together with their relationships within the case. We then conducted a cross-case analysis to compare the results collected in the previous stage, highlighting patterns and differences between data from different cases.

To evaluate the rigor and validity of the research process and results, Table 4 presents information on internal, external, and construct validity, as well as reliability, based on the model by Gibbert et al. (2008).

5. Results

In this section, we present the results of our analysis across the case studies, first in terms of the uncertainty generating the IPN and second in terms of the mechanisms for increasing IPC. Ultimately, we utilize cross-tabulation to uncover correlations between the uncertainty surrounding AI adoption in spend classification and the capabilities devised by IT providers. To streamline our research presentation, we connect our empirical findings with established IPT frameworks, mirroring our approach from the research design phase. This linkage of emerging discoveries with established literature fortifies the internal validity, generalizability, and theoretical depth of theory construction through case study research (Eisenhardt, 1989), and also strengthens the coherence between our findings and existing knowledge.

5.1. Information processing needs

Summarizing the findings from the case studies, the IPNs in spend classification are described in this section. A detailed reference to the case studies is described in the cross-case tables in Annex C and Annex E while a synthesis of the results in the case studies is presented in Fig. 2.

5.1.1. Environmental uncertainty

Environmental dynamism is primarily impacted by product technical complexity, as described by IT providers about their past relationship with the buyer firms adopting AI tools for category management. The technical complexity in running a spend classification consists of managing huge volume of heterogeneous data, coming from different sources, not systematized within the enterprise systems. This makes the analysis extremely complicated and its outcome uncertain (Provider A). This is particularly true before doing a spend analysis, when the systematization of the data hardly converges into a structured category tree (Provider B).

IT providers described the maturity of the underlying technology as a very impacting factor as well. Considering the maturity of the AI technology underlying the category management solutions addressed, Providers C, E, F, and I mentioned that buyers are unwilling to invest in a non-consolidated technology, forcing IT providers to develop it internally and make it perceivable as an easy and not-risky tool. Indeed, the deployment of a well-established portfolio of technologies, already trained and ready-to-use, tends to push buyers to trust it for the adoption. Thus, the maturity of the underlying technology depends on the advancements achieved by IT providers in deploying AI-based solutions and on the readiness of procurement in accepting the change introduced by AI.

The **socio-political component** firstly introduced by Duncan in 1972, is considered as an additional source of uncertainty because of the presence of many regulations with a high pace of change. Hence, new legislations force buyers to adapt quickly to a more complex environment. In the experience of the sampled IT providers, an additional

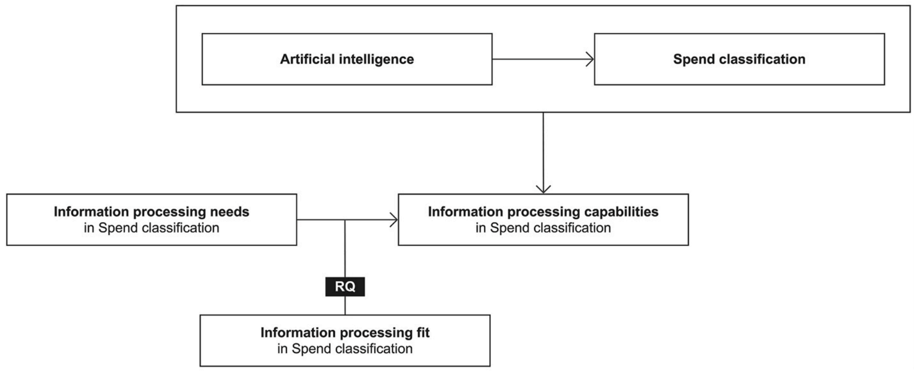


Fig. 1. Research framework.

Table 3
Respondents in the sample.

Provider	Type of Provider	Turnover	Number of employees	Headquarter
Provider A	Start-up	$4 Million	11–50	Italy
Provider B	Start-up	$4 Million	40	Italy
Provider C	Established IT Provider	$180 Million	1325	Finland
Provider D	Start-up	$3 Million	20	Sweden
Provider E	Established IT Provider	$1.3 Billion	2360	California
Provider F	Start-up	$4 Million	25	Sweden
Provider G	Start-up	$4 Million	25	Norway
Provider H	Established IT Provider	$250 Million	1200	North Carolina
Provider I	Established IT Provider	$63 Million	300	New York
Provider J	Established IT Provider	$1 Billion	5000	New Jersey

element of uncertainty for buyer firms is government control over the industry due to the presence of many regulations with a high rate of change. Thus, new legislation forces buyers to adapt quickly to a complex environment (Provider E).

When dealing with the spend classification, the buyer firm needs to collect and integrate data about the suppliers, also checking for their compliance to the requirements imposed by local or international regulations. Thus, a lot of unstructured information are required in the analysis of the spending, mainly related to certifications and legal constraints. This is necessary for maintaining a regulation-compliant supplier base.

Thanks to the case studies, we can highlight an additional variable not considered before through the lens of IPT. Specifically, IT providers described the presence of **other unpredictable factors,** such as the pandemic, the global chip shortage, or international conflicts (Provider J).

Environmental uncertainty is a significant source of uncertainty strongly influencing the phenomenon under study. Providers unanimously report a complexity related to the adoption and deployment of the solutions they develop, as these solutions must adapt and be tailored to the specific contingencies and requirements of spend classification conducted by each buyer firm. Indeed, spend classification inherently requires adaptive strategies, given that high underlying environmental uncertainty leads to a greater variety of performance measures. Therefore, a detailed analysis of the sources of environmental uncertainty in spend classification is the first step for a buyer firm aiming to adopt AI to support procurement analytics. Understanding the technical characteristics required for such a solution, as well as the digital maturity of the technology and the adopting firms—both buyers and suppliers—is crucial to determining the demands on the AI solution and the feasible

Table 4
Validity and rigor in the research process (adapted from Gibbert et al., 2008).

	Description	Reference in the paper
Internal validity	The constructs and the research framework have been deducted from the literature review. Codes result from identifying the relevant variables in the academic literature at the intersection of purchasing (with a focus on spend classification) and AI. Results have been compared with the results of the literature review.	Refer to the theoretical background, coding tree (Annex A), methodology, and discussion of the results.
External validity	Information and data have been collected from different providers of procurement AI-based tools, delivering solutions specific to spend classification. Results have then been presented to respondents to validate them and ensure that information has been well interpreted.	Refer to the case study sample (Table 3) and the cross-case tables (Annexes B, C, D, and E).
Construct validity	Data and information have been collected predominantly from primary data from the selected IT providers. Data have been further triangulated with secondary sources to enhance data collection. Two researchers performed data analyses, and results were compared and validated among authors in dedicated meetings.	Refer to the case study sample (Table 3), and the cross-case tables (Annexes B, C, D, and E).
Reliability	The coding tree has been provided. All the theoretical constructs have been explained starting from the seminal paper on OIPT, then applied to the field of purchasing and specifically to spend classification. The coding tree has been defined based on these theoretical constructs, transitioning from Table 2 to the coding tree in Annex A. The interview protocol and the cross-case tables have been thoroughly discussed in the results section and are provided in Annexes B, C, D, and E.	Refer to the coding tree (Annex A), and the cross-case tables (Annexes B, C, D, and E).

level of sophistication. This ensures the AI spend classification solution is designed coherently. Similarly, sources of uncertainty arising from other external factors, such as regulatory requirements or disruptions in supplier relationships, like those experienced during the pandemic, must be considered.

Understanding the multidimensional nature of environmental uncertainty in spend classification is critical for designing effective AI-supported solutions that meet the information needs of decision-makers. Thus, *environmental uncertainty* manifests through its pervasive influence on spend classification and proved to be undoubtedly high in all its aspects in all the case studies.

5.1.2. Task uncertainty

The case studies brought interesting results about the uncertainty arising within the firm boundaries, tied to the **organizational personnel component**. The importance of knowledge on new technologies is strongly supported by the respondents, experiencing different situations in buyer firms. Indeed, Provider C, G, I and J mention the missing buyers' capabilities and skills enabling the understanding of the value of AI, leading to a lack of trust. Procurement professionals' interest for technology is low, being them on average older than in other departments and less familiar with digital advancements. On the contrary, Provider H claimed that the perception of the support provided by AI to spend classification triggers purchasing people to develop the necessary capabilities. These contradictory perceptions of the providers can be explained with a heterogeneity among the buying firms: a few more advanced ones are open and capable of adopting AI, while a vast majority still lacks the necessarily skills and capabilities to understand its value.

The technological characteristics comprise all the communication systems employed within the purchasing department to exchange information with other departments. Looking at the **organizational functional and staff unit component**, the focus of IT providers is mainly the lack of integration between the systems and subunits rather than the type of systems exploited. Indeed, IT providers in the sample experienced low system alignment by buyers, generating data silos which are detrimental to AI tools application. This situation may originate from two different situations. First, mergers and acquisitions lead to the proliferation of category trees, causing the same product category to appear in different branches depending on the taxonomy used. This creates ambiguities that persist in data maintenance, as stated by Provider J. Second, the tendency of *intrapreneurship* within organizations, breaking up companies into many different units, each one with its Profit and Loss, database, ERPs or category taxonomy. Particularly, IT providers asserted that the main reasons behind these issues are geographical dispersion and language heterogeneity.

Based on the information gathered from the case studies, task uncertainty can significantly influence organizational design strategies in buyer firms approaching their initial AI implementations. This includes the creation of lateral relationships with IT providers and, of course, investment in information systems. Managers' competence in AI can mitigate this uncertainty by enhancing the quality of information systems usage and data quality, which is crucial for accurate spend classification. The human element, including subjectivity and competence, plays a critical role in defining the limits and applications of AI in this domain. Thus, the competence of managers in AI is pivotal in reducing uncertainty and optimizing spend classification processes.

Another factor described as generating task uncertainty, especially related to geographical dispersion, is the stratification of different e-procurement suites. Over time, buyer firms adopt numerous best-of-breed solutions to support specific tasks, which may have temporary utility. However, when these solutions are no longer needed or when upgraded versions are implemented, the previous systems are rarely dismantled. This leads to a stratification of IT systems. This issue increases the information processing needs underlying spend analysis due to the lack of data systematization and integration among different systems.

To conclude, the perceived *task uncertainty* results high, considering the complete set of case studies (see Annexes C and E).

5.1.3. Partnership uncertainty

Consistent with the theoretical foundations provided by Bensaou and Venkatraman in 1995, partnership uncertainty may increase or deteriorate the level of trust underneath the relationship. Bensaou and Venkatraman in 1995 applied the IPT to the partnership between buyer and supplier. In our research we take as unit of analysis the adoption of an AI-based solution for spend classification and the subsequent relationship between the adopting buyer firm and the IT provider, so the partnership uncertainty concerns these two actors.

Indeed, in the context of software development, we translated the traditional meaning of **supplier asset specificity** into one more suitable with the scope of the research, i.e. the specificity of the AI-based solution offered by the IT provider. Provider B mentioned a specific case where they accommodated the buyer's needs in a very targeted manner. The case involved a defense sector company with strict cybersecurity requirements, which requested that Provider B develop the solution on-site, avoiding the usual cloud-based deployment. Conversely, Provider I stated that any requests from the buyer for solution customization would not be considered, to avoid the proliferation of diverse and difficult-to-manage situations. Both cases represent a specificity related to the platform deployment and its layout, thus describing the variable *layout, facilities and tooling* introduced by Bensaou and Venkatraman in

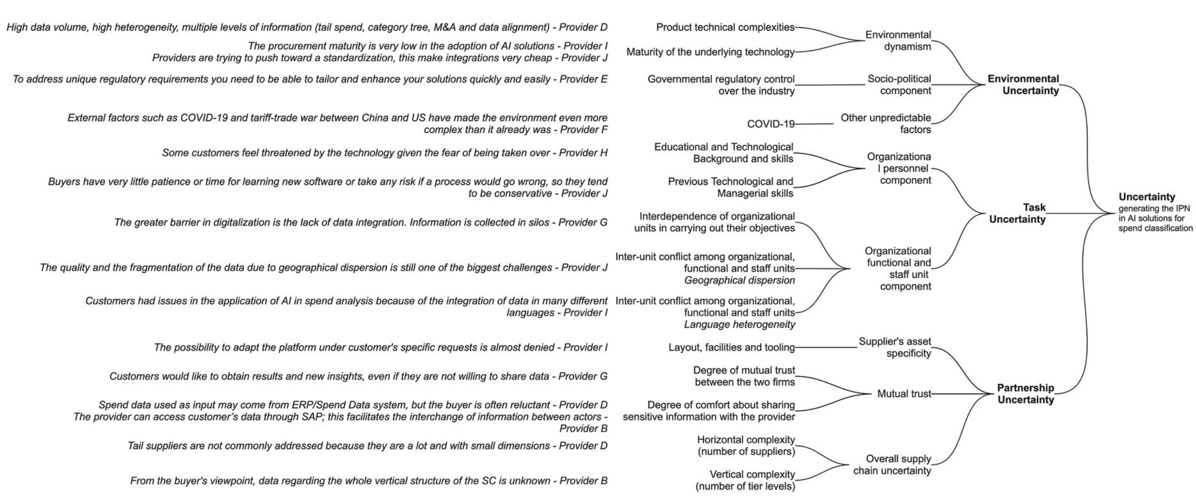


Fig. 2. Uncertainty from the case studies.

1995. According to case studies, the approach of providing a generic, ready-to-implement application to support procurement is no longer tenable when it comes to AI, which is too complex to be customized by the buyer firm after implementation. For this reason, the buyer firms are increasingly concerned about customization, innovativeness and service level when selecting an AI-based procurement solution (Provider I). The specificity of the AI solution is crucial as it directly impacts its ability to align with the buyer firm's requirements, thus influencing adoption intentions. In general, the high specificity of the solution, manifested in its platform layout, is due to the unique needs of the deploying buyer firm.

The level of **mutual trust** underlying the relationship is a major component for data sharing. However, IT providers showed contrasting opinions on the topic. On the one hand, some of them reported that the use of ERPs deployed in cloud had facilitated data sharing. Indeed, IT providers only need to access their systems to extract transactional data. On the other hand, a portion of them mentioned that buyers are unwilling to share sensitive data, thus damaging the possibility of applying AI. So, the level of trust towards the IT provider leads to a dual situation: although some buyers ask for proofs about the obtainable results through successful applications, others feel uncomfortable in sharing their list of suppliers with the IT provider. In these circumstances, it is difficult for the IT providers to invite buyers' suppliers to the platform, creating a network effect that grants the generation of valuable data.

Furthermore, the acceptance of recommendations provided by these solutions, often in the form of chatbots (Provider D), is generally low among buyers unless they operate in environments characterized by low uncertainty. In such environments, buyers can make decisions with a high degree of confidence and are therefore more likely to trust the platform and its suggestions. Otherwise, another way to enhance the credibility of these solutions in the eyes of the buyer is through human validation by a competent consultant from the IT provider. This underscores the significant impact of trust that the buyer firm places in the solution, both in terms of providing input data to the IT provider and in interpreting the generated outputs.

Other than the relationship between IT provider and buyers, the latter may suffer from uncertainties arising from the interconnection with other actors in the supply base. IT providers in the sample reported a high **overall supply chain complexity**, both vertically and horizontally, measured through the number of tiers and number of suppliers within a tier, respectively. The vertical complexity was mentioned by Provider C affirming that buyers encounter significant barriers in understanding the structure behind first tier. This complexity is originated either because the suppliers' upstream information is hidden, making it harsh to communicate beyond the first level of the supply chain, or because their structure is unknown, resulting in the impossibility for buyers to achieve that kind of level. Horizontal complexity arises from the breadth of the buyer's supply base, because of the complexity in running the spend analysis including information for all suppliers, in terms of systematization of the data base, and data availability and quality. This issue is even more urgent for tail spend, as described by Provider D.

In adopting AI for spend classification, the number of suppliers significantly impacts these dynamics. A higher number of suppliers increases the complexity and volume of data that organizations must process, thereby elevating the associated uncertainty. Additionally, the complexity introduced by a large supplier base and an extensive number of tiers in the supply chain necessitates advanced information systems to ensure flexibility and adaptability in supply chain management, thus increasing what we define as *partnership uncertainty*.

To draw some general conclusions, *partnership uncertainty* can be defined low or high, mainly depending on the level of mutual trust between buyers and IT providers (see Annexes C and E). Data sharing is the main element in the partnership established between the buyer and the spend classification solution provider, so the level of uncertainty is strongly influenced by the willingness of the buyer to engage the collaboration with the IT vendor.

5.2. Information processing capabilities

Summarizing the findings of the case studies (Fig. 3), the IPCs enabled by IT providers through AI-based spend classification solutions are presented in this section (cross-case tables in Annexes D and E).

5.2.1. Structural mechanisms

The mechanisms related to the organization's structure may strongly influence the capabilities pushing towards AI adoption in spend classification. The importance of designing and implementing an effective data-driven strategy is deemed fundamental in analyzed case studies. However, few buyer firms have experienced a solid and well-established transformational program. In the first instance, Provider D stated that the strategic management of suppliers is critical for a successful implementation of AI in category management, describing the presence of a **data-driven environment** as the main enabler for the procurement digital transformation.

In the second instance, a different set of approaches is well described by Provider H, that divided the customer base into three cases, based on the type of strategy they establish. The first case depicted is the buyer firms oriented to entail ambidexterity within procurement, meaning that they exploit current resources and carry out activities following their point of strengths. The second case is considered as *early-adopters,* according to Rogers' definition (1983), serving as a role model for other companies to assess the impacts of the technology and decide whether to adopt the solution. In third case, most IT providers report that buyers lack of a well-defined and effective strategy leading towards a digital transformation. Moreover, even if buyers are aware of the role of strategy in tackling uncertainty, many of them design one but never apply it. IT providers confirm that most buyers are still at the early stages of digitizing the processes, forcing them to focus first on the basics and then consider the next steps. Closely related to the concept of data-driven strategy, change management has been mentioned multiple times and defined as a critical component for transitioning to digital technologies successfully (e.g., Provider G).

The case studies unanimously highlight the critical role of a data-driven environment within the buyer firm. A data-driven culture significantly enhances the firm's ability to process and utilize information effectively, which is essential for the successful implementation of AI-based solutions. This environment fosters mechanisms for data utilization that lead to substantial improvements in the deployment and daily operation of AI-based spend classification solutions. In this way, *structural mechanisms* will depend on buyer firm's approach in front of the implementation of the new technology.

5.2.2. Process mechanisms

The variable **commitment**, intended between IT providers and buyers, was acceptably supported by case studies. Following the experience of Provider D, "*Procurement should enhance its value creation capability though the development of collaborations provider-buyer-supplier and innovation programs*". Such an approach could lead towards more accessible communication and data sharing activities. The commitment mechanism is mainly exercised by the IT provider intermediating between the suppliers and the buyer, as the procurement platform guarantees the security of data provided by the actors and the objectivity of the analyses. The commitment component is even more relevant when dealing with AI. Indeed, the accuracy of the spend classification run through the AI-based solution is fundamental for gaining credibility with the buyer firm. The dimension of commitment corresponds to the willingness of the involved parties (i.e., the buyer firm and the IT provider) to collaborate closely and work together to achieve the buyer's objectives in spend classification optimally. This is confirmed by the strongly project-oriented nature described by the providers in the sample regarding the solutions implemented at the buyer firm. These solutions are often the result of experiments and innovative projects carried out by committed providers who believe in the potential of AI.

Joint action entails several elements becoming relevant for the scope of this study. Looking at the *long-range planning* pertaining the digital procurement initiatives, Provider J reported the commitment of supporting the customer along the deployment of the AI solution starting from a future-state development followed by a roadmap designed together for the implementation. Regarding the *process engineering* aspect, given the nature of the solution involved, the re-engineering is conceived as tailoring the solution around buyers' requirements and is only performed by three among the respondents (Providers B, C, J). These providers offer set-up projects to prepare the solution around customers' processes, avoiding too many changes in their routines, still ensuring an active role to the buyer firm, and enhancing their capabilities in the process engineering (Provider J). *Technical assistance* is also deployed by IT providers to support buyers before and along the adoption and the utilization of the solution (Provider J; Provider C) through a dedicated consultant along the different stages. In Provider I's specific case, assistance is provided through a chatbot. A big effort performed by the IT provider is the training carried out before the implementation. Indeed, Provider E, H and I offered an extensive *training* phase based on the level of *education* that buyers already possess and their technological equipment.

The importance of technical assistance, training, and education is widely confirmed by the case studies in which the involved providers describe a much more extensive customer support process during and after implementation compared to previous projects with less advanced technologies. The human project manager from the IT provider offers increased technical support, and enhanced assistance is provided through recommendation systems and chatbots to help the buyer navigate the AI-based platform. This combination significantly improves technical assistance for the buyer, as well as the continuous learning from the system.

Synthetizing, thanks to many initiatives of training, joint development, and customization, the overall capabilities within the *process mechanisms* are high (see Annexes D and E).

5.2.3. Technological mechanisms

The Mechanisms based on technologies coping with Uncertainties are strongly based on the IT provider's Capabilities. In the empirical data gathered in the research, the **use of information technology** presents a duality. Indeed, the respondents describe a low data quality in the buyer firms' databases, counteracted by the tools they offer. In this way, the missing capabilities of the buyer firms are compensated by innovative solutions for category management, bearing the capabilities of IT providers. The ability to capture data always takes the lenses of integration with buyers' systems (e.g. ERPs), as internal systems are primary data sources from where IT providers extract information. Most IT providers can connect with buyers' systems directly, being them either the main ERP or other software used internally; in this case, the most common sources of information are transactional records and purchase orders.

Data integration is fundamental when dealing with AI, given the massive amount of data necessary to make AI work efficiently and effectively, as addressed by Provider D. As a confirmation, all the respondents affirmed they can integrate data from multiple sources. To go more in-depth, several integration alternatives have been discussed. First, the integration with info-provider data is discussed within two of the case studies. Remarkably, such data repositories are verified by external providers, guaranteeing the veracity and accuracy of data. For this reason, Provider C and Provider G enrich this information to verify data coming from their customers and add further insights based on a shared and verified information base. Second, the integration of data coming from buyers' suppliers was made explicit by Provider H, Provider G and Provider J. Moreover, those IT providers stated that information coming from suppliers' results, most of the time, more valuable than the one coming from buyers. Third, the integration with other data sources is described by Provider C, E, H and I. In most cases, such integration is performed by crawling the web, with Provider E being the most advanced one by executing semantic research upon more than 600,000 data sources (e.g. newspapers, publications, research). In addition to all these different approaches, IT providers are endowed by nature with a joint knowledge base on which AI engines have been built. Usually, this common knowledge is constructed upon a huge amount of data accumulated over time, either through data from buyers or other types of external information. This amount of information can be further enriched by *knowledge engineering* activities like Provider B is currently doing.

The ability to analyze data entails all those specifications on how providers carry out their elaborations on data. Disambiguation is possible in this regard since there are two different approaches common to the respondents in the sample. Providers A, B and F exploit their analytics capability to pinpoint errors contained in data, misalignments and main issues related to information quality. Through advanced systems, they can solve them and guarantee higher data quality to start with further analyses. Instead, Providers G and H described their analytics capability to extract value from data. For instance, a powerful implementation is Natural Language Processing tools applied to product description; another example is the exploitation of some analytic services provided by external partners which are integrated directly on the

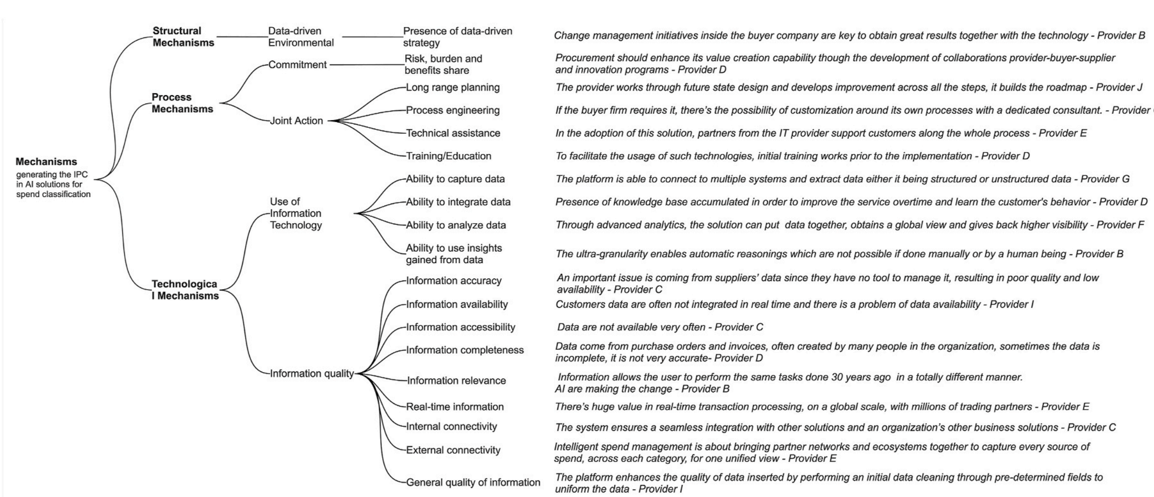


Fig. 3. Mechanisms from the case studies.

IT provider's platform. Through the application of advanced analytics, IT providers can extract new insights and value from it. Specifically, the ability to build the category tree starting from Natural Language Processing extractions of product descriptions results of great value. The ultra-granularity achieved through advanced techniques to analyze data grants an automatic generation of new insights that allow buyers to perform negotiations and deal with their suppliers with more solidity.

As far as the **information quality** is pertained, accuracy and availability have been widely discussed, either because of low accuracy/availability from buyers' side or due to enhanced accuracy/availability by IT providers.

Accuracy is mainly related to misclassifications, errors inside data and duplications of buyers' data; however, the accumulated knowledge base allow the IT provider to fix these issues, notably increasing the accuracy. This application of AI to improve data correctness and solve problems results being the most common among IT providers.

Data availability deal with information issues often covered by integrating external sources of data or sharing the knowledge base among different buyer firms. Real-time information is also crucial to deliver insights that may be fruitful immediately. Internal and external connectivity are also important to ensure systems alignment and integration inside and outside buyers' boundaries. Information relevance and completeness were described as essential to apply AI to data; indeed, gaps inside information may deteriorate the system's capability of learning from data, thus making it difficult to provide an efficient and effective service. Moreover, data used as input should be relevant for the objective pursued; this is required especially when the buyer shares data autonomously, making it fundamental to understand the relevant information to be supplied to the IT provider.

Data quality is still the major hurdle in the implementation of AI applications for business, and this is claimed in several streams of literature. All the respondents in our case study emphasize the importance of data quality, as even the best algorithms cannot perform well without good data. Approaches that autonomously generate the classification for the category tree and adjust their difficulty based on the performance of the classification agent, with the option to include a human in the loop, can help in refining and improving AI models (Providers B, G, I). Additionally, an initial effort spent for data quality can enhance the overall performance of AI systems by ensuring the right prioritization to improve data quality where it matters most.

In conclusion, *technological mechanisms* put in place by the buyer firms in spend classification are still insufficient, but they can be greatly augmented through the capabilities of the IT provider, directly transferred to the buyer through the digital procurement platform (see Annexes D and E).

6. Discussion

6.1. Fit between information processing needs and capabilities

By operationalizing the constructs of information processing needs and capabilities in the actual implementations described by the respondents in the sample, we can determine whether the capabilities enabled by IT providers through AI-based solutions sufficiently meet the information processing needs of companies in their spend classification (see Table 5).

In spend classification, the buyer firm is exposed to several sources of uncertainty. The case studies revealed how uncertainty often stems from the degree of customization required to the category management solution to meet the business specificities of the buyer firm. A certain degree of specificity is also required in the data collection and integration: an in-depth spend analysis requires reliable and up-to-date data from company systems and external sources, and data management is often problematic for buyer firms, increasing the uncertainty behind spend classification. This is even more complex when it comes to a purchasing process which is fragmented and decentralized in different units, making data management and process optimization confined in company silos (Lorentz et al., 2021). To support this, the existing literature identifies the quality and completeness of input data as a significant source of uncertainty, as AI algorithms heavily rely on accurate data to produce reliable outputs. Incomplete or incorrect data can lead to misleading results, as evidenced by instances where misclassified requisitions required manual correction, highlighting the challenges in maintaining data integrity (Burger et al., 2023; Spreitzenbarth et al., 2024). Furthermore, the complexity of taxonomies such as eCl@ss can exacerbate these issues, making it difficult to harmonize data and design effective category trees (Spreitzenbarth et al., 2024).

AI in spend classification is also invalidated by the co-existence of different company systems, layered over time due to new technological implementations or mergers and acquisitions. The problematic situation in managing data and conducting spend analysis is exaggerated by the low digital maturity of buyers, who often lack the appropriate skills to consciously approach a structured spend classification and maintain it over time. This issue can be summarized in the topic of *knowledge base management*, as outlined by Pandit and Marmanis (2008), and supplemented with the appropriate arguments on digital readiness and skills in buyer firms (Kosmol et al., 2019; Bals et al., 2019). Many procurement departments continue to use outdated systems alongside new AI solutions, resulting in disorganized databases and hindering the realization of expected benefits (Guida et al., 2023a). Additionally, the absence of a formalized process for information collection, storage, and democratization can create uncertainty, as organizations may struggle to predict and gather the necessary data for AI-based procurement solutions (Nandy and Seetharaman, 2019).

According to the received literature and corroborated by our case study, cultural resistance within procurement teams, rooted in traditional practices and tacit knowledge, further complicates the integration of AI, as these elements are not easily transferable to algorithms (Kosmol et al., 2019; Bals et al., 2019).

Further adding to the uncertainty in the deployment of an AI-based category management solution is the complex relationship between the buyer firm and the IT provider: according to the case studies, their relationship generates friction in the design of the solution and in the sharing of data to carry out an appropriate spend classification (Shore and Venkatachalam, 2003; Cox, 2001). Additionally, the ambiguity in interpreting organizational processes and the multiplicity of meanings associated with data further contribute to the uncertainty in adopting AI for spend classification (Nandy and Seetharaman, 2019).

Thus, the uncertainty described in the case studies is high, and this leads to the high IPN in spend classification.

Coping with the high level of uncertainty, proper capabilities are required (Tushman and Nadler, 1978) and the mechanisms developed by the IT providers are essential for the transfer of capabilities to the buyer firm. Structural mechanisms are strongly conditioned by the presence of a data-driven strategy in the buyer firm and the support of the IT provider in its development. Then, if the buyer firm does not have any transformational programs, mechanisms available to respond to the environment and other sources of uncertainty are weak (Enrique et al., 2022). In some cases, the IT provider play a pivotal role, managing the relationship with the buyer firm as a project rather than a service delivery and instilling within the client company a certain strategy associated with the adoption of AI in spend classification (Pandit and Marmanis, 2008; Kosmol et al., 2019).

In parallel to the digital strategy, change management at the procurement department level plays a key role for the adoption of AI to bring a viable improvement. The adoption of AI in spend classification requires the buyer firm to address potential challenges such as workforce adaptation and the integration of AI with existing systems, which can present certain difficulties (Durach and Gutierrez, 2024). As such, the adoption of AI in spend classification is affected by the initial strategic choices of the buyer firm and by the degree to which the relationship with the IT provider is nurtured. The technology component plays a key role as well. Although the capabilities developed by the IT provider are substantial and often address the buyer's data management issues, many providers in the sample reported significant challenges in developing these capabilities when the buyer's initial IT environment is complex. It is well described by Provider C: "*Handling customer data is very difficult since there are lots of gaps and no structured data which may prevent the good functioning of the AI technology*". Enhancing the capabilities of a buyer firm in conducting spend classification requires consolidating and automatically cleaning spend data, as well as normalizing and categorizing suppliers, which are essential for accurate spend analysis (Guida et al., 2023a). Additionally, AI systems must integrate with existing ERP systems to ensure seamless data sharing and validation, crucial for maintaining data accuracy and relevance (Burger et al., 2023). AI should support decision-making processes by providing actionable insights through interactive dashboards that visualize spend data and recommend potential savings. The integration of AI into procurement processes also demands a hybrid human-AI collaboration model, where human intelligence moderates and enhances AI outputs to ensure accuracy and relevance. This underscores the critical role of collaboration between the buyer and IT provider, facilitated by the iterative interaction with AI solutions, in handling abstract concepts that are informed by the user's business knowledge (Burger et al., 2023). This adaptation to new situations enhances overall the overall capabilities of the buyer firm in conducting spend classification.

Building on this, the alignment between the high Information Processing Needs (IPNs) and the Information Processing Capabilities (IPCs) facilitated by the IT provider may or may not be achieved. In certain instances, the AI-based spend classification solution achieves this alignment, where the high level of needs is complemented by high capabilities. Hence, this successful outcome can only be obtained when the buyer firm entails effective transformational programs supported by innovative tools supplied by IT providers. The buyer firm is highly aware of technological advancements, envisioning a clear digital transformation and the strategic leverage of AI. So, the AI-based solution for spend classification leads to a *match* between IPN and IPC, where significant uncertainties are counteracted by appropriate mechanisms (Tushman and Nadler, 1978).

In some other cases, the data-driven strategy is still lacking in the buyer firm, far from envisioning the digital transformation in the procurement department. However, the low level of Structural Mechanisms from the buyer side is partially solved by the high Capabilities of IT providers, transferred to them by deploying innovative solutions on their platforms. The buyer firm experiences the early approaches to innovations and a tactical usage of AI. Thanks to the IT provider's expertise and jointly project work of the parties involved, the AI-based solution bridges the uncertainties of the buyer firm and the capabilities of the IT provider, achieving a *match* (Tushman and Nadler, 1978).

The worse setting we encoded in the case studies describes a weak relationship between the buyer firm and the IT provider. The main reason is the low understanding of AI potentialities, due to the missing digital culture and strategy and the inability of the IT provider in conveying the values of digital transformation in the purchasing department of the buyer firm. Reasonably, both Structural and Technological Mechanisms are too low to overcome great Uncertainties within and outside companies' boundaries, as the buyer firms seem to be blinded in their routine activities. In this case, the extensive IPNs are not properly handled through IPCs, and a *mismatch* occurs (Tushman and Nadler, 1978).

Few case studies in the research relate to one single type of match, as each case study describes the characteristics of multiple IPN-IPC configurations recognized in the adoptions of AI-based spend classification solutions at different buyer firms. This is because the mechanisms at the base of capabilities are achieved gradually, through different states of digital maturity and readiness for change (Kosmol et al., 2019), so that clear-cut categories to describe the approach of buyers cannot be identified. A continuum of maturity and strategic relevance of purchasing digitization is recognized, which leads to a higher role for AI.

AI per se does not make a spend classification solution necessarily advantageous for the buyer, and each structural, process and technological aspect must be appropriately tailored to the requirements, skills, and readiness of the buyer firm, through strategic innovation and change management projects, jointly managed with the IT provider (Pandit and Marmanis, 2008; Patrucco et al., 2023).

6.2. Theoretical contributions

Our theoretical contribution lies in unraveling the intricate dynamics that determine how the adoption of AI in spend classification influences the alignment between information processing needs and capabilities. In procurement, this alignment is crucial due to the inherent uncertainty of the supply base (Busse et al., 2017). According to the OIPT, organizations use structural mechanisms like rules and procedures to manage information processing needs, which must align with their capabilities to reduce uncertainty (Bensaou and Venkatraman, 1995). The most significant mechanism identified in the research is technological. Information technology, through tools like machine learning and natural language processing, enhances information processing capabilities and better aligns with organizational needs. The flexibility and adaptability of IT infrastructures support the dynamic adjustment of information processing capabilities to meet evolving procurement needs. This finding confirms and extends prior knowledge, where OIPT has been applied to study the role of digital technologies in the purchasing and supply management domain (Cegielski et al., 2012; Zhu et al., 2018; Guida et al., 2023b). Indeed, the alignment between information processing capabilities and needs is directly linked to competitive advantage, especially when buyer firms adopt relatively unknown or emerging technologies. This advantage is amplified when the capabilities transferred by the IT provider during implementation are valuable, rare, difficult to imitate, and non-substitutable (Cao et al., 2015). In this context, decision-making effectiveness, linked to structural and process mechanisms, plays a key role in mediating the relationship between capabilities and competitive advantage, emphasizing the importance of strategic alignment in AI adoption.

The concept of task equivocality, as defined in received literature (Trautmann et al., 2009; Spreitzenbarth et al., 2024), also underscores the need for appropriate information processing mechanisms—such as specialized features, user support, direct contact, and integrator mechanisms—to manage varying levels of task uncertainty in procurement (Lorentz et al., 2021). Process mechanisms, including commitment and joint actions, help manage high task interdependence, shifting from impersonal rules to personalized exchanges when necessary (Bensaou and Venkatraman, 1995). This shift is reflected in the findings of our research. One of the most prominent results is the transition from the use of impersonal rules, typical of relationships with generic IT providers, to more personalized exchanges with specialized IT providers in the context of specific, strategic implementation projects. This also highlights the importance of domain-specific expertise, which must be integrated into AI-based spend classification solutions. Following the paradigm of hybrid intelligence (Burger et al., 2023), the involvement of procurement professionals becomes essential, as they contribute to the process either *in-the-loop* or *on-the-loop*, depending on the specific task.

6.3. Managerial implications

Current research on AI in purchasing, particularly in spend classification, remains limited and primarily technical, focusing on algorithm development and performance rather than practical business benefits (Zou et al., 2020; Roberts et al., 2014; Lee and Yoon, 2018). This lack of actionable guidelines for companies transitioning to AI-based tools represents a gap that this study aims to address, offering valuable managerial implications.

According to our research, AI is extensively utilized in spend analysis

Table 5
Information processing fit.

	Information Processing Needs	Information Processing Capabilities	AI	IPN-IPC fit
Provider A	**HIGH** High product technical complexity due to the high amount of data. High inter-unit conflict among organizational, functional and staff units because of many dispersed offices. Low degree of comfort about sharing data due to voluntary data sharing of suppliers. High horizontal complexity.	**HIGH** High ability to capture data, to integrate data, to analyze data, from the IT provider Low accuracy of the information coming from the buyer very often, preventing the exploitation of the IT provider capabilities. However, data-related services are provided, such as disambiguation, quality assurance and expedite.	Intelligent data processing for predictive and prescriptive analyses supporting spend analysis.	**Match**
Provider B	**HIGH** High product technical complexity due to the high amount of data. High inter-unit conflict among organizational, functional and staff units due to low alignment, to many dispersed offices, to categorization dependence on language. Low degree of comfort about sharing data on the digital platform.	**HIGH** The presence of a data-driven environment is key: depending on the change management initiatives within the buyer firm, it can be low to high. High level of joint actions thanks to set-up projects made to prepare the Software to provide the Service. High ability to capture data: software connectors enabling the interchange of data previously standardized from SAP, spend analysis modules directly integrated with ERP systems. High ability to integrate data: data integration with tacit knowledge from people ("knowledge engineering"). High ability to analyze data: flexibility and ability to adapt to the buyer firm data. Ability to use insights gained from data: the ultra-granularity of data enables automatic reasonings about spending. High information completeness and relevance: thanks to data cleaning algorithms, smart data gathering and automated analysis.	Natural Language Processing for the analysis of product description to design the category tree, to support the user in searching for materials that match with the description provided in natural language, for Master Data Management tool for cleansing, enriching, deduplicating, semantic search. Virtual assistants to prevent errors in purchasing processes by identifying the most suitable commodity code in the tree. Machine Learning, Deep Learning in particular, techniques are applied to autonomously learn from data starting from information provided by the customer in order to understand its past categorization schema.	**Match**
Provider C	**HIGH** Covid pandemic and new legislations increases the uncertainty. Low educational and technological background and skills, since companies do not trust the technology and its outcome. Low previous technological and managerial skill, as people working in procurement still work manually and with external systems. Interdependence of organizational units is affected by procurement silos. Data comes from more than one system, and it is difficult to access or aggregate it. High vertical complexity (Number of tier levels): data regarding the whole vertical structure of the SC is unknown.	**LOW to MEDIUM** Often missing data-driven strategy, because of the low level of digital maturity in the procurement department. High level of technical assistance and process engineering due to a complete platform customization. High ability to capture data (from purchase orders taken from customer's ERP). High ability to integrate data (e.g., DUNS number to check the financial stability of the supplier, integrating with data coming from info-providers for a cross-check). Low information accuracy, due to low-quality data coming from suppliers. Low information availability and completeness, due to missing data provided by suppliers. High internal connectivity (seamless integration with other solutions).	Intelligent Data Processing to forecast the future spend based on past data, to match purchase orders and invoices, to reach visibility into authorized and contract-based spend. Dynamic, data-driven recommendations to highlight the top spend drivers, to recommend actions to optimize the supplier base and minimize risk.	**Mismatch**
Provider D	**HIGH** High product technical complexity due to the specificity of this solution (tail spend management). High interdependence of organizational units in carrying out their objectives thanks to the database centralization. Good degree of mutual trust between the buyer and the supplier (almost 80% of supplier are willing to share data). Medium degree of comfort of the buyer about sharing information with the IT provider (buyers have no visibility on tail spend).	**MEDIUM** Variable presence of data-driven strategy, as few buyer firms applies a strategic approach in the management of tail suppliers. Medium commitment in adopting technology: missing provider-buyer-supplier collaboration. High technical assistance and high level of training/education provided by the IT provider. High ability to capture and integrate data from existing ERP, to have a continuous monitoring on spending (knowledge base). High information connectivity and availability.	Intelligent Data Processing to design and automatize the analysis Recommendation, or AI-driven communication, to observe and learn customer buyer firm's behavior and define a certain type of action plan in managing the spend analysis.	**Match Mismatch**
Provider E	**HIGH** High product technical complexity due to the high amount of data. High government regulatory control over the industry (industry specificities and tailored solutions). Low integration of organizational units: procurement silos in different units.	**MEDIUM to HIGH** The presence of a data driven strategy is key: digital transformation strategies are present in many buyer firms, but they are not implemented. Change management is too embedded in the company's culture, being a barrier for this solution. Need for evidence about ROI. High level of tactical assistance in the whole process. High level of training and education (very structured initial deployment). High ability to capture data from material management module and ERP. High ability to integrate data with semantic scan to enrich the knowledge base. High accuracy of data, even if data from suppliers are poor (ability to learn from data and accumulate knowledge based upon the customer-base, to fix some of data quality issues). Real-time processing of relevant information.	Natural Language Processing for the analysis of product description and for semantic search. Intelligent Data Processing to generate new insights and integrate data. Chatbot to support the buyer firm in the choice of the template/model to get some outcomes from data. Neural Networks to improve the quality and coverage of classification and to enhance delivery time for quarterly refreshes. Convolutional neural networks – a machine learning technology often applied to analyzing visual imagery – enrich spend data to provide enhanced	**Match**

(continued on next page)

Table 5 (*continued*)

	Information Processing Needs	Information Processing Capabilities	AI	IPN-IPC fit
		High internal and external connectivity (network of firms to capture every source of spend, across each category, for one unified view).	features like parent company information and standardized vendor naming. Neural Networks are used for image recognition, where images are transactional data.	
Provider F	**HIGH** High product technical complexity due to the high amount of data. External factors such as Covid pandemic and tariff-trade war between China and US increase uncertainty. Previous technological and managerial skill are low because of infrastructural and skills' issues. Low integration of organizational units: huge difficulties in having data under a common base, procurement silos. Geographical dispersion: huge size of the company, lot of people working from different places (cloud-based solution needed). Low degree of comfort in sharing data between the buyer firm and the IT provider.	**MEDIUM to HIGH** Presence of a data-driven strategy: buyers with a continuous-improvement behavior or early-adopter buyers. High ability to capture data (e.g., data are captured from PLM module for CAD systems rather than transactional records in SAP). High ability to integrate data (e.g., external data sources such as the supplier's data are integrated to the ERP data). High ability to analyze data (data consolidation and systematization, obtaining a global view and higher visibility).	Intelligent Data Processing is applied on the web to scout additional information to enrich data. Natural Language Processing used to process BOM information to clean, enrich and categorize data about the purchasing category. Supervised and unsupervised techniques are used for data cleaning.	**Match**
Provider G	**HIGH** High product technical complexity due to the high amount of data. Low educational and technological background and skills due to low awareness and trust about the potential of AI. Low previous technological and managerial skill. Low integration of organizational units: huge difficulties in having data under a common base, procurement silos. Low trust and comfort in data sharing.	**MEDIUM to HIGH** Presence of a data-driven strategy is a key, but many buyer firms miss it. Purchasing maturity: most of the companies are not mature enough as to adopt AI systems. High level technical assistance and training, based on the buyer firm's maturity and the previous technology adopted. High ability to capture data, as the platform is able to connect to multiple systems and extract structured and unstructured data. High ability to integrate data, thanks to the connection with external systems and info-providers; network effect from the data lake of many firms. High ability to analyze data (e.g., Integration with Tableau, predictive/prescriptive techniques). High data accuracy, even if data from suppliers is dirty (the knowledge base is integrated within the classification activity of the commodity tree, data are cleaned and maintained).	Recommendation systems are adopted to facilitate the platform navigation. Intelligent Data Processing is applied to analyze and classify data and to run what-if scenarios and prescriptive/predictive analyses.	**Match**
Provider H	**HIGH** Low educational background, mainly due to the buyer's fear of being-taken-over. Low previous technological and managerial skill in the purchasing dept., managed with traditional tools and processes. Low integration of organizational units: huge difficulties in having data under a common base, procurement silos, local old-style BI systems.	**MEDIUM** The presence of a data-driven environment and change management initiatives is key, the success of the solution depends on it. Procurement is at early-stages of development of this technology, even in advanced companies. High ability to capture data, from the ERP and suppliers' systems. High ability to integrate data, integration with info-providers (knowledge base at multiple tier in the SC). High ability to analyze data (integration with the data-lake of all the information of other firms). High ability to use insights gained from data (extracting value from the descriptions in the ERP, creating knowledge). Low data accuracy in the information from the suppliers. Data cleaning and processing algorithms allow to detect and correct inaccurate data, increasing data quality.	Advanced data processing to crawl the web to enrich the classification process. Natural Language Processing applied to text descriptions contained in ERP transactions, which are analyzed by text classification. Recommendation systems are used to support customers along the categorization process.	**Match Mismatch**
Provider I	**HIGH** Educational and technological background and skills, due to the missing knowledge and awareness about technology. Low integration of organizational units: huge difficulties in having data under a common base, procurement silos, data dispersion due to mergers and acquisitions. Inter-units conflicts coming from problems in integrating data from different locations and in many different languages.	**MEDIUM** Often missing data-driven strategy, because of low level of digital maturity in the procurement department. Change management supports the digital strategy, it is not present in all the buyer firms. Low procurement maturity in the adoption of AI. High technical support (also through chatbots) and high training/education to the buyer firm High ability to capture data, from the ERP. High ability to integrate data, integration with info-providers. Low data accuracy the information from the supplier (basic usage of AI for the duplicate removal, advances AI application for data cleaning and analysis). Low data availability from the supplier.	Intelligent Data Processing to design and automatize the analysis. Recommendation systems to drive the customer along the process, suggesting actions and next steps. Chatbot to provide technical assistance.	**Match Mismatch**
Provider J	**HIGH** High product technical complexity due to the high amount of data.	**HIGH** Increasing digital maturity of the purchasing dept. Change management supports the digital strategy, it is	Combined techniques of intelligent data processing and classification to extrapolate and	**Match**

(*continued on next page*)

Table 5 (*continued*)

	Information Processing Needs	Information Processing Capabilities	AI	IPN-IPC fit
	Educational and technological background and skills, because of the reluctance to change. Low previous technological and managerial skill, due to the conservative mindset. Low integration of organizational units: huge difficulties in having data under a common base, procurement silos, data dispersion due to mergers and acquisitions. Inter-units conflicts coming from problems in integrating data from different locations and manufacturing facilities, and in many different languages.	not present in all the buyer firms. High level of process engineering (spend analysis is built around the buyer firm taxonomy). High technical support and training, always available. High ability to capture data, from the ERP and other sources with high granularity. High ability to integrate data, integration with info-providers (knowledge base in the SC). High ability to use insights gained from data. Low data accuracy and availability the information from the supplier. Low information completeness, considering data from purchase orders, invoices, and other documents made by procurement people. Cleansing algorithms to compensate ow data accuracy and completeness (increasing input data quality).	connect information from imperfect data sets to make assumptions about how to classify data, suggesting them to the buyer firm.	

to enhance and accelerate various processes, such as automatically classifying expenditures within category trees, cleaning datasets, and analyzing spending patterns. AI also plays a crucial role in managing supplier data by ensuring accurate records across all business systems. Through web-crawling techniques and the integration with information providers, AI leverages external data sources—such as market indices, suppliers' credit ratings, and publicly available supplier information. Despite these advancements, current procurement software applications integrate AI primarily for narrow and specific use cases, reflecting the limitations and developmental state of the technology. This scenario introduces a new paradigm for managing IT systems and the relationship with IT providers.

Our research identified the strategic partnership between the buyer firm and the IT provider as a critical factor. This was revealed through the analysis of the buyer's IPNs and the matching IPCs. The study formalizes the essential capabilities that IT providers offer to buyers, addressing existing deficiencies and bridging gaps in their current processes. Indeed, the fit between IPNs and IPCs is critical in inter-organizational relationships, where effective information sharing and appropriate structural mechanisms enhance performance (Bensaou and Venkatraman, 1995; Bag et al., 2020). This concept is well applied in the specific cases analyzed in our study, focusing on the buyer-IT provider relationship in the joint implementation of AI-based spend classification solutions.

Buyer firms are provided with a valuable guideline for exploring the potential of AI, enabling them to better understand how to leverage these technologies for procurement and spend classification. On the other hand, IT providers can use the presented findings to identify the key activities and support areas required to address buyers' challenges effectively. This dual perspective offers actionable insights for both parties, creating a foundation for smoother technology adoption.

Additionally, IT providers should prioritize offering tailored solutions that align with buyers' specific needs, fostering a strategic partnership rather than a transactional relationship. This includes proactive guidance during platform implementation, ongoing support for system optimization, and ensuring the scalability of solutions to accommodate future requirements. By mitigating these pain points, IT providers can accelerate adoption and help buyers maximize the value of AI-powered tools.

From the buyers' perspective, the insights provided in this study highlight the factors critical to ensuring a successful investment in AI technologies. Buyers are encouraged to focus on internal preparation, such as enhancing organizational readiness, fostering cross-functional collaboration, and developing employees' digital competencies. Properly aligning their structure, processes, and culture with the demands of AI implementation will enable buyers to fully capitalize on the benefits of the technology. Furthermore, understanding the long-term strategic impact of these investments ensures that buyers can prioritize resources effectively and achieve a sustainable competitive advantage.

6.4. *Limitations of the study and future research*

The first limitation is related to the sampling of case studies in the presented research: we examined the perspective of the IT providers only. Since there are currently few adopters, the contributions from the buyers' viewpoint are limited, but this will be an important area for future research as more cases become available.

Also, given the specificity of the solutions provided, some AI solutions constituted a stand-alone application case, making it difficult to assess a common practice among IT providers. Future research can build on the foundational insights presented in this paper to investigate advancements in other AI applications supporting spend classification or strategic procurement activities and examine their impact on performance improvements. Additionally, future studies could investigate specific applications or tools with similar characteristics. Indeed, practitioners and academics assuming the lenses provided in this study may provide complementary resources to bridge the gaps mentioned above.

7. Conclusions

This study advances our understanding of how AI influence the alignment between information processing needs and capabilities in spend classification. By elucidating the intricate dynamics of this alignment, our research highlights the crucial role of advanced information processing capabilities in managing the uncertainty underlying spend classification. The findings contribute to existing literature by offering a comprehensive view of the rationale behind AI adoption in procurement processes and clarifying how AI can bridge gaps between current capabilities and needs. Furthermore, the study provides actionable insights for both buyers and IT providers, emphasizing the importance of addressing practical challenges and leveraging strategic partnerships to optimize technology adoption. As the field evolves, these insights offer valuable guidance for firms seeking to navigate the complexities of digital transformation and improve procurement efficiency through AI-driven solutions.

CRediT authorship contribution statement

Michela Guida: Writing – original draft. **Federico Caniato:** Conceptualization. **Antonella Moretto:** Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

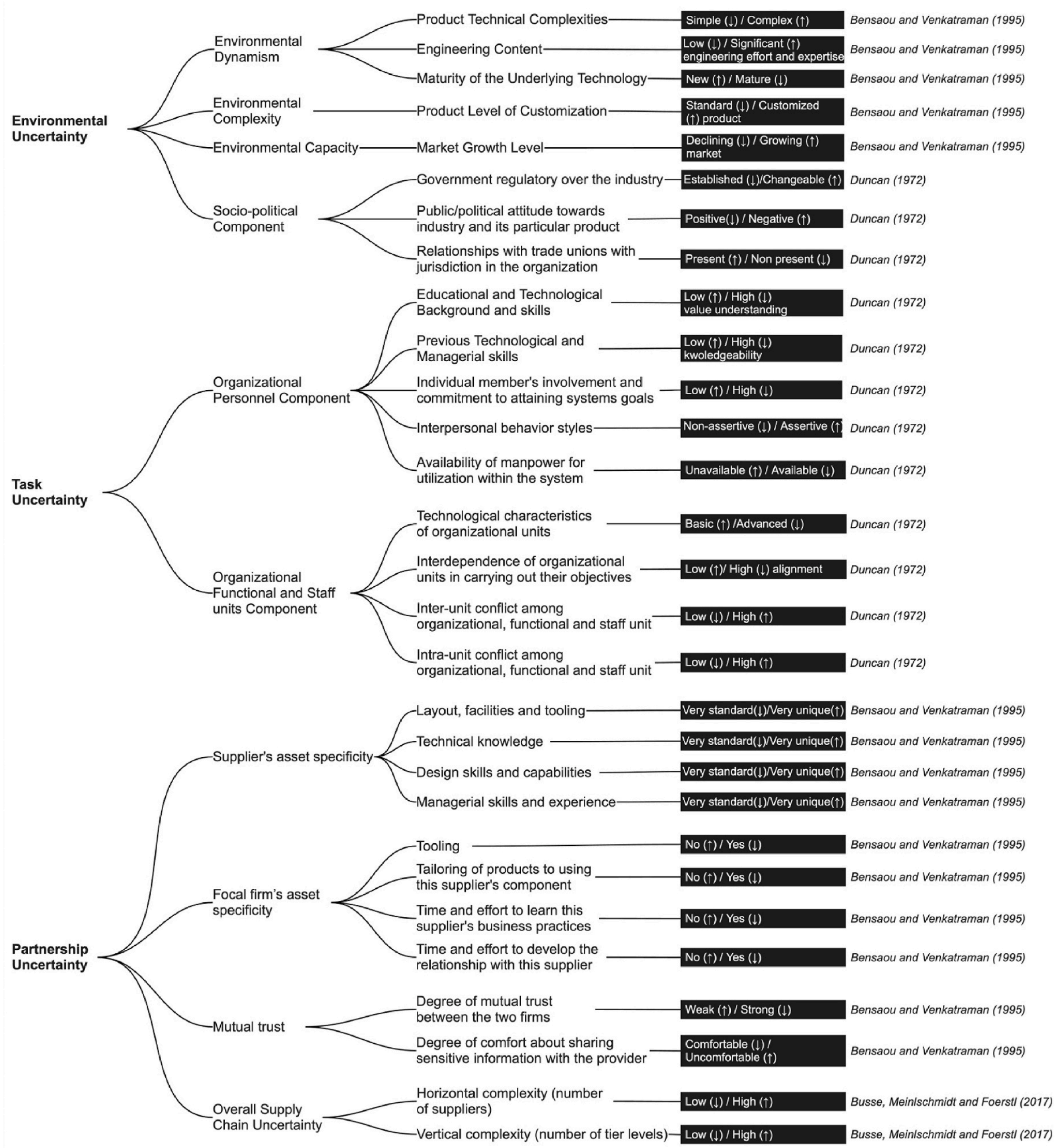
Acknowledgements

This research is part of the HumanTech Project, which is financed by the Italian Ministry of University and Research (MUR) for the 2023–2027 period as part of the ministerial initiative "Departments of Excellence" (L. 232/2016).

This study was carried out within the MICS (Made in Italy – Circular and Sustainable) Extended Partnership and received funding from the European Union Next-GenerationEU (PIANO NAZIONALE DI RIPRESA E RESILIENZA (PNRR) – MISSIONE 4 COMPONENTE 2, INVESTIMENTO 1.3 – D.D. 1551.11-10-2022, PE00000004). This manuscript reflects only the authors' views and opinions, neither the European Union nor the European Commission can be considered responsible for them.

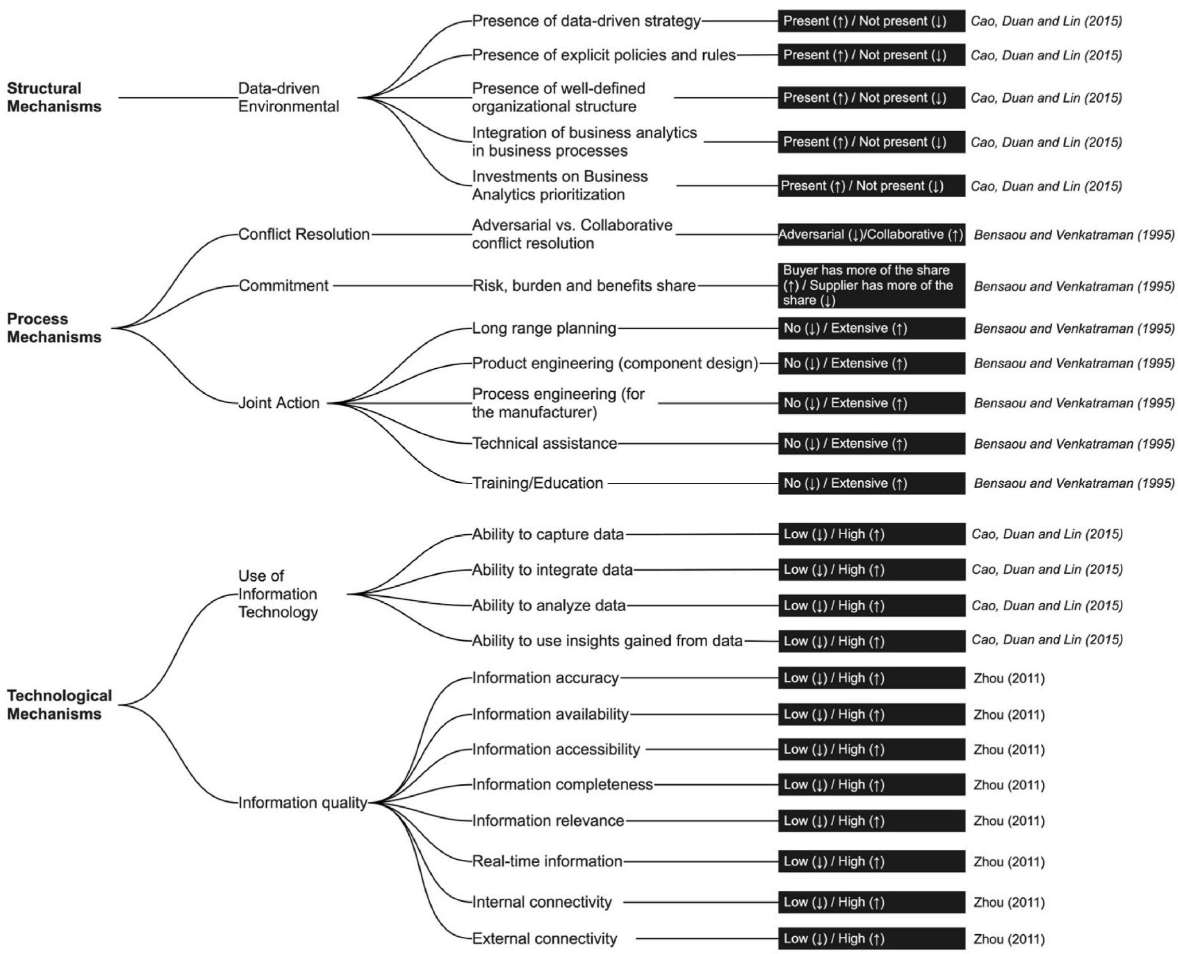
Annex A.

Coding Tree: Information Processing Needs – Uncertainty.



Coding tree: Information processing needs - Uncertainty

Coding Tree: Information Processing Capabilities – Mechanisms



Coding tree: Information processing capabilities - Mechanisms

Annex B. Cross case analysis – AI techniques and algorithms for spend classification

		Provider A	Provider B	Provider C	Provider D	Provider E	Provider F	Provider G	Provider H	Provider I	Provider J
AI techniques	**Intelligent Data Processing**	–	–	**Spend analysis** - The "Spend Insights" dashboard presents the data in a simplified user interface that enables a logical flow to an organization's data history; it provides granular details, such as visibility into authorized and contract-based spend. In addition to facilitating a more intuitive spend analysis experience, the dashboard introduces dynamic, data-driven recommendations. It also offers recommendations on the actions they can take to optimize their supplier base and minimize risk.	–	–	**Category tree** - Intelligent Data Processing is applied on the Web to scout additional information to enrich data and ensure powerful insights. Through the application of AI engines based on ML on customer's BOM (very likely, NLP), our solution is able to clean, enrich and categorize data so that customers can use it with BI systems with a deeper granularity. **Spend analysis** - Intelligent Data Processing is applied on the Web to scout additional information to enrich data and ensure powerful insights.	**Spend analysis** - Advanced Data Processing is applied to analyze and classify data, and to run what-if scenarios and prescriptive/ predictive analyses.	**Category tree** - Advanced Data Processing is used to crawl the web to enrich the classification process.	–	**Spend analysis** - Intelligent analytics extrapolates and connects dots from that imperfect data set in order to make good assumptions about how to classify spending data.
	Natural Language Processing	–	**Category tree** - The algorithm does not start from the customer's category tree, it starts from the description of the product written in Natural Language. The solution supports the user in material searches by suggesting the most suitable materials that match with the description provided		–	**Category tree** - Our solutions for category tree definition are based upon semantic research (NLP).	–	–	**Category tree** - Lot of value is extracted from text descriptions contained in ERP transactions, which are analyzed by text classification (Natural Language Processing).	–	–

(*continued on next page*)

(*continued*)

	Provider A	Provider B	Provider C	Provider D	Provider E	Provider F	Provider G	Provider H	Provider I	Provider J
		by the user in his natural language. Master Data Management tool is designed for cleansing, enriching, deduplicating and governing Materials Master data through semantic research.								
Recommendation Systems	–	**Category tree** - Virtual Assistants embedded in the system to prevent errors in purchasing processes by identifying the most suitable commodity code in the category tree.	**Spend analysis** - Advanced Data Processing can forecast the future spend based on past data In matching purchase orders and invoices, our machine learning algorithm determines the match automatically, fostering efficiency. The "Smart Coding" technology automatically searches and analyses the historical data and invoice coding templates to recommend the right match. Learning from company financial data, the machine learning engine improves the accuracy of its recommendations.	**Spend analysis** - Smart communication, or AI-driven communication, is employed in order to observe and learn customer behaviors and define a certain type of communication based on that	–	–	**Category tree** - Recommendation systems are adopted to facilitate the platform usage for the customers and have a dynamic support onto it.	**Category tree** - Recommendation systems are used to support customers along the categorization process and the definition of the category tree.	**Category tree and Spend analysis** - Recommendation systems drive the customer along the process, suggesting actions to do and next steps.	–
Virtual Assistant/ Chatbot	–	–	–	–	**Spend analysis** - A Chatbot was introduced to support the customer in the choice of the template/model to get some outcomes from data. The Chatbot on the platform is not perceived as a tangible benefit by the buyer firm. The smart technology is appreciated whenever it is capable of capturing non-structured data and	–	–	**Spend analysis** - A chatbot is available on the platform and functioning as a tool to assist customers	**Category tree** - A chatbot is available on the platform, as a tool to assist customers	–

(*continued on next page*)

(*continued*)

		Provider A	Provider B	Provider C	Provider D	Provider E	Provider F	Provider G	Provider H	Provider I	Provider J
						extracting useful information to take decisions, so some customers are highly proactive towards					
Algorithms	**Supervised/ Unsupervised Algorithms**	–	–	–	–	-	**Category tree** - There's a mixed usage of both supervised and unsupervised techniques since it is still impossible to obtain 100% data cleaned through an automatic activity. **Spend analysis** - There's a mixed usage of both supervised and unsupervised techniques since it is still impossible to obtain 100% data cleaned through an automatic activity.	–	**Category tree** - Both supervised and unsupervised techniques are applied. **Spend analysis** - Both supervised and unsupervised techniques are applied.	-	–
	Neural Networks	–	**Category tree** - In a part of the process, Machine Learning, Deep Learning in particular, techniques are applied in order to autonomously learn from spending data starting from information provided by the buyer firm, in order to understand its past categorization.	–	–	**Spend analysis** - We are using neural networks to improve the quality and coverage of classification and to enhance delivery time for quarterly refreshes. Convolutional neural networks – a machine learning technology often applied to analyze visual imagines –	–	–	**Category tree** - Our solutions for the definition of the category tree and spend analysis are often based on Recurring Neural Network. **Spend analysis** - Our solutions for the definition of the category tree and spend analysis are often based on	-	–

(*continued on next page*)

(*continued*)

	Provider A	Provider B	Provider C	Provider D	Provider E	Provider F	Provider G	Provider H	Provider I	Provider J
		NLP nowadays is performed through the implementation of neural networks.			enrich spend data to provide enhanced features like parent company information and standardized vendor naming in a fraction of the time formerly required. CNNs are a type of artificial intelligence that is based on “image” recognition. In the context of commodity enrichment, the “image” is the transactional data.			Recurring Neural Network.		

Annex C. Cross case analysis (1st order) - Uncertainty

		Second-order Variable	Provider A	Provider B	Provider C	Provider D	Provider E	Provider F	Provider G	Provider H	Provider I	Provider J
Environmental Uncertainty	**Environmental dynamism**	**Product technical complexity**	High data volume, high heterogeneity in buyer master data. ***Complex***	High data volume, high heterogeneity, multiple levels of information (category tree). ***Complex***		High data volume, high heterogeneity, multiple levels of information (tail spend, category tree, M&A and data alignment). ***Complex***	Complex invoice classification. High data volume, high heterogeneity. ***Complex***	High data volume. ***Complex***	High data volume and long processing time. ***Complex***			Need for SC complexity mapping. High data volume, high heterogeneity, multiple levels of information. ***Complex***
		Maturity of the underlying technology			Even though AI sounds well known, there's no evidence of companies already using it actively; anyway, they are in the		The implementation of intelligent systems provided by big players with a great portfolio of technologies already trained		Generally, the willingness of companies to invest in technologies such as chatbots, NLP, AI is moderated; they are cautious and still not ready		The industry is not ready for the implementation of AI. The procurement maturity is very low in the adoption of AI solutions, this is	Provider is trying to push toward a standardization, this make integrations very cheap, which would allow to sell products to much smaller

(*continued on next page*)

(*continued*)

	Second-order Variable	Provider A	Provider B	Provider C	Provider D	Provider E	Provider F	Provider G	Provider H	Provider I	Provider J
				development phase. ***New***		and well-established makes the customer more willing to go for it; they are ready-to-use and they don't require much time for the implementation, which may represent a barrier. ***Mature***		to burden risk by investing in non-consolidated technologies. ***New***		due also to the maturity of the technology. The 80% of implementations are first adoptions. ***New***	companies. ***Mature***
Socio-political component	**Governmental regulatory control over the industry**			The interlocutor reckons that the pace at which the environment is evolving is a factor pushing towards changes and innovations. Also, new factors such as COVID, new legislations and so on, make things evolve even more quickly. ***Changeable***		To address unique regulatory requirements you may face or other nuances specific to your business, you need to be able to tailor and enhance your solutions quickly and easily. ***Changeable***	External factors such as COVID-19 and tariff-trade war between China and US have made the environment even more complex than it already was. ***Changeable***				
Other unpredictable factors	**COVID-19, chip shortage, international conflicts**			The pace at which the environment is evolving is a factor pushing towards changes and innovations. Also, new factors such as COVID, new legislations, supply chain disruptions, make things evolve even more quickly ***"in vivo" code: ↑IPN***	COVID-19 has shifted the focus on short-term decisions (like savings), making it difficult to conceive an investment in AI technologies ***"in vivo" code: ↑IPN***	As the speed and complexity of change increase for businesses, managing spending becomes increasingly critical. Unpredictable market forces put a new strain on budgets, plans, and business models, while customers and employees continue to demand more from the organizations from which they buy and work. ***"in vivo" code: ↑IPN***	External factors such as COVID-19 and tariff-trade war between China and US have made the environment even more complex than it already was. ***"in vivo" code: ↑IPN***	COVID-19 has functioned as an accelerator for the adoption of these technologies in an already changing environment. ***"in vivo" code: ↑IPN***		COVID-19 made things evolve really quickly, enhancing the pace of the processes' digitalization. ***"in vivo" code: ↑IPN***	With COVID, three different reactions by buyers emerged: someone gave up and deleted the project, someone postponed to the next year, and for other clients COVID was an accelerator of the process of transition. ***"in vivo" code: ↑IPN***

(*continued on next page*)

(*continued*)

		Second-order Variable	Provider A	Provider B	Provider C	Provider D	Provider E	Provider F	Provider G	Provider H	Provider I	Provider J
Partnership Uncertainty	**Supplier's asset specificities**	**Layout, facilities and tooling**		This provider delivers both legacy as well as on-premises systems which are not run in Cloud for security reasons. ***Very standard***							The possibility to adapt the platform under customer's specific requests is almost denied. ***Very unique***	
	Mutual trust	**Degree of mutual trust between the two firms**		The provider has the grants to access directly to the customer's data through SAP platforms; this level of digitization has facilitated the interchange of information between actors. ***Strong***		Data sharing by suppliers is not a barrier, almost 80% of the invited are willing to register. ***Strong***			An important issue is that customers would like to obtain some results and new insights, even if not willing to share data in order to process information. ***Weak***	Customers always want a proof of the value that may arise by implementing the solution; this is shown by sharing successful use-cases with customers. ***Weak***		Thanks also to the cloud computing paradigm companies started to change their perspective and trust providers and the data sharing process. ***Strong***
		Degree of comfort about sharing sensitive information with the provider	The higher tangible benefit is the access to buyers' suppliers' data, who can freely register on the platform, sharing their own data to the provider. ***Confortable***	The provider has the grants to access directly to the customer's data through SAP platforms; this level of digitization has facilitated the interchange of information between actors. ***Confortable***		Spend data used as input may come from whatever ERP/ Spend Data system but is voluntarily shared by the buyer, that is often reluctant. ***Unconfortable***		When talking about the relationship with the customers, the provider states that even though they can go beyond customers' systems, data accessibility is a typical issue that is detrimental to the functioning of AI-based solutions. ***Unconfortable***		Source of data is mainly the ERP systems, but there's also a source of suppliers' data which results better, sometimes. ***Confortable***	Customers have no problem in sharing their data because the platform is considered a better and safer environment for data sharing. ***Confortable***	
	Overall Supply Chain Uncertainty	**Vertical complexity (number of tiers)**			From the buyer's viewpoint, data regarding the whole vertical structure of the SC is unknown. In fact, suppliers' organization list may be available (list of suppliers' partners), but							

(*continued on next page*)

(*continued*)

		Second-order Variable	Provider A	Provider B	Provider C	Provider D	Provider E	Provider F	Provider G	Provider H	Provider I	Provider J
					usually hidden; the structure, instead, is usually unknown, making it impossible to reach that level of data ***High***							
		Horizontal complexity (number of suppliers)	Complex management of clients' suppliers master data. Customers adopting the solution already have a supply base, which may count of hundreds or even thousands of suppliers. ***High***			Tail suppliers are not commonly addressed because they are a lot and with small dimensions. For this reason, buyers have no visibility on that kind of data nor knowledge on what is happening. ***High***					When dealing with tail spend, the multitude of suppliers to be handled represents a relevant problem for customers. ***High***	
Task Uncertainty	**Organizational personnel component**	**Education and technological background and skills**			Regardless the AI technique considered, customers tend not to trust the technology, preferring to do everything by themselves with simple extractions from spreadsheets. Apart from not trusting the technology as a starting point, the outcomes provided are not trusted either way. Trying to sell AI technologies usually tends to get a rejection from buyers. Regardless to the AI technique we are			When answering about the fear about having an automated system doing the job for you or perceiving the technology when using it, the provider states that its customers are not afraid of it nor lack of trust. ***High value understanding***	Companies are intrigued by this new technology but still are frightened by it because they have not fully captured the potentiality and how to apply it within their business boundaries. ***Low value understanding***	Some customers feel threatened by the technology given the fear of being taken over. ***Low value understanding***	The average age of procurement people is quite high and their ability to use new technologies as well as understand and trust them is not well developed. ***Low value understanding***	People are hesitant to try something new because they are used to work in the same way for 10 years. ***Low value understanding***

(*continued on next page*)

(*continued*)

	Second-order Variable	Provider A	Provider B	Provider C	Provider D	Provider E	Provider F	Provider G	Provider H	Provider I	Provider J
				considering, there's a lack of trust by the user which makes them feel like they can do better by themselves. ***Low value understanding***							
	Previous technological and managerial skills						Both infrastructural and skills changes and advancements have been perceived by the provider. Companies started to perceive the value under data and appreciate that with small changes they can obtain huge results. ***High knowledgeability***	The advent of new technologies has facilitated the changes in the skills. 50% of the clients of this provider state that they possess a partial if not null digitalization knowledge. The ability to use efficiently new technologies is a critical factor: our study reveals that with a proportion of 50-50 of professionals affirm being updated on recent developments and those without sufficient knowledge. ***Low knowledgeability***	When dealing with procurement and data, there's a gap in the skills required in order to understand the potentiality and put some analysis in place. For this reason, the provider has to make it as easy as possible In many cases, Procurement is carried out by old people that are not expert about technology. ***Low knowledgeability***		Buyers have very little patience or time for learning new complicated software or take any risk if a process would go wrong, so they tend to be conservative, they're slow and adapting. ***Low knowledgeability***
Organizational functional and staff units component	**Interdependence of organizational units in carrying out their objectives**		Once the automatic categorization is implemented, each category will be automatically inserted in the system, creating an internal alignment within buyer's boundaries by using the same data and talking the same "language".	Procurement silos burden staff with manual tasks and ad-hoc workarounds that hamper responsiveness and speed. When dealing with procurement departments, the problem of silos is well acquainted. Data comes from	One further goal of this platform is the centralization of the systems around the data that enables a higher visibility within the company, as the buyer firm has many issues in data integration. ***Low alignment***	The view of data is further complicated as companies are automating systems to address individual needs like travel, expenses, and procurement, without ensuring these systems talk to each other. Information silos create a lack of visibility that inevitably impacts	Even the "best" companies show important difficulties in having data under a common base, showing data silos based on the department they are working for. Usually companies show very differentiated departments and way of doing, but they want to maintain a certain	The greater barrier in digitalization is the lack of data integration regardless the system you have in place. Information is collected in silos and is mandatory to unify the source as guarantee of data integration and quality. ***Low alignment***	Companies tend to create different analytical departments that are not working aligned. For this reason, they tend to outsource to such activities and the provider presents a solution suitable to develop the capability of dealing with such complexities. In addition, most of	The problem arises when a company has many ERPs corresponding to each company's BU and they have to be integrated all together We have also clients that are the results of many mergers and acquisitions and as a consequence there isn't a unique company	Data is often a challenge since it resides in a lot of different systems. Might be in ERP systems and typically a client probably has 40 Different ERP systems because of continuous acquisitions going through. Data is spread across every different manufacturing

(*continued on next page*)

(*continued*)

Second-order Variable	Provider A	Provider B	Provider C	Provider D	Provider E	Provider F	Provider G	Provider H	Provider I	Provider J
		This solution support the buyer in solving data alignment issues. ***Low alignment***	more than one system and therefore is difficult to access or aggregate. The struggle is especially apparent for global corporations that communicate not just across departments but also across countries with different rules and regulations. Also, continuous mergers and acquisitions make the situation even more complex. ***Low alignment***		the bottom line with 50% of CFOs citing margin erosion due to inefficient decision making. Eliminating Silos: Taking on these challenges requires total control of each category of spending as well as a broader, comprehensive way to orchestrate spending and policy across categories. But traditional solutions can't do both. Certainly, each category of spend - from travel and expenses to direct and indirect to consultants, contractors, and an extended workforce - have unique nuances that require specific workflow, functionality, and processes. ***Low alignment***	global view in order to have benefits from bulk purchasing. The provider can ensure both aspects under a single platform in cloud. ***Low alignment***		the companies are endowed with internal BI solutions, but these are becoming slow, old-style and difficult to maintain ***Low alignment***	standard, each warehouse ***Low alignment***	facility, hence applying a different approach based on where data is handled. With 10 factories on 4 different ERP systems, you need to carry out about 4 different integrations, which is not a quick and cheap thing. ***Low alignment***
Inter-unit conflict among organizational, functional and staff units - Geographical dispersion		Companies receive cleaned and structured data back since it is very difficult to collapse data in different languages, codifications, … Once the data is obtained, the customer can work on it. ***High***				The internal complexity given by geographical dispersion, huge size of the company, lot of people working from different places make it fundamental to adopt a cloud-based solution. ***High***			A customer experimented the application of AI in Spend analysis because of problems in integrating data coming from different locations and in many different languages ***High***	The quality and the fragmentation of the data due to geographical dispersion or great difference in languages or culture is still one of the biggest challenges and one of the biggest impediments to getting to the power of AI. ***High***
Inter-unit conflict among organizational,	The provider is able to give a global view on	This provider gives examples of big							A customer experimented the application of AI	Data cleaning is tough because is spread across

(*continued on next page*)

(*continued*)

		Second-order Variable	Provider A	Provider B	Provider C	Provider D	Provider E	Provider F	Provider G	Provider H	Provider I	Provider J
		functional and staff units - Language heterogeneity	data of the same company but with dispersed location that, otherwise, would be difficult to harmonize. ***High***	companies that are currently facing big complexities in terms of geographical dispersion, different culture and languages, continuous expansion, and volume of transactional data. This represents a difficulty in data integration and alignment. ***High***							in spend analysis because of problems in integrating data coming from different locations and in many different languages. ***High***	every different manufacturing facility, doing it a different way. There are big companies operating in 30/40 countries, maybe 200 facilities, and they are in the process of transforming their indirect procurement department but is not so easy. ***High***

Annex D. Cross case analysis (1st order) - Mechanisms

		Second-order Variable	Provider A	Provider B	Provider C	Provider D	Provider E	Provider F	Provider G	Provider H	Provider I	Provider J
Structural Mechanisms	**Data-driven Environment**	**Presence of data driven strategy**		Change management initiatives inside the buyer company are key to obtain great results together with the technology. ***Present/Not present depending on the buyer firm***	We are going into the direction of a full digitization, but we are still far away. So what procurement is really asking is to potentially digitize the basics first. Maturity level of procurement is low: you have the zero level, then the basic (where they're putting into	Organizations applying a strategic approach in the management of tail suppliers are examples of the provider's successful cases of adoption. However, few buyer firms applies a strategic approach in the management of tail suppliers. ***Present***	Everyone has a digital transformation, but when it comes to put it in place, concretely, it is not so easy. In today's unpredictable world, implementing a real-time, intelligent spend management strategy is the best way to minimize uncertainty. Change management is	There are two kinds of customer adopting these solutions: either the ones with a continuous-improvement behavior or the other who are early-adopter of the technologies. There are some companies which are not sophisticated enough as to capture the	The presence of a good top management able to understand the benefits, perceive the potentiality and push the adoption is key to have a successful implementation. The issue for many organizations is the lack of a formal strategy. Studies reveal that most teams within procurement do not own a complete plan to	When companies have transformational programs in act, it helps in the adoption. When change management is carried out in companies, this is tangible for the provider since a transformation program is key to change the way in which procurement is done. Even though most of the companies	Big Italian companies have no interest in digitalizing part of the processes because of used to work in their old-fashioned way. Real transformational strategies, therefore, do not exist. There is no trust in the digital tool proposed and this is a problem related to the change management,	There's a technology adoption issue for sure related to training and getting people to adopt different processes and different ways of working through new strategies and policies, is a difficult challenge. Things are maturing very quickly; buyers are moving to a data lake environment by

(*continued on next page*)

(*continued*)

		Second-order Variable	Provider A	Provider B	Provider C	Provider D	Provider E	Provider F	Provider G	Provider H	Provider I	Provider J
					place procurement in organization) then the intermediate (where they know already a little bit how to do it), then the advanced (they are quite strong already). Then the expert's side of procurement organizations is very rare, expert type of procurement organization that would embrace this new technology already, because they have their processes in shape and ready for a real data-strategy. ***Not present***		literally too embedded in the company's culture, they have great difficulties in changing even for a little step, concretely. Change management mechanisms may result as a barrier in the implementation process since companies tend to focus on the modelling of the process rather than the strategic initiative embedded in it. The approach to AI technologies and advanced algorithms in the three steps was slow but continuous, pushed by higher ROI more tangible. ***Not present***	value of such solution. Procurement always results as being the least developed part of an organization too advanced, so that companies are too confident in what they're doing by themselves and do not think that the provider could help them at all. ***Present/Not present***	carry out activities effectively. Research conducted by this provider shows that only 32% of procurement within organizations have a formal digital strategy in place. Most of the companies are not mature enough as to adopt AI systems. ***Not present***	show data-driven approaches, procurement results being at early-stages of development and with high potentiality in using such innovations. ***Not present***	people don't want to change their processes and procedures. The digitalization process is being adopted by companies following the providers. The procurement maturity is very low in the adoption of AI solutions, this is due also to the maturity of the technology. The 80% of implementations are first adoptions. ***Not present***	developing their systems to prepare the transformation. Companies are seeing it as a viable investment and now is the time to upgrade from what they have. The buyer firms are ready for it, they're hungry for the digital transformation. ***Present***
Process Mechanisms	**Commitment**	**Risk, burden and benefits share**				Procurement should enhance its value creation capability though the development of collaborations provider-buyer-supplier and innovation programs. (—)<						
	Joint Action	**Long range planning**										The provider works through future state design and develops improvement across all the steps, it builds the roadmap and an implementation plan. ***Present***

(*continued on next page*)

(*continued*)

		Second-order Variable	Provider A	Provider B	Provider C	Provider D	Provider E	Provider F	Provider G	Provider H	Provider I	Provider J
		Process engineering		A set-up project is necessary to prepare the Software to provide the Service. ***Present***	If the customer (i.e., the buyer firm) requires it, there's the possibility of customization around its own processes followed by a dedicated consultant. ***Present***							The IT Provider builds the spend analysis around customer's taxonomy, thus adapting the processes to it. ***Present***
		Technical assistance			If the customer (i.e., the buyer firm) requires it, there's the possibility of customization around its own processes followed by a dedicated consultant. ***Present***	To facilitate the usage of such technologies, project-related works prior to the implementation by the provider is necessary. ***Present***	The additional competitive advantage of the provider is the possibility of having a partner who can support customers along the whole process. ***Present***		The provider follows an approach to support the customer along the adoption and is dependent upon the maturity of the customer and the technological adoptions. ***Present***		In the platform there is a chatbot, a software able to help customers and suppliers driving them along the customer journey. ***Present***	A team of people is always available to provide technical support. ***Present***
		Training/ education				To facilitate the usage of such technologies, initial training works prior to the implementation by the provider is necessary. ***High***	In the initial deployment and training of the system, the project team 1) Identifies all team members that need to be trained 2) Determines level of training needed (Super User, Basic) 3) Develops long term training plans for quarterly refresher trainings 4) Identifies key areas for additional development ***High***		The provider follows an approach to support the customer along the adoption and is dependent upon the maturity of the customer and the technological adoptions. ***High***	Customers always want a proof of the value that may gain by implementing the solution; this is shown by sharing successful use-cases with customers. ***High***	The training department offers a continuous support to customers, whether it is for increasing the knowledge on the solution or to onboard suppliers. ***High***	
Technological Mechanism	**Use of Information Technology**	**Ability to capture data**	The service provided is integrated with P2P platforms such as Oracle and SAP. The availability of data is ensured by the access on SAP	Nowadays there are some software connectors which enable the interchange of data previously standardized from SAP. The	Data coming from Purchase Orders taken from customer's ERP. ***High***	By connecting with big existing ERP systems there are lot of opportunities arising such as getting the data in a seamless and easier way. The	The main source of data is represented by the Material Management module in SAP; anyway, when dealing with spend analysis,	Core source of data is PLM module for CAD systems rather than transactional records in SAP. Transactional records of ERP	The platform is able to connect to multiple systems and extract data either it being structured or unstructured data. ***High***	Source of data is mainly the ERP systems, but there's also a source of suppliers' data which results better, sometimes. ***High***	The platform is able to manage the Maverick spending of the customers hence there is the necessity of integration with customers' ERP to capture all the	Provider pulls data from multiple ERP sources of the customers. Provider is able to capture data with high granularity. ***High***

(*continued on next page*)

(*continued*)

Second-order Variable	Provider A	Provider B	Provider C	Provider D	Provider E	Provider F	Provider G	Provider H	Provider I	Provider J
	customer's data. ***High***	solution represents a module directly implementable on whichever ERP system, thus taking autonomously data from it. ***High***		connection with main ERP systems to catch spend data would enable the provider to have a continuous monitoring on spending. ***High***	data is extracted from lot of queries considering all the transactions inside the ERP. ***High***	are too superficial, the provider uses one level below in order to perform some analysis. ***High***			remaining spending data. The power of the AI stems in the possibility of integration with customers' ERP. ***High***	
Ability to integrate data	On the platform there's a match between the buyer's categorization and the one developed by the provider. This means that new suppliers may emerge from which the customer can analyze and choose new business opportunities. ***High***	Knowledge Engineering is based upon the idea that some tacit knowledge is contained inside people and cannot be learned by AI itself, you need to teach it and give it an interpretation ***High***	There's the possibility to integrate external data which makes the tool even more powerful. The provider considers mandatory to have all customers' suppliers with relative DUNS number as to check the financial stability of the supplier, hence they integrate with data coming from info-providers to have a cross-check. ***High***	Presence of knowledge base accumulated in order to improve the service overtime and learn the customer's behavior. ***High***	The semantic scan is performed to enrich the knowledge base of the technology by looking at more than 600,000 different sources like newspapers, publications, … ***High***	ERP systems are not sufficient as data source; hence the provider also relies on external data sources such as the supplier's data. The provider is enriching the data with many different features such as price standards, technical information and so on by scouting the web with intelligent systems. ***High***	There's a connection both between buyer's platform and the provider as well as a connection with external systems/ providers who can supply new kind of services linked to the data. Having a great user base and from multiple types of industries, they have accumulated and created a unique knowledge base that enrich the types of analysis that can be performed. ***High***	The provider also integrates third party data coming from info-provider or suppliers' data and creates a common knowledge base available for the whole customer-base. ***High***	The provider solution is able to integrate also external data. The integration of the platform is of fundamental importance, a platform without integration makes no sense. ***High***	The tool performs a comparison with data across all the pool of customers' spend, thus accumulating knowledge. The IT provider also integrates data coming from the supply base, thus creating an even stronger knowledge base. ***High***
Ability to analyze data	The provider guarantees data-related services such as disambiguation, quality assurance and expedite. ***High***	The potential value under the spending descriptions is huge, if caught. A competitive advantage of this provider is the ability of coping with problematic data related to procurement, their systems are highly flexible and adapt to the customer's data. ***High***				The provider through advanced data analysis is able to put the data together, obtains a global view and gives back higher visibility. ***High***	The integration of Tableau allows new insights based on AI algorithms with predictive/ prescriptive techniques. ***High***	The analysis provided for spending are based on best practices from different customers. ***High***		
Ability to use insights		The ultra- granularity						Descriptions have lot of hidden value		The ultimate benefit is the

(*continued on next page*)

(*continued*)

	Second-order Variable	Provider A	Provider B	Provider C	Provider D	Provider E	Provider F	Provider G	Provider H	Provider I	Provider J
	gained from data		enables automatic reasonings which are not possible if done manually or by a human being. ***High***						in the ERP transactions and clients are always surprised when finding out the insights. By putting together multiple customers coming from different industries, the provider has accumulated knowledge creating specific trees depending on the industry is dealing with. ***High***		ability of obtaining better insights to go to the market with better results. ***High***
Information quality	**Information availability**		Problematic transactions may cause some issues within the IT system since records unproperly inserted may result in invisible items inside the warehouses. ***Low***	This provider finds it difficult to handle customer data since there are lot of gaps and no structured data which may allow a good functioning of the technology. ***Low***	When dealing with tail spend management, most of the data we need come from the databases of the buyer firms. ***High***	When dealing with the commodity tree the issues arising are due to data availability and the correctness of the tree defined by the buyer. ***Low***		The key to have a successful implementation of these technologies stays in the match between data availability and the presence of smart technologies such as AI able to use such data. ***High***		Customers data are often not integrated in real time and there is a problem of data availability. ***Low***	
	Real-time information					There's huge value in real-time transaction processing, on a global scale, with millions of trading partners. ***High***					Being able to access to real-time data is the other trick about spend analysis. AI needs just to clean up data and maintain it cleaned overtime. ***High***
	Internal connectivity			The system ensures a seamless integration with other solutions and an organization's other business solutions. ***High***	Strong integration with internal data about tail spend categories. ***High***	Intelligent spend management is about bringing partner networks and ecosystems together to capture every source of spend, across each category, for one unified view. ***High***					
	External connectivity					Intelligent spend management is about bringing					

(*continued on next page*)

(*continued*)

Second-order Variable	Provider A	Provider B	Provider C	Provider D	Provider E	Provider F	Provider G	Provider H	Provider I	Provider J
					partner networks and ecosystems together to capture every source of spend, across each category, for one unified view. ***High***					
Information accuracy	Once the supply base is imported, this has to be classified inside the system. Most of the times, 20% of data from our customers results to be not properly classified, preventing the good results of our solutions ***Low to High***	The whole analysis is done taking for granted a good level of codification previously performed. However, in big companies there's a mean of 30% of errors. Some big enterprises have established a structured commodity tree, but it results useless in case of so many errors contained in the data. AI tries to cope with this. By applying AI for categorization through NLP by reading the descriptions you can obtain a 95% of accuracy. Having a quality data is an issue but IT and AI are making a change. The quality of data allows the user to perform the same tasks done 30 years ago but in a totally different manner. ***High***	An important issue is coming from suppliers' data since they have no tool to manage it, resulting in poor quality and low availability. In addition to unavailable data, there's an issue of data correctness. ***Low***		The data available and supplied by the customer is often poor and results difficult to start from it to build intelligent systems. Anyway, innovative systems able to learn from data and accumulate knowledge based upon the customer-base can fix many of these issues. ***High***	Customer with greater success show performances in terms of improved data quality, accuracy, and speed. ***High***	The data provided by the customer is usually dirty and not well classified, so every time there's the need of re-classifying them. Also, if there's no maintenance overtime, you need to start the process again. By integrating the knowledge base within the classification activity of the commodity tree, the provider can reach 80% accuracy of automated classification of data. ***High***	Most of the times when dealing with customer's data it results dirty and difficult to handle. When customer presents their own classification, they show lot of misclassifications in the data. ***Low***	The basic usage of the AI could be for the removal of duplicate data. The result of the AI application is the data cleaning in order to use the data in the platform. ***High***	Sometimes the data is incomplete, data is not very accurate. ***Low***
Information completeness		The quality of data allows the user to perform	The provider finds it difficult to handle				The data provided by the customer is usually dirty and			You have to try to understand everything you

(*continued on next page*)

(*continued*)

	Second-order Variable	Provider A	Provider B	Provider C	Provider D	Provider E	Provider F	Provider G	Provider H	Provider I	Provider J
			the same tasks done 30 years ago but in a totally different manner. Having a quality data is an issue but IT and AI are making a change. ***High***	customer data since there are lot of gaps and no structured data which may allow a good functioning of the technology. ***Low***				not well classified, so every time there's the need of re-classifying them. Also, if there's no maintenance overtime, you need to start the process again and our solution provides the new classification. ***High***			bought is in the form of purchase orders, which is often created by many people in the organization, sometimes the data is incomplete, sometimes the data is not very accurate. ***Low***
	Information relevance		The quality of data is what allows the user to perform the same tasks done 30 years ago but in a totally different manner. Having a quality data is an issue but IT and AI are making a change. ***High***								
	Information accessibility			In addition to unavailable data, there's an issue of data correctness. ***Low***							
	General quality of information	Moreover, the provider guarantees data-related services such as disambiguation, quality assurance and expedite. ***"in vivo" code:*** **↑IPC**					Customers usually do not have control on data and if they have, they often make the tagging wrongly. So, first of all is important to understand whether data		Buyer firms can enhance the value of their data. Intelligent data cleaning and processing algorithms enable the buyer firms to detect and correct inaccurate data. More consistent data ensures higher	The platform enhances the quality of data inserted by performing an initial data cleaning through pre-determined fields to uniform the data. The provider face problems with data	Data source is usually really dirty, low in quality. The challenge is in cleansing it all increasing the quality of data to be able to classify it correctly. ***"in vivo" code:*** **↑IPC**

(*continued on next page*)

(*continued*)

	Second-order Variable	Provider A	Provider B	Provider C	Provider D	Provider E	Provider F	Provider G	Provider H	Provider I	Provider J
							exists or not, then is important to look at how good is it. We has developed an AI engine that uses machine learning to scrub our customers' CBOMs and engineering data to get it 100% clean, correct, complete and up-to-date. ***"in vivo" code:* ↑IPC**		data quality and added value for your business. ***"in vivo" code:* ↑IPC**	on a daily basis. The customer by applying AI is able to make uniform the initial data. ***"in vivo" code:* ↑IPC**	

Annex E. Cross case analysis (2nd order) – Uncertainty and Mechanisms

			Provider A	Provider B	Provider C	Provider D	Provider E	Provider F	Provider G	Provider H	Provider I	Provider J
UNCERTAINTY:	**Environmental**	**Product technical complexity**	*Complex*	*Complex*	-	*Complex*	*Complex*	*Complex*	*Complex*	-	-	*Complex*
		Maturity of the underlying technology	-	-	*New*	-	*Mature*	-	*New*	-	*New*	*Mature*
		Governmental regulatory control over the industry	-	-	*Changeable*	-	*Changeable*	*Changeable*	-	-	-	-
		COVID-19	-	-	*"in vivo" code: ↑IPN*	*"in vivo" code: ↑IPN*	*"in vivo" code: ↑IPN*	*"in vivo" code: ↑IPN*	*"in vivo" code: ↑IPN*	-	*"in vivo" code: ↑IPN*	*"in vivo" code: ↑IPN*
	Task	**Education and technological background and skills**	-	-	*Low value understanding*	-	-	*High value understanding*	*Low value understanding*	*Low value understanding*	*Low value understanding*	*Low value understanding*
		Previous technological and managerial skills	-	-	-	-	-	*High knowledgeability*	*Low knowledgeability*	*Low knowledgeability*		*Low knowledgeability*
		Interdependence of organizational		*Low alignment*	*Low alignment*	*Low alignment*	*Low alignment*	*Low alignment*	*Low alignment*	*Low alignment*	*Low alignment*	*Low alignment*

(*continued on next page*)

(*continued*)

			Provider A	Provider B	Provider C	Provider D	Provider E	Provider F	Provider G	Provider H	Provider I	Provider J
		units in carrying out their objectives										
		Inter-unit conflict among organizational, functional and staff units - Geographical dispersion		*High*	-	-	-	-	-	-	*High*	*High*
		Inter-unit conflict among organizational, functional and staff units - Language heterogeneity	*High*	*High*	-	-	-	*High*	-	-	*High*	*High*
	Process	**Layout, facilities and tooling**	-	*Very standard*	-	-	-	-	-	-	*Very unique*	
		Degree of mutual trust between the two firms	-	*Strong*	-	*Strong*	-	-	*Weak*	*Weak*	-	*Strong*
		Degree of comfort about sharing sensitive information with the provider	*Confortable*	*Confortable*	-	*Unconfortable*		*Unconfortable*	-	*Confortable*	*Confortable*	-
		Vertical complexity (number of tiers)	-	-	*High*	-	-	-	-	-	-	-
		Horizontal complexity (number of suppliers)	*High*	-	-	*High*	-	-	-	-	*High*	-
IPN:			**HIGH**	**HIGH**	**HIGH**	**HIGH**	**HIGH**	**HIGH**	**HIGH**	**HIGH**	**HIGH**	**HIGH**
MECHANISMS:	**Structural**	**Presence of data driven strategy**	-	*Present*	*Not present*	*Present*	*Not present*	*Present/Not present*	*Not present*	*Not present*	*Not present*	*Present*
	Process	**Risk, burden and benefits share**	-	-	-	-	-	-	-	-	-	-
		Long range planning	-	-	-	-	-	-	-	-	-	*Present*
		Process engineering	-	*Present*	*Present*	-	-	-	-	-	-	*Present*
		Technical assistance	-	-	*Present*	*Present*	*Present*	-	*Present*	-	*Present*	*Present*
		Training/ education	-	-	-	*High*	*High*	-	*High*	*High*	*High*	-
	Technological	**Ability to capture data**	*High*	*High*	*High*	*High*	*High*	*High*	*High*	*High*	*High*	*High*
		Ability to integrate data	*High*	*High*	*High*	*High*	*High*	*High*	*High*	*High*	*High*	*High*
		Ability to analyze data	*High*	*High*	-	-	-	*High*	*High*	*High*	-	-
		Ability to use insights gained from data	-	*High*	-	-	-	-	-	*High*	-	*High*

(*continued on next page*)

(*continued*)

	Provider A	Provider B	Provider C	Provider D	Provider E	Provider F	Provider G	Provider H	Provider I	Provider J
Information accuracy	*Low to High*	*High*	*Low*	-	*High*	*High*	*High*	*Low*	*High*	*Low*
Information availability	-	*Low*	*Low*	-	*Low*	-	*High*	-	*Low*	-
Real-time information	-	-	-	-	*High*	-	-	-	-	*High*
Internal connectivity	-	-	*High*	-	*High*	-	-	-	-	-
External connectivity	-	-	-	-	*High*	-	-	-	-	-
Information completeness	-	*High*	*Low*	-	-	-	*High*	-	-	*Low*
Information relevance	-	*High*	-	-	-	-	-	-	-	-
Information accessibility	-	-	*Low*	-	-	-	-	-	-	-
General quality of information	"*in vivo*" *code:* $\uparrow$IPC	-	-	-	-	"*in vivo*" *code:* $\uparrow$IPC	-	"*in vivo*" *code:* $\uparrow$IPC	initial data. "*in vivo*" *code:* $\uparrow$IPC	"*in vivo*" *code:* $\uparrow$IPC
IPC:	**HIGH**	**HIGH**	**LOW to MEDIUM**	**MEDIUM**	**MEDIUM to HIGH**	**MEDIUM to HIGH**	**MEDIUM to HIGH**	**MEDIUM**	**MEDIUM**	**HIGH**

Data availability

The data that has been used is confidential.

References

Allal-Cherif, O., Simon-Moya, V., Ballester, A.C.C., 2021. Intelligent purchasing: how artificial intelligence can redefine the purchasing function. J. Bus. Res. 124, 69–76. https://doi.org/10.1016/j.jbusres.2020.11.050.

Åström, J., Reim, W., Parida, V., 2022. Value creation and value capture for AI business model innovation: a three-phase process framework. Rev. Manag. Sci. 16 (7), 2111–2133. https://doi.org/10.1007/s11846-022-00521-z.

Bag, S., Wood, L.C., Mangla, S.K., Luthra, S., 2020. Procurement 4.0 and its implications on business process performance in a circular economy. Resour. Conserv. Recycl. 152.

Bals, L., Schulze, H., Kelly, S., Stek, K., 2019. Purchasing and supply management (PSM) competencies: current and future requirements. J. Purch. Supply Manag. 25 (5), 100572.

Bensaou, B.M., Venkatraman, N., 1995. Configurations of inter-organizational relationships: a comparison between US and Japanese automakers. Manag. Sci. 41 (9), 1471–1492.

Boyatzis, R.E., 1998. Transforming qualitative information: Thematic analysis and code development. Sage, Thousand Oaks, CA.

Burger, M., Nitsche, A.M., Arlinghaus, J., 2023. Hybrid intelligence in procurement: disillusionment with AI's superiority? Comput. Ind. 150, 103946.

Busse, C., Meinlschmidt, J., Foerstl, K., 2017. Managing Information Processing Needs in Global Supply Chains: A Prerequisite to Sustainable Supply Chain Management. J. Supply Chain Manag. 53 (1), 87–113. https://doi.org/10.1111/jscm.12129.

Cao, G., Duan, Y., Li, G., 2015. Linking business analytics to decision making effectiveness: a path model analysis. IEEE Trans. Eng. Manag. 62 (3).

Cegielski, C.G., Jones-Farmer, L.A., Wu, Y., Hazen, B.T., 2012. Adoption of cloud computing technologies in supply chains - an organizational information processing theory approach. Int. J. Logist. Manag. 23 (2), 184–211.

Chaugule, A., Natu, M., 2021. Mining Mavericks-A data-driven approach to detect spend leakage. In: 2021 *IEEE 8th International Conference On Data Science And Advanced Analytics* (DSAA). IEEE, pp. 1–2.

Cox, A., 2001,"The. power perspective in procurement and supply management. J. Supply Chain Manag. 4, 4–7.

Crafts, N., 2021. Artificial intelligence as a general-purpose technology: An historical perspective. Oxford Rev. Econ. Pol. 37 (3), 521–536. https://doi.org/10.1093/oxrep/grab012.

Cox, A., 2015,"Sourcing. portfolio analysis and power positioning: towards a'paradigm shift' in category management and strategic sourcing. Supply Chain Manag.: An Int. J. 20 (6), 717–736.

Cui, R., Li, M., Zhang, S., 2022. AI and procurement. Manuf. Serv. Oper. Manag. 24 (2), 691–706.

Culot, G., Podrecca, M., Nassimbeni, G., 2024. Artificial intelligence in supply chain management: a systematic literature review of empirical studies and research directions. Comput. Ind. 162, 104132.

Dubey, R., Bryde, D.J., Dwivedi, Y.K., Graham, G., Foropon, C., 2022. Impact of artificial intelligence-driven big data analytics culture on agility and resilience in humanitarian supply chain: a practice-based view. Int. J. Prod. Econ. 250, 108618.

Duncan, R.B., 1972. Characteristics of organizational environments and perceived environmental uncertainty. Adm. Sci. Q. 17 (3), 313–327.

Durach, C.F., Gutierrez, L., 2024. "Hello, this is your AI co-pilot"–operational implications of artificial intelligence chatbots. Int. J. Phys. Distrib. Logist. Manag. 54 (3), 229–246.

Eisenhardt, K.M., 1989. Building theories from case study research. Acad. Manag. Rev. 14, 532–550.

Enrique, D.V., Lerman, L.V., de Sousa, P.R., Benitez, G.B., Santos, F.M.B.C., Frank, A.G., 2022. Being digital and flexible to navigate the storm: how digital transformation enhances supply chain flexibility in turbulent environments. Int. J. Prod. Econ. 250, 108668.

Fan, H., Li, G., Sun, H., 2017. and Consequences. Int. J. Prod. Econ. 185, 63–75.

Galbraith, J.R., 1974. Organization design: an information processing view. Interfaces 4 (3), 28–36.

Gibbert, M, Ruigrok, W, Wicki, B, 2008. What passes as a rigorous case study? Strateg. Manag. J. 29 (13), 1465–1474.

Guida, M., Caniato, F., Moretto, A., Ronchi, S., 2023a. The role of artificial intelligence in the procurement process: state of the art and research agenda. J. Purch. Supply Manag. 29 (2), 100823. https://doi.org/10.1016/j.pursup.2023.100823. ISSN 1478-4092.

Guida, M., Caniato, F., Moretto, A., Ronchi, S., 2023b. Artificial intelligence for supplier scouting: an information processing theory approach. Int. J. Phys. Distrib. Logist. Manag. 53 (4), 387–423. https://doi.org/10.1108/IJPDLM-12-2021-0536.

Gurney, K., 1997. An Introduction to Neural Networks, 1st ed. CRC Press https://doi.org/10.1201/9781315273570.

Hallikas, J., Immonen, M., Brax, S., 2021. Digitalizing procurement: the impact of data analytics on supply chain performance. Supply Chain Manag. 26 (5), 629–646.

Handfield, R., Jeong, S., Choi, T., 2019. Emerging procurement technology: data analytics and cognitive analytics. Int. J. Phys. Distrib. Logist. Manag. 49 (10), 972–1002.

Hendriksen, C., 2023. Artificial intelligence for supply chain management: disruptive innovation or innovative disruption? J. Supply Chain Manag. 59 (3), 65–76.

Hoffman, R.R., Elm, W.C., 2006. HCC implications for the procurement process. IEEE Intelligent Syst. 21 (1), 74–81.

Huang, Y.-Y., Handfield, R.B., 2015. Measuring the benefits of ERP on supply management maturity model: a "big data" method. Int. J. Operat. & Prod. Manag. 35 (1), 2–25. https://doi.org/10.1108/IJOPM-07-2013-0341.

Jarrahi, M.H., Askay, D., Eshraghi, A., Smith, P., 2023. Artificial intelligence and knowledge management: A partnership between human and AI. Business Horizons 66 (1), 87–99. https://doi.org/10.1016/j.bushor.2022.03.002.

Jhaveri, R.H., Revathi, A., Ramana, K., Raut, R., Dhanaraj, R.K., 2022. A Review on Machine Learning Strategies for Real-World Engineering Applications. Mobile Info. Syst. 2022 (1), 1833507. https://doi.org/10.1155/2022/1833507.

Jilke, S., 2020. Impact of technological uncertainty and technological complexity on organizational information processing capability: the moderating role of work experience. Eur. J. Innovat. Manag.

Kosmol, T., Reimann, F., Kaufmann, L., 2019. You'll never walk alone: why we need a supply chain practice view on digital procurement. J. Purch. Supply Manag. 25 (4).

Lee, H., Yoon, Y., 2018. Engineering doc2vec for automatic classification of product descriptions on O2O applications. Electron Commer. Res. 18, 433–456. https://doi.org/10.1007/s10660-017-9268-5.

Liddy, E.D., 2001. Natural Language Processing. In: Encyclopedia of Library and Information Science, 2nd ed. Marcel Decker, Inc, NY.

Lorentz, H., Aminoff, A., Kaipia, R., Srai, J.S., 2021. Structuring the phenomenon of procurement digitalisation: contexts, interventions and mechanisms. Int. J. Oper. Prod. Manag. 41 (2), 157–192.

Lu, J., Wu, D., Mao, M., Wang, W., Zhang, G., 2015. Recommender system application developments: a survey. Decision Support Systems 74, 12–32.

Mandl, C., 2023. Data-driven spend management. In: Procurement Analytics. Springer Series in Supply Chain Management, vol. 22. Springer, Cham. https://doi.org/10.1007/978-3-031-43281-1_3.

McCarthy, J., 2007. From here to human-level AI. Artificial Intelligence 171 (18), 1174–1182. https://doi.org/10.1016/j.artint.2007.10.009.

Mehrbod, A., Zutshi, A., Grilo, A., Jardim-Goncalves, R., 2017. Matching heterogeneous e-catalogues in B2B marketplaces using vector space model. Int. J. Comput. Integrated Manuf. 30 (1), 134–146.

Mishra, C., Gupta, D.L., 2017. Deep machine learning and Neural Networks: an overview. IAES Int. J. Artif. Intell. 6 (2), 66. https://doi.org/10.11591/ijai.v6.i2.pp66-73.

Monczka, R.M., Handfield, R.B., Giunipero, L.C., Patterson, J.L., 2016. Purchasing and Supply Chain Management, sixth ed. Cengage Learning, Boston.

Nair, A., Yan, T., Ro, Y., Oke, A., Chiles, T., Lee, S., 2016. How environmental innovations emerge and proliferate in supply networks: a complex adaptive systems perspective. J. Supply Chain Manag. 52 (2), 66–86.

Nandy, M., Seetharaman, P., 2019. Interorganizational processes in buyer–supplier dyads: An information intensity perspective. J. Organizat. Comput. Electron. Commer. 29, 96–114.

Pandit, K., Marmanis, H. Spend Analysis: The Window into Strategic Sourcing. https://api.semanticscholar.org/CorpusID:168400884.

Patrucco, A.S., Marzi, G., Trabucchi, D., 2023. The role of absorptive capacity and big data analytics in strategic purchasing and supply chain management decisions. Technovation 126, 102814.

Pellini, A., Jones, H., 2011. Knowledge Taxonomies - A Literature Review.

Priore, P., Ponte, B., Rosillo, R., de la Fuente, D., 2018. Applying machine learning to the dynamic selection of replenishment policies in fast-changing supply chain environments. Int. J. Prod. Res. 57 (11), 3663–3677. https://doi.org/10.1080/00207543.2018.1552369.

Qaffas, A.A., Ben HajKacem, M.A., Ben Ncir, C.E., Nasraoui, O., 2023. An explainable artificial intelligence approach for multi-criteria ABC item classification. Journal of Theoretical and Applied Electronic Commerce Research 18 (2), 848–866.

Richey Jr, R.G., Chowdhury, S., Davis-Sramek, B., Giannakis, M., Dwivedi, Y.K., 2023. Artificial intelligence in logistics and supply chain management: a primer and roadmap for research. J. Bus. Logist. 44 (4), 532–549.

Riedl, D.F., Kaufmann, L., Zimmermann, C., Perols, J.L., 2013. Reducing uncertainty in supplier selection decisions: Antecedents and outcomes of procedural rationality. J. Operat. Manag. 31 (1), 24–36. https://doi.org/10.1016/j.jom.2012.10.003.

Roberts, P.J., Mitchell, R.J., Ruiz, V.F., Bishop, J.M., 2014. Classification in e-procurement. Int. J. Appli. Pattern Recog. 1 (3), 298–314. https://doi.org/10.1504/IJAPR.2014.065770.

Ronchini, A., Guida, M., Moretto, A., Caniato, F., 2024. The role of artificial intelligence in the supply chain finance innovation process. Operations Management Research 1–31.

Roßmann, B., Canzaniello, A., von der Gracht, Hartmann, E., 2018. The future and social impact of big data analytics in supply chain management: results from a Delphi study. Technological Forecasting and Social Change 130, 135–149. https://doi.org/10.1016/j.techfore.2017. 10.005.

Samoili, S., Cobo, M.L., Gómez, E., De Prato, G., Martínez-Plumed, F., Delipetrev, B., 2020. AI Watch. Defining Artificial Intelligence. Towards an Operational Definition and Taxonomy of Artificial Intelligence.

Shaham, E., Westerski, A., Kanagasabai, R., Narayanan, A., Ong, S., Wong, J., Singh, M., 2021. Using Unsupervised Learning for Data-driven Procurement Demand Aggregation. Proceedings of the AAAI Conference on Artificial Intelligence 35 (17), 15175–15184. https://doi.org/10.1609/aaai.v35i17.17781.

Shawar, B., Atwell, E.,2007. Chatbots: are they really useful?,LDV Forum 22, 29–49. https://doi.org/10.21248/jlcl.22.2007.88.

Shore, B., Venkatachalam, A.R., 2003. Evaluating the information sharing capabilities of supply chain partners: a fuzzy logic model. Int. J. Phys. Distribut. Logist. Manag. 33 (9), 804–824. https://doi.org/10.1108/09600030310503343.

Singh, M., Kalagnanam, J.R., Verma, S., Shah, A.J., Chalasani, S.K., 2005. Automated cleansing for spend analytics. In: *Proceedings of the 14th ACM International Conference on Information And Knowledge Management*, pp. 437–445.

Spreitzenbarth, J.M., Bode, C., Stuckenschmidt, H., 2024. Artificial intelligence and machine learning in purchasing and supply management: a mixed-methods review of the state-of-the-art in literature and practice. J. Purch. Supply Manag., 100896

Swink, M., Schoenherr, T., 2015. The Effects of Cross-Functional Integration on Profitability, Process Efficiency, and Asset Productivity. J Bus Logist 36, 69–87. https://doi.org/10.1111/jbl.12070.

Tapkan, P., Özbakır, L., Kulluk, S., Baykasoğlu, A., 2016. A cost-sensitive classification algorithm: BEE-Miner. Knowl. Base Syst. 95, 99–113.

Trautmann, G., Turkulainen, V., Hartmann, E., Bals, L., 2009. Integration in the Global Sourcing Organization — An Information Processing Perspective. J. Supply Chain Manag. 45 (2), 57–74. https://doi.org/10.1111/j.1745-493X.2009.03163.x.

Tushman, M.L., Nadler, D.A., 1978. Information processing as an integrating concept in organizational design. Acad. Manag. Rev. 3 (3).

Urbinati, A., Bogers, M., Chiesa, V., Frattini, F., 2019. Creating and capturing value from Big Data: a multiple-case study analysis of provider companies. Technovation 84, 21–36.

van Hoek, R., 2024. Insight from industry-early lessons learned about AI adoption in core procurement processes, directions for managers and researchers. Supply Chain Manag.: Int. J.

Viale, L., Zouari, D., 2020. Impact of digitalization on procurement: the case of robotic process automation. Supply Chain Forum Int. J. 21 (3), 185–195.

Wang, G., Gunasekaran, A., Ngai, E.W., Papadopoulos, T., 2016. Big data analytics in logistics and supply chain management: certain investigations for research and applications. Int. J. Prod. Econ. 176, 98–110.

Zhou, H., 2011. An empirical test of the information processing theory. Int. J. Inf. Syst. Supply Chain Manag. 4 (1).

Zhu, S., Song, J., Hazen, B.T., Lee, K., Cegielski, C., 2018. How supply chain analytics enables operational supply chain transparency: An organizational information processing theory perspective. Int. J. Phys. Distribut. & Logist. Manag. 48 (1), 47–68. https://doi.org/10.1108/IJPDLM-11-2017-0341.

Zou, X., Zhou, L., Li, K., Ouyang, A., Chen, C., 2020. Multi-task cascade deep convolutional neural networks for large-scale commodity recognition. Neural Comput. Appl. 32, 5633–5647.