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Where Human Judgment and AI Analytics converge in Modern Procurement: The New Role of the Strategic Buyer

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Introduction

Procurement has historically been conceptualized as a function based on rationality, analytical rigor and procedural formalization. Over the years, organizations have developed a variety of frameworks and managerial approaches to structure purchasing activities and support decision making in increasingly complex markets. Models for supplier segmentation, performance assessment systems, and strategic purchasing analyses have all contributed to improving procurement as a business function focused on efficiency, consistency, and alignment with organizational goals.

However, procurement practice has never been entirely governed by formal models and analytical techniques. Purchasing decisions are made in environments marked by uncertainty, imperfect information and constantly changing relationships with external stakeholders. Interactions with suppliers, negotiation processes and evaluations of potential risks often involve factors that are difficult to quantify and impossible to predict with complete accuracy. As a consequence, procurement professionals frequently rely not only on established tools and methodologies but also on judgement, experience and a deep understanding of the specific business context in which decisions are made.

Recent developments in Artificial Intelligence (AI) and data analytics are introducing significant changes to this landscape. The growing availability of data together with advances in machine learning and computational capabilities has considerably expanded organizations' ability in order to extract insights from large volumes of information. Given its strong dependence on data and information flows, procurement has become one of the functions most directly affected by these developments. Activities that traditionally required substantial manual effort, including spend analysis, supplier assessment and demand forecasting can now be supported by technologies capable of identifying patterns and generating insights with a speed and scale that were previously unfeasible through conventional analytical methods.

This technological transformation introduces a substantive shift by the foundations of Procurement Department. The growing reliance on data-driven systems modifies the way in which knowledge is generated, validated, and applied within decision-making processes. Analytical outputs produced by AI-based systems contribute not only to improving informational accuracy, but also to influencing the framing of buyer's decisions, thereby affecting how alternatives are evaluated and how risks are perceived and managed. Consequently, the integration of Artificial Intelligence does not simply represent an incremental enhancement of existing practices, but rather a structural change in the interaction between data, analysis, and managerial judgment.

The present research originates from a set of considerations based on my professional experience as an Information and Communication Technology Buyer. In this capacity, I have directly observed the progressive integration of digital tools and advanced analytical systems into everyday procurement activities. Such exposure has extended beyond the mere observation of technological innovation as an external phenomenon, fostering instead a sustained and critical reflection on its practical implications. While managing ICT sourcing initiatives, I often encountered situations in which AI-based analytics suggested supplier choices that differed from the recommendations emerging from stakeholder discussions and prior supplier experience. These situations prompted me to question how procurement professionals balance algorithmic insights with practical judgement.

This study is grounded in the observation that procurement decisions cannot be understood as purely analytical exercises. While Artificial Intelligence can improve the availability, organisation and processing of information, the results generated by these systems still need to be assessed in light of organisational priorities, business conditions and managerial objectives. Elements such as strategic fit, supplier relationships and the long-term consequences of purchasing decisions continue to require human judgement and cannot be fully addressed through algorithmic models alone. For this reason, understanding how analytical outputs and managerial evaluation interact has become an increasingly important area of investigation.

In this regard procurement provides a particularly suitable context for examining the relationship between emerging technologies and decision-making processes. The function is characterised by a constant interplay between quantitative evidence and qualitative assessment, with decisions that often have immediate and tangible effects on organisational performance. As organisations expand the use of AI-based tools, procurement offers valuable opportunities to explore how technological capabilities can support managerial judgement while preserving the role of human expertise in complex decision environments. Consequently, the study of procurement processes provides a concrete basis for assessing how Artificial Intelligence is operationalised within real-world contexts and how it interacts with established managerial practices.

In this context, this thesis investigates the evolving relationship between procurement activities and Artificial Intelligence. By examining both the traditional foundations of the procurement function and the transformations driven by digital technologies, this thesis seeks to develop a structured and comprehensive understanding of the ways in which decision-making processes are being reconfigured. The analysis is based on the integration of theoretical perspectives and empirical observations, aiming to contribute to a more nuanced interpretation of the role of data-driven systems in contemporary procurement environments.

Chapter 1

Procurement Function Fundamentals in the Supply Chain Management

1.1 Purchasing Marketing and Strategic Analysis of Commodity Categories

During this era, the rapidly changing of the environment involves the Procurement Department to purchase under the principle of saving but always following the company's strategy to sustaining competitiveness, minimize risks and ensure the supply.
Purchasing Marketing refers to the knowledge of the market, in particularly economic situation, supply and demand and price trends. After the study of these information, Procurement Professionals must develop a Positioning Matrix for defining purchasing policies that will internally and externally apply.

Indeed, the Procurement has a unique operating environment as the intersection and connection point among actors and solving all communications with suppliers (Carter et al., 2000) to grant the continuous supply.
The Procurement Professionals must figure out how to make the right decisions regarding the purchasing procedures, defining which factors can influence the operation processes and procurement decisions.
The first publications related to Procurement developing strategy maps such as the BSC – Balanced Scorecard (Kaplan & Norton, 1992, 1993, 1996).
The Balanced Scorecard translates an organization's strategy into actions, balancing financial metrics with customers' perspective, internal process, innovation and learning indicators. It promotes comprehensive performance management and strategic alignment.
The Balanced Scorecard was introduced in 1992 by Robert Kaplan and David Norton to address the shortcomings of performance measurement systems that, up to that point, had relied predominantly on short terms economic metrics. The term Balanced stands for balancing financial and strategic objectives. In addition, the tool links all the organization's strategic areas with corresponding actions, following a cause-and-effect logic and it integrates both qualitative and quantitative metrics.

The Balanced Scorecard provides a framework for connecting performance measurement with strategic objectives. The tool helps organizations avoid decisions based entirely on short-term financial outcomes. Focusing only on financial success may encourage individuals to focus on short-term gains, but it may hinder their ability to achieve larger objectives in the future.

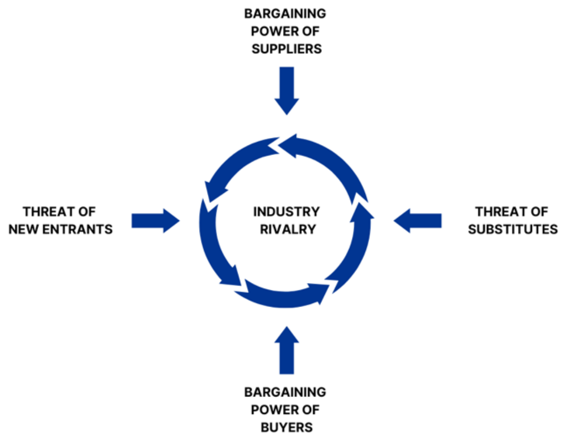
For instance, the Inventory management offers a clear example of this dynamic. From a financial perspective, maintaining high inventory levels is often viewed negatively because it increases working capital requirements and related costs. However, from a strategic and customer perspective, higher inventory levels may be justified if they enable faster deliveries, greater product availability and a more reliable service to customers.

The Balanced Scorecard helps balance different perspectives (financial, customer, internal processes, learning and growth) enabling management to make decisions consistent with long-term strategic objectives rather than short-term financial pressures.

Porter during his studies (2008; 1985) identified factors and synthesized them into one model as five competitive forces which help companies to determine the weaknesses and strengths. Indeed, the model can be used to identify the business structure and to determine corporate strategy.

Understanding the five competitive forces and the pressures they create helps a company identify and defend its position within an industry, to achieve and sustain profitability.

Figure 1.1 5 Porter's forces: Forces shaping Industry Competition



Source: *Art of Procurement*

1. Industry Rivalry

This force concerns the level of competition among firms operating within the same industry: how intense the rivalry is among existing competitors.

Key factors influencing rivalry include:

- Similarity among firms. When competing firms tend to resemble each other in terms of costs, strategies, and business models, they can more easily coordinate on pricing decisions. However, when companies offer similar products, competition tends to increase, since customers can switch more easily from one offering to another.
- Changes in productive capacity and exit barriers. Situations such as economic recession, a sharp increase in investments, or a decline in demand can lead companies to have unused production capacity. To reduce fixed costs, firms may lower their prices to secure more orders. When these unfavourable conditions persist over time and exit barriers are high, competition tends to become increasingly intense.
- Cost structure. high fixed costs often lead firms to compete more aggressively. The higher the fixed costs, the stronger the incentive for firms to lower prices during competitive pressure, since they aim to cover at least their variable costs and keep production running.

2. Threat of new entrants

If an industry has no entry barriers, the threat of new entrants is enough to keep prices competitive, regardless of the number of firms currently operating in the market. The industry is said to be contestable. Existing firms know that new companies can enter the market easily at any time and erode their profits by lowering prices.

Barriers to entry:

- High fixed costs
- Economies of scale allow existing firms to reduce prices by leveraging large production capacity and achieving lower unit costs.
- Product differentiation: low level of differentiation means for new entrants high investments in promotion, visibility, communication.
- Access to the local network, liability of outsider ship (obstacles to accessing distribution channels, commercial relationships, etc).
- Accumulated knowledge (climate change for example has led Norway to produce wine, but it is unable to match the Italian or the French quality).
- Presence of patents, licences, copyrights.
- Switching Costs.

3. Threat of substitute products or services

Substitute products are products that satisfy the same needs of consumers of existing products but in a different way. The price consumers are willing to pay depends on substitute product's availability.

The presence of substitutes makes the demand more elastic, increasing consumers' sensitivity to price changes.

4. Bargaining power of buyers

Buyers are price-sensitive when:

- The product they purchase represents a significant share of their production costs or usage value (e.g., wood accounts for 75% of the cost of a picture frame).
- There is little or no differentiation among suppliers' products.
- Competition among buyers is high: there is an increasing pressure to obtain more favourable purchasing conditions.

The bargaining power of buyers depends on:

- Size and concentration of buyers relative to suppliers. Few buyers making large purchases have greater power than smaller buyers.
- The more informed buyers are about the prices and products they purchase, the greater their bargaining power.
- Vertical (upstream) integration capability: it is the way through which buyers reduce their dependence on suppliers.

5. Bargaining power of suppliers

Suppliers power is low when their products are available in the market, when substitutes exist, and switched costs are low. Their bargaining power increases when:

- They are few
- Switching costs are high (they have a high-level specialization)
- They have a vertical integration capability (downstream)

Kraljic's portfolio model represents one of the most influential frameworks in the purchasing and supply management literature. According to Kraljic (1983), the appropriate supply strategy for a purchased item is determined by the profit impact and the supply risk. Organizations can classify their purchases into distinct categories and define differentiated approaches to supplier management and sourcing decisions combining those two variables.

Although the original model does not explicitly address the concepts of power and dependence, the actions that help someone gain an advantage in supplier talks or spread out the supplier list to lower risk show worries about having strong bargaining power and being too reliant on one supplier.

This interpretation is coherent with Kraljic's broader objective of reducing supply vulnerability while maximizing the organization's purchasing leverage (Kraljic, 1983). Therefore, the balance of power is shared between buyers and suppliers has a substantial impact on how purchasing strategies are made and how well they work.

Gelderman and Van Weele (2003) argue that power and dependence relationships provide an important perspective for understanding how firms respond to the challenges associated with each portfolio category. Likewise, Dubois and Pedersen (2002) observe that the role of inter-organizational dependency has received limited attention within applications of the Kraljic model. While the portfolio approach is widely used in practice, little is known about what drives organizations to change their position within the matrix rather than preserve established supplier relationships.

From this perspective, analysing buyer–supplier power relationships helps explain how organizations manage supplier relationships and develop purchasing strategies within the different portfolio categories.

In his seminal contribution, Kraljic (1983) argued that organizations should strengthen their supply management capabilities in response to increasing market complexity, technological developments and the growing strategic importance of purchased goods and services. He famously stated that "*purchasing must become supply management*" (Kraljic, 1983, p. 109) emphasizing the need for a more strategic and proactive approach to managing external resources. According to Kraljic (1983), adopting a more strategic approach to supply management becomes particularly important when purchasing represents a significant share of organizational expenditure and supply markets are uncertain or complex.

To support strategic decision-making, Kraljic (1983) proposed a four-stage process for developing supply strategies. In the first stage purchased items are classified following their profit impact and their supply risk. The first stage involves classifying purchased items according to their profit impact and supply risk. The second stage requires an assessment of the relative strength of the buying organization and its suppliers. Moreover, the products identified as strategically important are positioned within a portfolio matrix that combines internal and external considerations. In the final stage, firms develop sourcing strategies and action plans based on their position within the matrix and the prevailing balance of power in the supplier relationship.

Kraljic identified three broad strategic options. When the buyer possesses stronger bargaining power, organizations should seek to exploit this advantage and secure favourable conditions. A balancing strategy aimed at cooperation and mutual benefit is recommended in situations where neither party dominates the relationship. On the other side when suppliers hold a stronger position, firms should pursue diversification strategies to reduce dependency and mitigate supply risk. While these recommendations were developed primarily for strategic items, Kraljic also outlined specific managerial priorities for the remaining categories of purchases, thereby extending the practical relevance of the framework across the entire purchasing portfolio.

Figure 1.2 Krlajic Matrix

Source: *Procurement Tactics*

The overall importance of purchasing is determined by aspects such as costs of material, total costs of production, added value, profitability etc. The risks on the supply side might be from different sources like situations of monopolies and oligopolies, speed of progress in technology, obstacles for new suppliers to enter this market, costs of logistics, complexity of the product etc.

Kraljic (1983) gives for each segment suggestions for the purchasing policy.

Table 1.1 The Different Purchasing Strategies

	Non critical items	Leverage items	Bottleneck items	Strategic items
Procurement focus	purchasing management	materials management	sourcing management	supply management
Time horizon	limited: normally 12 months or less	varied, typical 12 to 24 months	variable, depending on availability versus short term flexibility	up to 10 years determined by long term strategic impact
Key performance indicators	functional efficiency	cost/price and material flow management	cost management and reliable short-term sourcing	long term availability
Items purchased	commodities and some specific materials	mix of commodities and specific materials	mainly specified materials	scarce and/or high value materials
Typical sources	established local suppliers	many suppliers mainly local	global, predominantly new suppliers with new technology	established global suppliers
Supply	abundant	abundant	production based scarcity	natural scarcity
Decision authority	decentralized	mainly decentralized	decentralized but centrally coordinated	centralized

Source: "*Importance of the Kraljic Matrix as a strategic tool for modern purchasing*"

The four categories identified within Kraljic's portfolio framework require different managerial approaches, reflecting the varying levels of risk and strategic importance associated with purchased items. As the strategic relevance of a category increases, purchasing decisions generally demand more sophisticated forms of analysis and planning.

For strategic items, organizations often rely on a range of analytical tools to support decision-making. These may include market and industry analyses, risk assessment techniques, forecasting methods, simulation models, and other forms of economic evaluation aimed at understanding both supply market conditions and long-term sourcing implications (Kraljic, 1983).

On the other hand, items classified as leverage purchases call for approaches centred on commercial optimization and supplier negotiation. In these situations, organizations may employ techniques such as value analysis, cost assessment, and price forecasting to strengthen their bargaining position and obtain more favourable purchasing conditions.

However, managerial attention is usually directed toward administrative efficiency and process simplification for non-critical items. Hence, to support decision-making it has to be included basic market evaluations, standardized procurement procedures, and inventory optimisation methods. (Kraljic, 1983).
The portfolio model is characterized by its dynamic nature. The position of a purchased item is not fixed over time, because of changes in market conditions, technological developments, regulatory factors, or shifts in supply and demand. These circumstances can alter both supply risk and business impact. Kraljic (1983) noticed that some items, which were once seen as routine purchases, can become very important in a strategic sense when the market conditions change. Following this approach, portfolio classifications should not be identified as permanent categories but rather as managerial assessments that require periodic review and updating. Regular reassessment aims to adapt sourcing strategies to evolving market conditions and to maintain alignment between procurement decisions and business objectives.

1.2 The Process of Supplier Scouting, Qualification, and Evaluation

Scouting is a strategic activity which starting from the identification of an organisational need, uses a series of skills useful for locating and contacting suppliers who are potentially able to satisfy the need underlying the activity. This activity involves the supplier search and selection process of new potential suppliers.

The activity's success and effectiveness are largely determined by the attention paid to explicitly defining the organisational need and how to determine the entire process in measurable parameters, in fact the ability to correctly focus on the initial need is crucial.

The scouting process is a continuous one, and the ability to identify new suppliers is a key factor in the success of the process.
Scouting aims to expand the number of potential suppliers with the right qualifications to participate in corporate purchasing processes.
Having a broader range of qualified companies to approach increases the possibility of receiving high-quality offers. Furthermore, covering individual product categories with an adequate number of suppliers allows for more effective response to emergency situations, such as a supplier default, disruption within a specific logistics chain, etc.

The scouting process may be driven by the need to explore new supply areas (emerging countries, start-ups using emerging technologies, etc.), but scouting itself can provide insights into trends and opportunities, creating the conditions for contacting innovative ideas and solutions that can constitute a valid alternative to traditional supplies, which may no longer be suitable.
The intensity can be adjusted based on strategic needs or because there are any operational emergencies, however it is necessary to establish an organizational structure that allows scouting to be managed with a rolling operational plan, with allocated time slots.
Ideally, scouting is a structured activity integrated into purchasing processes, and it should be carried out systematically and continuously over the time.

Supplier Scouting is the natural consequence of Procurement Marketing activities.
When preceded by Market Analysis, it accelerates the process and increases the success rate.
The effectiveness of the Scouting activity is largely determined by the accuracy and soundness of the scouting profile, that is, the profile of the ideal company we are looking for, which lists the key requirements for contributing to the success of the project.

Guida et al. (2023) define supplier scouting as the process of identifying potential suppliers even outside the existing base and show how AI solutions allow us to move from a passive scouting (waiting for applications/contacts) to a proactive one based on systematic research on databases, web, networks.

Passive Scouting is the process that stems from the collection and analysis of spontaneous applications to companies wishing to apply as potential suppliers for one or more product categories.
Even today, it is the only way for many companies to connect with new supply sources.
Spontaneous applications from supplier companies generate the greatest number of applications in low- to medium-relevance product groups, while leaving the most critical groups uncovered.
The effectiveness of passive scouting is strongly linked to the development of a dedicated supplier portal where applications can be collected in an orderly management and channelled to buyers for specific product categories.

The portal must be structured to immediately "sort" applications into the correct product group.
Hence, it is also important to have correctly structured company product groups.
Specific forms/questionnaires must be prepared for the most relevant product categories, collecting key information that can immediately provide evidence of the potential suitability or otherwise of the candidate company, thus enabling the Primary Selection process to be carried out.
Passive scouting is effective if it is highly automated.

Proactive scouting, on the other hand, involves an authoritative search for potential suppliers.
It consists of a set of actions implemented by the purchasing function to identify companies that could become suppliers with the aim of

- Repopulating product groups for which an insufficient number of active and potential suppliers are available;
- Meeting the immediate need to select new suppliers for tenders for which the company's supplier list does not provide enough suppliers.
- Meeting the need for developing new products and services by identifying companies with suitable solutions, technologies, and expertise

The scouting directory feeds the Supplier Register through two steps:

1. Preliminary evaluation of the companies identified during the scouting phase to confirm or deny their presence in the scouting directory. This phase is necessary because:
    - the data collected in the directory is based more on the principle of mass research than on quality;
    - data collected online is influenced by companies' promotional purposes;
    - it is advisable to eliminate clearly unsuitable operators at this stage, to avoid unnecessary burdens in the subsequent evaluation and qualification phases.

Even if they are unsuitable (fail the primary selection), they will remain listed as "registered".

2. If the preliminary evaluation is positive, operators may be invited to register their company on the Supplier Register portal (or through forms and questionnaires),

completing and/or correcting the information already entered through the scouting directory.

The final supplier evaluation (also commonly referred to as "Vendor Rating") is the process, conducted under the responsibility of the Procurement Department with the contribution of the Requesting Stakeholders and any other company interface involved in any capacity in the use, through which active suppliers are subjected to verification of their service levels.
Vendor Rating increase the overall quality of suppliers' output.
Evaluating a supplier's overall performance (both in the preliminary and, above all, final phases) must necessarily consider the ability to simultaneously satisfy several requirements, such as:

- Absolute transparency in all cost drivers, margins, and profits
- Medium- to long-term cost reduction
- Continuous research/waste reduction
- Constant participation in VA/VE (Value Analysis/Value Engineering) initiatives
- Proactiveness with alternative solutions aimed at optimizing costs and quality levels
- Maximum collaboration and support for the plant using the product
- Standardization/optimization of packaging and the transport system
- Support in the implementation of a lean production process (target: one-piece flow)
- Support for a logistics flow aimed at continuously reducing inventories
- Constant optimization of production lead times
- Management and constant monitoring of the subcontracting system

The post-sales evaluation of active suppliers is useful for monitoring the performance of the supplier to prevent its decline, possibly intervening with appropriate corrective actions, in a spirit of continuous improvement.
As an alternative to the post-sales evaluation, one could consider a system for managing active suppliers based exclusively on the comments and complaints from internal customers or other company interfaces involved in the supply process.

The final evaluation is designed and organized specifically to avoid comments and complaints, since careful observation of the supplier's performance, especially when combined with changes in the most significant company data, can lead to a timely identification of the supplier's inadequacy or, where the supplier's performance is consistently adequate, to further improvement.

Additional objectives of the post-contract evaluation include those of a purely communicational nature, such as its relevance in the relationship with suppliers and internal customers.

Communication with suppliers is often neglected. The reasons for this neglect lie in the difficulty, in many

business environments, in overcoming the age-old perception of suppliers as lesser-ranking actors. Within this concept, born of an era in which procurement was relatively easy due to the lesser complexity of sales markets, the supplier is conceived as a prospective customer who, at the customer's discretion, can be admitted to the court, and thus the communication methodology is primitive and simplified.

On these days, discussing an adequate system of communication with suppliers is of fundamental importance to ensure, especially for supplies relating to product groups with high and medium-high criticality and relevance, continuity and consistent quality.

And since the results of the final evaluation can be presented and discussed with suppliers, an optimal situation is created for experimenting, installing, and verifying communication methods and techniques that best meets the current complexity of the procurement market.

Subjecting all active suppliers to a final assessment is extremely costly and, equally, utterly useless.

If the primary objective of the final assessment is to prevent a decline in supplier performance, occasional or occasional suppliers and suppliers of product groups with a low status criticality score and a non-critical positioning are not worthwhile undergoing a final assessment because their performance is not crucial to the client company's activities in the sales markets.

Yordian Fachrie (2020) and Arkadiusz Kawa and Waldemar W. Koczkodaj (2015) have defined numerous measurement scales in their articles to evaluate suppliers. The following parameters are given as examples:

- Punctuality;

- Quality;
- Competitiveness;
- Innovation;
- Communication;
- Flexibility;
- Technology;
- Service and Support;
- Safety;
- Environmental;
- Social Responsibility;
- Consistency;
- Total Cost of Ownership;
- Competitiveness.

To be reliable and realistic, the final evaluation must be primarily based on objective parameters.

This is essential because, as mentioned above, the results of the final evaluation are communicated to and discussed with the suppliers themselves, and therefore, only a radical objectification of the evaluation can be a real tool for comparison with them. A final evaluation that is too biased with the subjectivity of the evaluators could lead to results that are not incontrovertible and therefore undefensible to the supplier.

For objective evaluations, it is essential to examine the type of company management system.

Specifically, whether it can make the data necessary for the final evaluation available (order and delivery/work completion dates, response times to calls, staff entry times, etc.) and whether this data is reliable.

For subjective evaluations, it is necessary to examine the company climate. Whether it is collaborative or non-collaborative, i.e., whether it allows the Procurement Department to easily request the active participation of internal customers in supplier evaluations, or whether the rigidity of relationships prevents this.

For objective evaluations, it is essential to examine the type of company management system.

Specifically, whether it is able to make the data necessary for the final evaluation available (order and delivery/work completion dates, response times to calls, staff entry times, etc.) and whether this data is reliable.
For subjective evaluations, it is necessary to examine the company climate. Whether it is collaborative or non-collaborative, i.e., whether it allows the Procurement Department to easily request the active participation of internal customers in supplier evaluations, or whether the rigidity of relationships prevents this.
The post-contractual assessment does not guarantee knowledge of the impending state of financial insolvency or, in general, of the supplier's inability or impossibility to initiate or continue a supply or contract.
Therefore, it is essential to have a series of economic and financial data and some precise market information, which allow the client to constantly monitor the supplier's reliability.

1.3 The Economic-Financial Dimension: Budget Construction and Supplier Selection

Procurement risk is classified among the company's exogenous risks; however, it can be used as an opportunity for risk reduction.
Qualifying a supplier is a costly process, and there are never sufficient and adequate resources.
The Pre-Qualification phase filters and selects supply sources to balance costs and information needs.
The qualification and evaluation questionnaire is often onerous and embarrassing for SMEs that lack visibility of the actual subject matter of the contract.
Risk in a company's supply chain lies in the policies and procedures used to manage it. Typical parameters include the quantity and frequency of orders, lot size, safety stocks, logistics variables including shipping and transportation, and fixed capital. Using supply chain management strategies based on vendor management inventory, consignment stock, inventory financing can help mitigate risks; adopting methodologies such as collaborative planning, forecasting, and replenishment also helps optimize performance and minimize working capital. Suppliers have a significant impact on supply chain risks in terms of punctuality, accuracy or defects in deliveries, and responsiveness to emergency situations; their behaviour must be monitored within the scope of supplier-related risk.

The risk of supplier default is one of the risks we must address. To manage it, we must prevent it.
The risk prevention process is composed by three phases:

- Identification
- Analysis
- Assessment

The pandemic has shown that risk evolves; it is not static, so it must be monitored and verified with a defined frequency.
ISO standards have supported, in times of unprecedented magnitude, the implementation of risk measurement methods at all levels, to increase corporate capabilities.
The purpose of the analysis is to understand the economic, financial, and equity performance of a company, whether ours or a third party.
This analysis can be adequately divided into these actions:

- identify corrective measures to improve the company's performance;
- calculate and interpret company ratings;
- complete financial statement information (Management Report);
- review financial statement information (Auditor's Report and Board of Statutory Auditors' Report);
- visit the customer and gather updated information;
- compare local information;
- gather extensive information on the supplier, the owner, and the objective brand reputation.
- evaluate the company's medium-term (10-year) performance using appropriate methodologies.

Philippe Burger and Ian Hawkesworth (2013) wrote that capital budgeting and procurement processes must be robust, and any possible situation that could undermine the pursuit of value for money should be minimized. Furthermore, a weak integration of the project planning and ex ante value-for-money assessment with the budgeting process may cause projected and realized value for money to deviate.
Although the notion of value for money is inherently complex, it may be defined as the government’s evaluation of the most appropriate balance between quality, functionality, and cost across the entire lifecycle of a project.

Value for money entails economy, efficiency and effectiveness. Combining these in an assessment, the Procurement Direction must establish whether a project represents positive value for money.

The procurement cycle entails planning and prioritisation of capital projects and the subsequent current expenditure and revenue flows that these projects generate. The procurement cycle also includes the preparation of tenders, the vetting of bidders, contract negotiations, awarding the contract, the construction phase, and the operational phase.

There is no perfect system, and accounting and budgeting systems have various strengths and weaknesses. The main lesson is that any illegitimate incentives to prefer one form of capital procurement to another due to budgeting and accounting treatments should be countered by complementary rules and procedures.

For Molusiwa Stephan Ramabodu (2014), the basic goals of cost management and the pricing of a project or product relate to the link between price and intrinsic value, affordability in relation to needs or investment, and managing the procurement process. Cost managers (cost planners) should therefore understand that they need to work with clients (investors) from the very inception of a project, even earlier, and then throughout the process to ensure the best results. This does not mean that a cost planner or cost manager is a "cost cutter" (Ferry and Brandon, 1991).

Ashworth (1994) proposes that the emphasis should always be on securing developments that best satisfy the criteria identified by the developer (client) at inception, including the type, scale, standards, funding, cost and timing of a project.

Different tasks need to be performed by different people involved in respect of design, cost, forecasting, planning, organizing, motivating, as well as controlling and coordinating the management functions (Ashworth, 1994). The cost managers should be continuously involved from the design to the co-ordination and auditing, to ensure best cost results. Other areas of cost management that need attention are cash flow, the timing of payments, interest rates and the availability of funds at specific times. These aspects also influence the total financial outlay and eventual returns on a property investment.

Kenley (2003) stresses the potential value of improved and strategic cash flow to enhance the profitability of the industry, with the further potential to offer reduced costs to the client and improved contractor performance. Cash-flow forecasts and management should therefore be part of the cost manager's service to ensure that the developers receive the full benefit of proactive attention. The cost manager's (technical contact) involvement must go beyond a reactive service.

Knipe et al., (2002) and Verster and Berry (2005) defined cost design as the process whose aim is to satisfy the parameters dictated by cost, cost of acquisitions, operation and management. The process may also be described as cost design, where such design is defined as designing a project in economic terms, considering the cost and cost benefit of each project to balance the interrelationship of all cost elements and the reason for its existence.

Cost planning is used to ensure that, in the early stages of a project, the developer knows what the anticipated final cost of the total development may be, including legal issues, financing and management. Building cost is only one of these items, but the technical contact or cost manager should include all costs in the cost plan or estimate of final cost. The cost planner should have a clear understanding of cost and budget targets to enable him to advise the Procurement Department about possible future overruns and proactively provide alternative solutions (Ferry and Brandon, 1991). One of the most effective tools that technical contact uses to assist with the planning and design process, is the elemental cost plan. The theory behind the analysis of building costs per element is that the total cost is a sum of the cost of individual elements (Morton and Jaggar, 1995).
Effective cost advice will place the client in a position where strategic budgeting can be performed based on sound knowledge of all influences (Knipe et al., 2002).
According to Knipe et al. (2002) the estimating process should add to a more comprehensive understanding of all benefits and associated costs.

Linked to auditing, cost control is an activity aimed not only at reactive reporting of decision results, but also at accounting for the decisions and visions of the client and advising the client on how best to achieve desired outcomes (Knipe et al., 2002). Cost control occurs throughout the deployment process, from the briefing stage to completion. Benefits are derived during all stages including the briefing, sketch plan, approved sketch plan, production drawing, receipt of tenders, and construction stages (Ferry and Brandon, 1991).

Cost analysis supports the technical contact service to the client and can provide technical contact with useful cost information and data. Three forms of cost analysis are identified by Ashworth (1994), namely:

- Identification of major cost items;
- Analysis of the annual user cost of ownership;
- Identification of those groups of items (elements) of cost importance.

The identification, analysis and comparison of costs and items, as well as element-related costs, enable the technical contact to assist the developer and designer in investigating more cost-effective alternatives, enabling them to deliver a project that yields the best results.

The technical contact should ensure that continuous, accurate cost information, analysis, cost results and cost influences are reported to the client and design team. The report must be based on sound information and data, ensuring continuous proactive action and effective management of the whole process.

The effective implementation of the above tools, techniques or methods should result in a better product at a better price (or cost), with lower maintenance cost and an increased return potential over a longer period. The buyer is the cost expert on the development team; indeed, he is the usual source of price information and should always be a viable source of critical information.

To be most effective, the activity of the Procurement Department should be used proactively from the earliest stage to the final stage of a project. Of all resources, money is probably one of the most limited, and the challenge is to use this resource optimally. The buyer is ideally positioned to continuously play an active role but should also become more involved in strategic decisions to empower clients even further.

1.4 Formalization of the Relationship: The Purchase Order

According to Global Execution Partners GEP (2026), every business wants to save costs and maximize profitability through standard procurement and sourcing activities.

One of the tools that organizations use to choose the right supplier or vendor is by issuing a Request for Information (RfI), a Request for Quotation (RfQ), and a Request for Proposal (RfP).

Request for Information is a tool through which an organization can collect information about the prospective suppliers, their solutions, and how their products and services can help a company grow.
Managing a RfI is the exclusive responsibility of the procurement function, which, when designing it, will share its contents, especially those of a technical nature, with the requesting entity and the engineering department. It is a powerful tool because it allows for the involvement of many supply sources, located anywhere and of any type (size, corporate form and structure, seniority, etc.), who are able to transmit valuable information that is unique and, often, difficult to obtain any other way.
RfI is neither a scouting nor a supplier evaluation methodology (although suppliers who respond to the RfI may, subsequently, be evaluated and possibly included in the supplier register). It is, in fact, an autonomous and independent tool with respect to the purchasing process, designed solely for the purpose of data and information research. This value must be communicated to the suppliers consulted, to dispel any different interpretations of their purposes.

Request for Quotation (RfQ) is a process where the Procurement Department asks a set of potential suppliers or service providers to submit their price quotations and gives a chance to supply or provide goods or services. Once the buyer receives the price quotation, he can choose the vendor that best matches its criteria for the goods or services. RfQs are essential for businesses that require a consistent supply of products with set specifications and standards. Therefore, suppliers or service providers that are better organized usually have higher chances of creating a streamlined RFQ that best matches the requirements of an enterprise. RfQs are used for cost planning.

Request for Proposal (RfP) is a document that asks for a comprehensive proposal from the prospective suppliers that includes documents like a company profile, a proposal for delivering goods or services asked for, a client list, and financial details. An RfP is issued when the organization plans to evaluate the vendors on factors beyond pricing and find the best vendor to work on a project.

GEP (2026) wrote that RFI, RFP, and RFQ are related to the sourcing and procurement functions of the business. All three activities are helpful in overall supply chain management, and the one would be used for business depends on the end goal of the activity.

Table 1.2 Key differences between RfP, RfQ, and RfI

	RFI	RFP	RFQ
Purpose	To collect the information about prospective suppliers when you are not sure about the solution that you are looking for	To evaluate the vendors on factors that range beyond price	To evaluate the vendors based on the price quoted for goods or services
Ask	RFI asks the prospective vendors to submit details about the business to stay informed about the possible solutions in the market	RFP asks the prospective vendors to submit a comprehensive proposal in response, including an elaborate technical and financial proposal	RFQ asks the prospective vendor to quote the price for the goods or services being sourced by the business
Style	The style for an RFI is casual and is more about asking for help from the prospective suppliers in the market	The style of an RFP is formal and direct	The style of an RFQ is structured and prescriptive
Advantage	An RFI is fast and easy to execute. It helps a business figure out the possible solution to business challenges	An RFP offers a fair comparison between vendors, and a business can judge the best possible vendor based on its capabilities	An RFQ provides a chance to reduce the overall costs incurred on sourcing a particular product or service

Source: "*Global Execution Partners GEP (2026) - RFI, RFQ, RFP: How to Differentiate*"

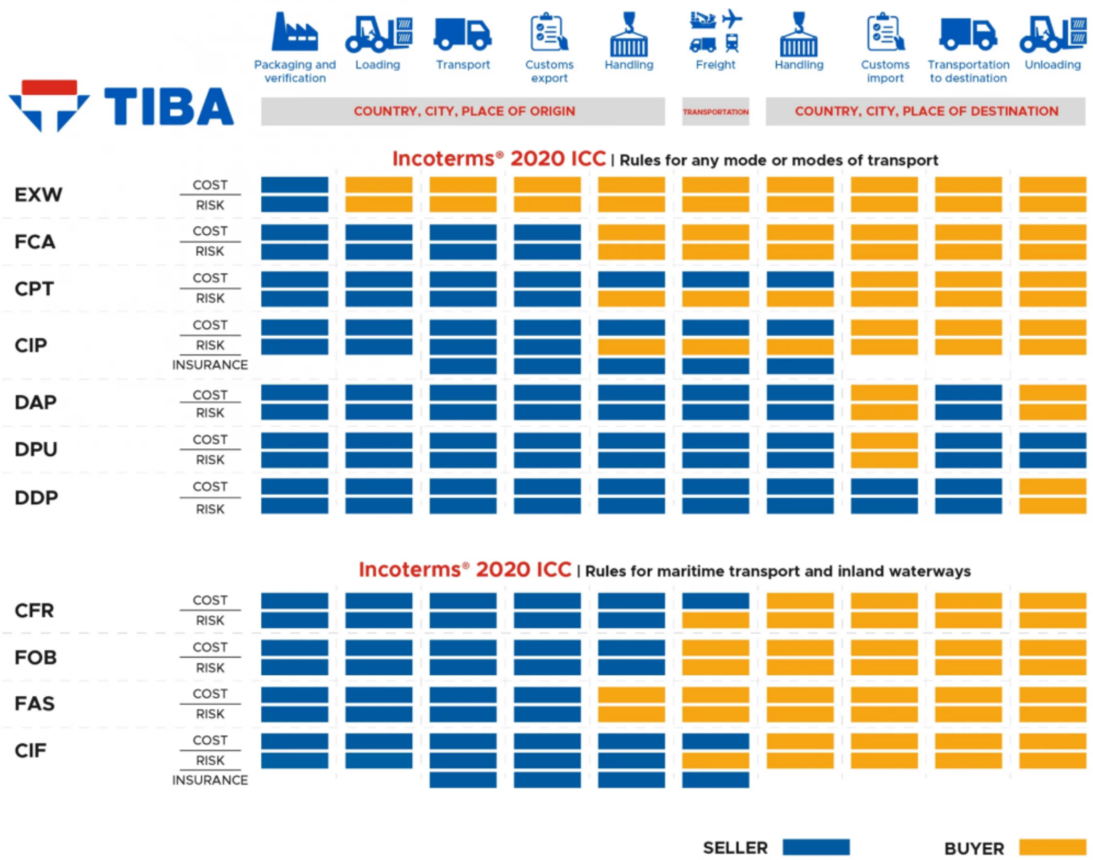
After having identified the tools whom the Procurement Department initially communicates with suppliers, the concept of Purchase Order (PO) must be introduced. The Purchase Order (PO) is a formal document to authorize and manage the acquisition of goods and services from external suppliers issued by the procurement function. It is

not only an official request to the vendor, in fact the PO is used to control, document, and track purchasing activities throughout the procurement process.
The sending out of a purchase order represents only one stage within a purchasing cycle. Before a PO can be generated, organizations typically undertake a series of preliminary activities such as verifying the availability of the requested goods or services, checking the availability of the required budget, defining purchasing requirements, and communicating conditions to potential suppliers. Furthermore, organizations must carry out controls in order to confirm that the products or services delivered correspond to what was originally requested (GEP, 2024).
In conclusion, the Purchase Order contributes to reducing misunderstandings, improving accountability, and ensuring the traceability of procurement transactions by formally documenting quantities, prices, delivery conditions and contractual requirements.
Starting with an RfX (RfI, RfQ and RfP), buyers have to research and select the necessary supplies from a new or existing supplier. Before making a purchasing decision, organizations need to understand the specific requirements of the product or service and assess the alternatives available in the market. Evaluating competing offers helps buyers select the solution that best fits their operational needs while balancing factors such as cost, quality and service levels. Procurement policies should provide clear guidance to employees and support compliance with both internal procedures and external regulatory requirements to ensure consistency throughout the process.
To create a more transparent and efficient procurement process it is necessary to determine responsibilities and approval authorities across the relevant functions. When roles are defined requests can be reviewed and authorized more quickly, reducing delays and limiting the risk of misunderstandings. Furthermore, the involvement of experienced decision-makers contributes to improving the quality of purchasing decisions by providing additional oversight and reducing the likelihood of errors throughout the procurement cycle.
The purchase order serves as a legal contract or agreement between the buyer and the supplier to ensure that deliveries comply with their procurement policies (Wilferd et al., 2025).
Acceptance of the PO entails a series of consequences that must then be managed in accordance with the Terms and Conditions signed and included in the PO document itself.

These conditions govern all possible situations that may arise and characterize the scope of supply covered by the PO. The provisions within them govern any scenario, from delays in delivery to partial delivery of the scope of supply, or even no-compliance.

Within the purchase order, buyers can also indicate the Incoterms (2020).
Incoterms are a set of commercial terms predefined by the International Chamber of Commerce (ICC) and widely used in international trade. They consist of three-letter acronyms that describe the most common practices for the sale and delivery of goods.
The main purpose of Incoterms is to clearly identify the duties and responsibilities of each party,
with particular reference to the costs and risks associated with the transport and delivery of goods.
They are optional (i.e., reference to them is not mandatory).

Figure 1.3 The Incoterms 2020



Source: TIBA Group (2020)

The Incoterms are:

The Incoterms rules define the allocation of responsibilities, costs, and risks between buyers and sellers involved in international trade transactions. Starting from the point of departure to final delivery, each term describes a different way responsibilities are shared during the transportation process.

At end of the final delivery process there is EXW (Ex Works), which means that the seller's job is just to have the goods ready at a set place, usually their own location.

The buyer is responsible for loading, transportation, export formalities, and all subsequent logistics activities. Therefore, EXW represents the minimum level of obligation for the seller.

A greater degree of involvement is required under FCA (Free Carrier). In this case, the seller delivers the goods to a carrier or another party designated by the buyer at a specified location and, where necessary, completes export customs procedures. Responsibility for the goods is then transferred to the buyer.

Under CPT (Carriage Paid To), the seller is responsible for arranging and paying for transportation to an agreed destination. However, although transportation costs are borne by the seller, the transfer of risk occurs earlier, once the goods have been handed over to the first carrier. In addition, CIP (Carriage and Insurance Paid To) requires the seller to provide insurance coverage protecting the buyer against loss or damage during transit.
Under DAP (Delivered at Place), goods are delivered when they are placed at the buyer's disposal at the agreed destination and they are ready for unloading. Moreover DPU (Delivered at Place Unloaded) requires the seller to complete the unloading operation before delivery is considered fulfilled. The highest level of seller’s responsibility is represented by DDP (Delivered Duty Paid), whereby the seller is fully responsible for all transportation, customs, and delivery obligations, including import clearance. The seller is responsible until the items arrive at the agreed location.
For maritime transport, the FAS (Free Alongside Ship) Incoterm is used, whereby the seller fulfils its delivery obligation by placing the goods alongside the vessel nominated by the buyer at the agreed port of shipment.
With FOB (Free On Board), delivery takes place once the goods are loaded onto the vessel. From that point onward, the buyer assumes the associated risks.
The terms CFR (Cost and Freight) and CIF (Cost, Insurance and Freight) also apply exclusively to sea transport. In both cases, the seller arranges and pays for transportation to the destination port while the transfer of risk occurs when the goods are loaded onto the vessel at the port of departure. The difference between CIF and CFR is the fact that in CFR the seller has to provide insurance coverage for the cargo during the voyage. The transfer of costs and the transfer of risk occur at different stages of the transaction for both terms. In conclusion, the choice of the appropriate Incoterms rule has significant implications for transportation management, customs compliance, risk allocation, and total procurement costs. Selecting the most suitable term therefore represents an important element of both commercial negotiations and supply chain planning.

In contracts with reciprocal performance, when one of the contracting parties fails to fulfill their obligations, the other may choose to request performance or termination of the contract, without prejudice, in any case, to compensation for damages.
Termination may also be requested when the lawsuit is initiated to obtain performance.
The contract cannot be terminated if the non-performance by one of the parties is of little importance, considering the interests of the other.

The contracting parties may expressly agree that the contract will be terminated if a specific obligation is not fulfilled according to the established methods. In this case, termination occurs automatically when the interested party declares to the other that it intends to avail itself of the termination clause. If the deadline set for performance by one of the parties must be considered essential in the interests of the other, if this deadline has elapsed without performance, the contract is considered automatically terminated.

Termination of the contract for breach has retroactive effect between the parties (exception: contracts with continuous or periodic performance with reference to services already performed. Therefore, both parties are required to return any amounts already received in performance of the contract.

Chapter 2

The Role of the Actual Buyer

2.1 Negotiation Fundamentals

Negotiation Fundamentals provides theoretical and practical foundations for understanding how buyers and sellers interact to reach mutually beneficial agreements. In Procurement, negotiation is not simply a discussion about price, but a structured process that requires planning, analysis, and strategic awareness of both risks and opportunities. Special attention is paid to the preparation phase, which is essential for shifting from a reactive to a proactive procurement function. Negotiation can be defined as:

- A formal communication process conducted face-to-face or via digital tools (electronic auction, internet, portals), in which two or more people converse to seek a mutually satisfactory agreement on one or more problems/issues.
- A process through which two or more interlocutors, with different perceptions, motivations, and interests, seek to reach agreement on a topic of common interest.

Effective negotiation ensures added value, where value means the achievement of a measurable result that generates satisfaction. Having a carefully prepared negotiation plan allows buyers to:

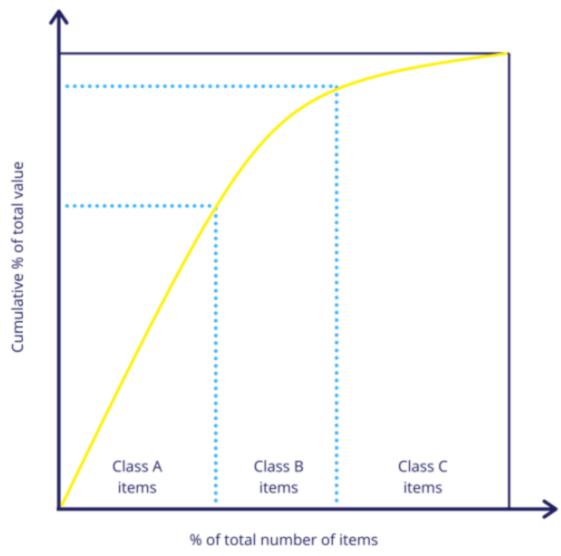
- Persuasively argue the other person's position
- Appropriately respond to critical questions/objections
- Recognize the other person's tactics
- Know when to insist on a given issue and when it is appropriate to avoid it

Not all purchasing situations require negotiation. The benefits of negotiation must outweigh its costs. In commercial negotiations, negotiation is not useful when:

- prices are fixed,
- the value of the supply is low,
- the result of the bid (request for quotation) is deemed satisfactory.

The preparation phase of a negotiation is the foundation of effective and efficient negotiation. In fact, the Procurement Department must move from an organization that rewards effectiveness to one that tends towards efficiency.
To prepare for the negotiation phase, a tool used by the Procurement Department is the ABC Analysis.
ABC analysis is based on the so-called "Pareto principle" and indicates a priority scale based on the impact that purchasing activities have on the total value of spending.
It focuses on the product categories that have the greatest impact on total spending, prioritizing the actions that have the greatest impact on the buyer's objectives: (cost optimization, process efficiency, etc.)
ABC analysis is one of the most widely adopted techniques for inventory management and control. Its primary objective is to support decision-making by grouping inventory items according to their relative importance, thereby enabling organizations to allocate managerial attention and resources more effectively (Chen et al., 2008).
The method is based on the Pareto principle, according to which a relatively small proportion of causes often accounts for a large share of the overall effects. Applied to inventory management, this principle suggests that a limited number of stock-keeping units are typically responsible for the majority of inventory value, while a much larger number of items contribute only marginally to total costs.
In practice, inventory is generally divided into three categories. Class A items represent the most valuable portion of inventory and therefore require close monitoring and tighter control procedures. Class B items occupy an intermediate position in terms of importance and management effort, whereas Class C items usually account for a large share of the total number of products but only a small fraction of inventory value.
As noted by Abdolazimi et al. (2021), ABC classification is commonly associated with the 80/20 rule, according to which approximately 20% of inventory items generate around 80% of the annual inventory costs, while the remaining 80% contribute only about 20% of total costs.

Figure 2.1 ABC Analysis based on the Pareto principle



Source: MRP easy

Supplier ABC analysis is a spend-based classification method used to identify the most important suppliers in terms of procurement expenditure. The underlying premise is that a relatively small number of suppliers often account for a large share of total purchasing spend.

For instance, the ABC Methodology system creates spending profiles for suppliers by sorting the values from highest to lowest, then dividing each value by the total spend. Then, a percentage cumulative calculation is used for each supplier, and they are given a grade A, B or C on their total value as indicated in the rubric below.

The table below shows the Percentage Score for ABC analysis

- A: 0% to 80% Supplier Spend Value
- B: 80% to 95% Supplier Spend Value
- C: 95% to 100% Supplier Spend Value

ABC Spend Analysis provides procurement with a robust data foundation to support faster, more informed decision making aligned with both company objectives and procurement goals. Using ABC Analysis, Class A are identified high value suppliers, B & C suppliers are classified as Tail Spend and make up 20% of the total spend. In addition, Class B is Mid Tail and Class C is Long tail. Effective Spend Analysis guarantees that procurement can focus on creating an efficient sourcing strategy.

Figure 2.2 Spend Analysis ABC & Tail Spend

Source: "*Accelerated Insight*"

Tail suppliers have low strategic value and make category management very difficult. Spend Analysis and Category Management are closely linked, in fact Spend Analysis, including ABC, provides the category manager with spend visibility.

The acquisition of Spend data and subsequent Spend Analysis improves the procurement process building supplier relationships, maintaining adequate service levels and delivering the best quality and price for goods and services bought.

Negotiation could be both internal and external. Internal negotiation is often the most difficult. Financial negotiation with the supplier is the deal.

Negotiate in the Procurement function refers to the buyer-seller deal and the tactics used to best close it.

The Deal is merely the final round of a negotiation process that begins with the definition of the technical and qualitative characteristics of the good or service to be purchased.

If negotiation refers to everything that adds value, then it is necessary, as already seen in the first chapter, to analyze each phase of the purchasing process, understand how best to structure it, and what needs to be done to maximize the client's benefits.

Internal negotiation aims to optimally define what needs to be purchased, along with its surrounding conditions (requirements in the RfP). It also addresses:

- the technical and logistical aspects of the supply
- the interfunctional decisions on which the various stakeholders may have different perspectives (sometimes extended to primary suppliers)

External negotiation or deal serves to:

- finalize the financial aspects
- find a compromise between the requirements indicated in the RfP and those proposed by the supplier

The primary or general objective is to reach a satisfactory agreement. Generally, there are multiple objectives, and they refer to the RfQ requirements that are not fully met by the supplier's offer.
The most common objectives are:

- price appropriate to the quality and service required
- compliance with delivery dates/schedule
- compliance with the main supply management methods
- obtaining maximum cooperation
- development of a mutually beneficial relationship

For complex supplies, it is necessary to create a negotiating team with representatives of the departments involved, plus any legal, financial, or other specialists.
If there is a team, there must be a team leader. The team leader must share negotiating strategies with the team. Any differences should be discussed before the plan is finalized. Each team member must support the team leader and renounce any personal positions that are not in line with the shared plan adopted by the team. The team leader must define the roles and responsibilities of the team members. Any disagreements between team members must be resolved privately (request a negotiating break).
When preparing for the negotiation, the buyer's goal is to gain detailed knowledge of the supplier's history, minimizing the knowledge gap to their advantage. Whoever has the most accurate and complete information wins. Type of information to acquire depending on the situation:

- Characteristics of the supply market (relationship positioning in the Kraljic matrix)
- Price trends in the relevant industrial sector
- Hourly production rates and overall business rates
- Supplier's technical and qualitative performance
- Strengths and weaknesses of both organizations
- Important negotiating factors for the supplier
- Who will negotiate on the supplier side? (Personal characteristics, professional characteristics, negotiating style, etc.)
- Average profitability and financial situation of the supplier

The supplier has an advantage due to its greater knowledge of its own industrial costs, structural costs and its own product's technical and qualitative characteristics.
This requires the buyer to analyse/estimate the costs associated with the supply.
Understanding each other's strengths and weaknesses allows you to set realistic objectives and approach the negotiation in concrete terms.
To understand the starting situation, the buyer must also evaluate:

a. Whether they operate in a buyer's or supplier's market (Kralijc matrix)
b. The supplier's interest in winning the contract
c. The supplier's perceived probability of winning the contract
d. The time available for the negotiation - rushing reduces their chances of success
e. The available alternatives - the existence of qualified alternatives strengthens the buyer's position
f. The ability and authority of the negotiating teams
g. The supplier's financial position
    i. A financially strong supplier is less willing to accept unprofitable business,
    ii. a weak supplier is more willing to accept more business, but in these cases the buyer must monitor quality and other performance.

Suppliers similarly have defined expectations and objectives, understanding mandatory requirements and strategic interests aimed at increasing turnover and acquiring additional volumes and/or customers.

The buyer should try to identify them during the preparatory phase of the negotiation. The buyer must focus on the requirements that have not been met (offer not compliant with the RfQ requirements), preparing, if necessary, to make concessions on those that are not vital to them.
For each primary factor to be negotiated, the buyer must establish its own position (objective to be achieved) and try to identify that of the supplier.
The buyer must define:

- realistic target
- optimal target
- pessimistic target or breaking point (maximum price above which the buyer is not willing to go)

•

Viewing conflict behaviour as a bargaining process is useful to avoid focusing solely on the conflict rather than on mutual interest.
In any negotiation, the choice is ultimately between two basic options: accept the agreement or keep the best alternative.
The negotiator's way of advancing his own interests cannot ignore the ability to propose an agreement that is better than the other party's alternative.
The challenge of negotiation, therefore, lies in protecting one's own interests, understanding and defining the other party's perception so that they accept our proposal in "their best interests."
Resistance to negotiation is an integral part of the process.
The willingness to negotiate stems from a state of mutual need. A negotiation therefore begins when both parties have a "reason" to participate.
The choice of negotiating tactics depends not only on one's own attitude but also on the interests of our stakeholders and the choices of the other party.

2.2 Supplier Relationship Management (SRM)

Supplier Relationship Management (SRM) represents a strategic approach through which purchasing organizations segment and manage their supplier base according to the value and risk associated with each relationship. This segmentation enables tailored strategies that align procurement practices with the specific characteristics of the items and services involved. By classifying suppliers into the categories of Kraljic Matrix (Fig. 1.2), companies can better allocate resources, mitigate risks, and leverage opportunities for collaboration.
In line with the logic of the Kraljic portfolio model, purchasing decisions should be adapted to the specific combination of market exposure and business relevance associated with each category of supply.
Non-critical items generally involve limited financial exposure and are usually available from a broad supplier market, which reduces the need for intensive relationship management.
These purchases rarely require intensive supplier management activities since supply risk is limited and switching costs are usually low. For those items procurement objectives focus on administrative efficiency, process simplification and transaction cost reduction.

To achieve these goals, organizations often standardize purchasing procedures and consolidate demand across business units in order to reduce complexity and enhance purchasing leverage (Gelderman & Van Weele, 2003).

Although these purchases may not have a substantial direct impact on financial performance, they are associated with elevated supply risk due to limited supplier availability, technological constraints or market-specific conditions.

For instance, companies accept a certain degree of dependence on the supplier and prioritize supply security, even when this results in higher costs or less favourable contractual conditions. Often, procurement managers conduct risk assessments to identify the most vulnerable items and develop measures useful for mitigating potential interruption. Such measures may include safety stocks, alternative sourcing scenarios, or emergency supply arrangements that can be activated when unforeseen events affect normal operations. Alternatively, firms may try to reduce their dependence on suppliers. This objective can be pursued by identifying substitute products, modifying technical specifications, qualifying additional suppliers, or encouraging greater competition within the supply market. Through these actions, organizations seek to decrease vulnerability and gradually improve their bargaining position.

Strategic items usually demand the closest management attention. These purchases combine a high impact on organizational performance with significant supply risks, making supplier relationships particularly important. In many cases, the number of available suppliers is limited, and organizations may depend heavily on a single source for critical products or services.

Therefore, procurement strategies frequently emphasize the development of long-term collaborative relationships. Strategic partnerships facilitate information sharing, joint problem-solving, and coordination across the supply chain. Scholars suggests that strong buyer-supplier relationships contribute to greater delivery reliability, shorter lead times, improved product development processes, and more effective risk management (Gadde & Snehota, 2000).

Nevertheless, strategic relationships do not always involve a balanced distribution of power. In some circumstances, buyers may find themselves dependent on suppliers that possess unique technological capabilities, intellectual property rights, or dominant market positions. Organisations are limited in their ability to negotiate favourable terms or switch to other providers due to these circumstances. Ulkhaq and Pratiwi (2024) associate this type of situation with supplier dominance, where the buyer may remain dependent on the supplier due to the absence of viable alternatives.

Despite the imbalance in bargaining power, the buyer keeps the relationship because there are no viable alternatives or are too costly.

Instead, organizations may decide to terminate the relationship when supplier performance declines radically and there are limited opportunities for improvement.

To reduce the dependence on those suppliers, companies have to identifying alternative suppliers and implementing transition plans. Lastly, supplier replacement can be costly and time-consuming, it is necessary when the existing relationship no longer supports organizational objectives or acceptable performance standards.

According to Olsen and Ellram (1997) routine purchases should be managed with the purpose of minimizing administrative effort and of reducing logistical complexity. Organizations often seek efficiency through framework agreements, standardization, automation, and consolidated purchasing arrangements instead of investing significant managerial resources in supplier relationships. These practices enable procurement departments to reduce transaction costs while maintaining adequate service levels.

Building on the purchasing portfolio literature, Habib et al. (2015) propose the use of a buyer-supplier dominance matrix to analyse the relative influence exercised by each party within a commercial relationship.

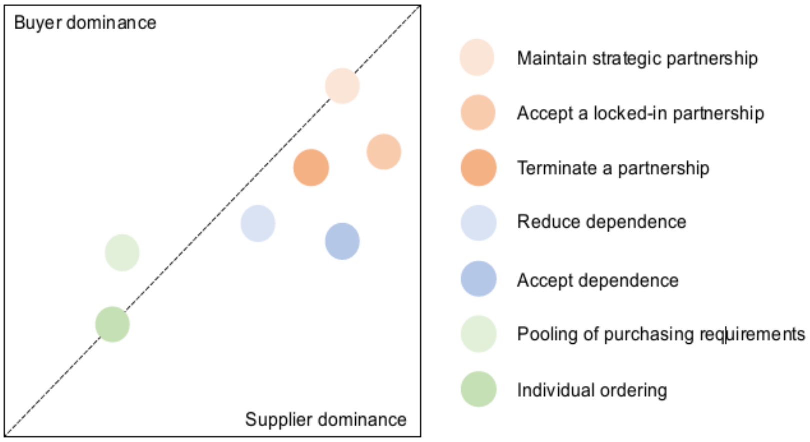
The framework evaluates buyer–supplier relationships using two key dimensions.

The first concerns the degree of influence that buyers can exert over suppliers, which is typically associated with factors such as purchasing volume, market attractiveness, and the availability of alternative customers. The second dimension displays the supplier's ability to influence the buyer which results from technological expertise, product uniqueness, switching costs and limited competitive alternatives.

The impact of buyers and suppliers on business deals can be explored by organizations using collaboration, competitive pressure, dependency reduction initiatives, or supplier development programs.

Power analysis extends the Kraljic framework by highlighting the relational dynamics that influence purchasing decisions.

Figure 2.3 Buyer vs Supplier dominance Matrix



Source: "*Jurnal Sistem dan Manajemen Industri Vol 8 No 2 December, 2024*"

Figure 2.3 presents the relationship between purchasing strategies and the distribution of power within buyer–supplier relationships. The framework highlights how procurement decisions can be influenced not only by the characteristics of purchased items but also by the relative dependence of buyers and suppliers on one another.

The diagonal line can be interpreted as a condition of relative balance, where neither the buyer nor the supplier holds a clearly dominant position in the relationship. The interaction is characterized by mutual interest in maintaining cooperation and neither side have a substantial advantage in negotiations. The balance of power shifts towards either the buyer or the supplier as distance from this equilibrium line increases. Organizations benefit from greater bargaining leverage when purchasing strategies are positioned on the side associated with buyer dominance. This situation occurs when multiple supply alternatives are available, switching costs are limited, or the buyer represents a significant source of business for suppliers. Indeed, procurement functions can negotiate more favourable contractual terms and reduce their exposure to supplier influence.

Contrarywise, supplier dominance arises when the supplier controls critical resources, specialized capabilities, or technologies that are difficult for the buyer to replace through alternative sources. Considering this perspective, buyers face a higher degree of dependence and may have limited ability to influence pricing, delivery conditions, or contractual arrangements. This is relevant because purchasing strategies are shaped not only by supply risk and economic value but also by the influence that buyers and suppliers exert within the relationship.

A locked-in relationship usually arises when a supplier occupies a unique position in the market, and the buying organization has few viable alternatives. In these cases, the buyer is constrained by its dependence on the supplier and must continue the relationship despite limited negotiating power.
Sometimes, organizations accept a degree of supplier dominance when the risk of supply disruption offsets the disadvantages associated with weaker bargaining power. However, instead of a purely passive acceptance of dependency, buyer can seek to reduce this vulnerability over time identifying alternative suppliers, modifying technical specifications, or promoting competition within the supply market. The effects of these actions should mitigate the buyer's position and decrease reliance on a single source.

Within the Strategic Quadrant, the relationships are typically founded on mutual dependence and long-term collaboration with the purpose of maintaining a strategic partnership. Both organizations are willing to invest resources to sustain the relationship. In this context, trust, information sharing and joint problem-solving become essentially to keep the cooperation.
Relationships associated with non-critical items tend to display a relatively balanced distribution of power. Since these products are standardized and widely available, neither buyer nor supplier is strongly dependent on the relationship.
The buyer's position can be influenced by the presence of multiple competing suppliers in fact; the existence of numerous alternatives increases the buyer's flexibility and strengthens its negotiating position.
In conclusion, the assessment of power relationships explains the feasibility of different strategic options and the constraints that organizations encounter when managing supplier relationships, while portfolio models classify purchases according to their economic importance and supply risk.

2.3 Essential Soft Skills

Today, procurement requires not only technical and analytical skills but emotional intelligence skills. SIPMM Publications (2024). In environments characterized by extensive stakeholder interaction and complex decision-making processes, skills such as "*communication, empathy, adaptability, negotiation, and leadership*" are required. SIPMM Publications (2024)

Emotional intelligence impacts to constructive dialogue, facilitates collaboration across organizational functions, and supports the management of conflicts. The ability to understand the perspectives of different stakeholders, to communicate expectations clearly, and to build trust-based relationships influence the success of procurement initiatives. These abilities are essential due to the globalization and increased complexity of the procurement process. In fact, procurement professionals interact with suppliers, internal clients, and external stakeholders from different culture and different organizational backgrounds, those skills are essential for procurement leadership.

SIPMM Publications (2024) outlined Procurement skills and the differences between Procurement Innovation Skills and Procurement Influence Skills.

Skills for innovative procurement are associated with sustainability, ethical sourcing, and engagement with suppliers. SIPMM Publications (2024). Professional should identify opportunities for promoting practices that contribute to improve operational performance and long-term sustainable goals.

The capacity to impact stakeholders is equally important. Procurement functions frequently interact with departments that have different goals and priorities.

Negotiation is one of the most important skills among the interpersonal ones. Hence, the ability to persuade, negotiate, and build consensus represents an important component of effective procurement management.

Procurement professionals engage in negotiations discussing prices, contract conditions, service levels and supplier performance.

Successful negotiations do not focus only on cost reduction but focus on balancing long-term objectives with the interests of supplier's interests.

Before buyers started negotiation, they collected information about market conditions, supplier capabilities, historical purchasing data, and alternative sourcing options.

During the negotiation process, they must communicate organizational needs such as contract duration, delivery schedules, service commitments, or payment conditions.

Professionals with strong negotiation skills may opt to sign a longer contract in exchange for negotiating prices, demonstrating their flexibility and ability to adjust their plans accordingly. This is particularly advantageous for businesses seeking better business outcomes.

They will encourage a positive outcome by proposing that both sides can benefit from the deal. The ability to combine analytical reasoning, interpersonal effectiveness, and strategic judgement enables procurement professionals to create value for their organizations while maintaining productive and collaborative partnerships with key suppliers.

2.3.1 Cross-Functional Leadership

Over the past few decades, procurement has moved beyond its traditional administrative role and become a strategic function within many organizations.

As companies have become more interconnected and business processes increasingly integrated across functions, the competencies required of procurement professionals have expanded well beyond traditional transactional responsibilities. According to Weigel and Ruecker (2017), the contemporary procurement environment requires a combination of technical expertise, market awareness, and interpersonal skills. Thus, it shifts the role of procurements professionals towards a more complex professional profile than in the past. From one hand, operational buyer requires in-depth knowledge of the logistics and procurement processes, on the other hand the strategic buyer must have extensive market knowledge and international negotiation skills. Weigel et Ruecker,(2017)

Moreover, buyers contribute to cross-functional projects dealing with different stakeholders.

Beyond technical and commercial expertise, nowadays interpersonal competencies have become important. In the past procurement activities focused only on order management and communication with suppliers. Today, "*the buyer is today faced with a far greater density of interaction*". Weigel et Ruecker, (2017). Purchasing facing the role of interface manager between internal company departments and external suppliers.

As shown in Figure 2.4, management skills, communicative and intercultural skils will become essential for the buyers. Leadership is a crucial skill that the modern Buyer should develop and continually refine. This is an important aspect when it comes to protecting company-wide purchasing interests. The following practical tip should help to explain this further.

Figure 2.4 Fields of competence for the Modern Buyer

Expertise	Soft skills
• Product competence	• Appearance
• Research competence	• Entrepreneurial skills
• Bidding competence	• Intellectual skills
• Supplier management	• Communication skills
• Negotiation competence	• Leading skills
• Controlling competence	• Emotional skills
• Value analysis	• Compliance
• Strategy development	• Internationality
• Risk Management	
• Process Management	

Source: The Strategic Procurement Practice Guide (2017)

2.3.2 Flexibility and Problem Solving

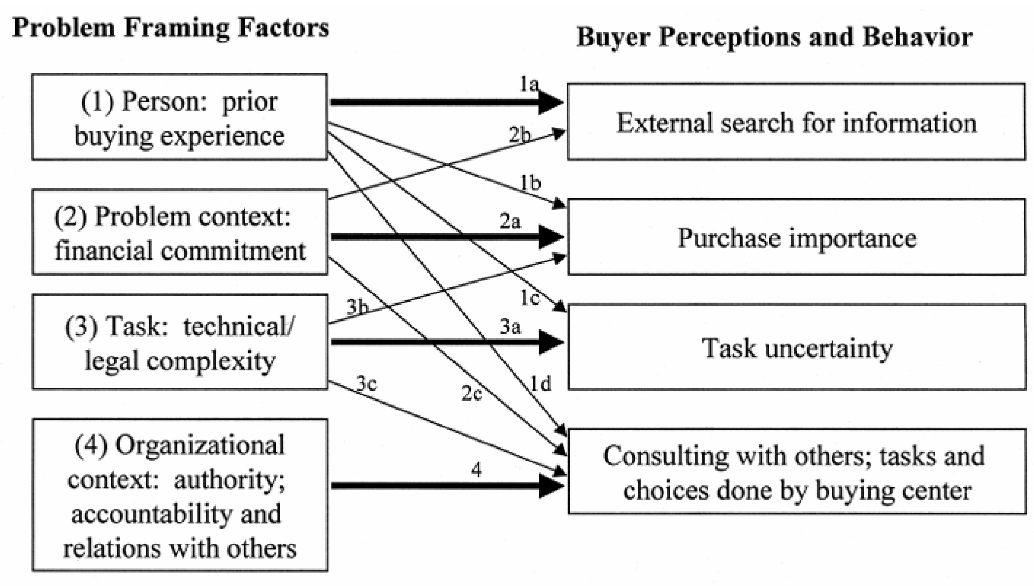
Youg et al. (2003) explained that the flexibility with which buyer–seller relationships are governed has been proposed to be an important antecedent to the productivity of knowledge. Conner and Prahalad (1996) suggested that one important premise of the resource-based view of the firm is that flexibility in trading relationships motivates the speed, ease, and cost of responding to new knowledge, new technologies, market changes, or other developments that arise during work. As flexible behaviour increases, trading partners increasingly adapt their duties and responsibilities to incorporate learning. According to Doz and Hamel (1998), the adaptability with which partner relationships are governed may have more to do with successful performance outcomes than does the initial formal agreement.

Volberda (1996) defined flexibility as the willingness of parties in a trading relationship to adapt, change, or adjust to new knowledge without resorting to a series of new contracts and renegotiations

Wilson et al. (2001) wrote that a positive (negative) answer implies less (more) search, less (more) necessary cognitive effort in solving the problem, and less (more) perceived risk in experiencing an unacceptable outcome. With prior knowledge, the buyer may perceive the problem-solving task with low uncertainty. In addition, the authors explained the problem may be perceived as less important because less search and cognitive effort are needed compared to those solved previously.

Based on the literature, Wilson et al. (2001) identified four major problem-framing factors which are explored as they affect buyer perceptions and behaviour. These factors are context based regarding the person (prior experience), problem (financial commitment), buying task (technical complexity), and organization. A few limitations related to Figure 2.5 are worth noting.

Figure 2.5 Problem framing factors and their influence on buyer perceptions and behavior



Source: "*How Buyers Frame Problems: Revisited, 2001*"

First, a buyer may use additional framing factors when categorizing a specific problem that affects subsequent perceptions and behaviours. For example, time pressure (a requirement to expedite the purchasing process) may be a context variable in framing the problem. Thus, several major subcategories of variables may be found for each of the four factors included in Figure 2.5.

Second, for some problems, buyers are likely to reframe the problem several times before making choices and moving on to frame and solve additional buying problems. Payne et al. (1993) note that this view of decision processing argues that the problem situation is constantly being redefined by the decision maker.

Third, to limit complexity, only main effects are shown in Figure 2.5 as propositions. Substantial interaction effects are likely to be recognized by buyers among major framing factors. Thus, the impact of prior buying experience on external search is likely to be moderated by the financial commitment required in the purchase. Although interaction effects of problem framing factors have been a major focus in cognitive psychology, heretofore, research on the buyer's recognition of such moderating influences has not been reported.

Fourth, propositions among the four framing are not included in Figure 2.5. The following statement is one example of such a proposition: as purchase importance increases, external search for information will increase. Such additional propositions serve to illustrate the potential in direct influence problem framing factors have on subsequent perceptions, attitudes, and behaviours. For example, a direct effect of prior experience on external search may occur and there could also be an indirect effect via the associations of prior experience with importance and importance with external search.

2.3.3 Emotional Intelligence and Intercultural Communication

In the procurement environment, buyer have to communicate data clearly, confidently, and persuasively to various stakeholders such as group individuals and executives. All of these characterises can be called communication skills. These skills are critical for developing relationships, negotiating contracts, and aligning procurement techniques with organizational goals. Buyers will analyse current market trends, the vendor's past overall performance, and competitors in the market.

The purchasing manager will use persuasive communication methods to highlight the long-term benefits of the partnership, in fact, he will try to achieve better rates and better performance from suppliers, while remaining open to the supplier's counterarguments. Buyers will look for solutions to maintain a positive relationship with the supplier. The objective of the negotiation process is not only to reach favourable contractual conditions but also to establish a cooperative relationship that can support future collaboration.

Porter and Samovar (1991) defined communication as occurring whenever meaning is attributed to behaviour. Communication has been recognized as an important construct in effective buyer-seller and channel relationship management. The role of communication in relationship marketing has historically been reduced to the assertion that "more communication" or "improved communication" is needed. Mohr and Nevin (1990) state that this view is not only simplistic but also inaccurate. Furthermore, simply stating that communication needs improvement does not give marketers any input on how to improve communication. Williams et al. (1985) addressed the need to investigate buyer-seller relationships from a more detailed communication perspective. Marketing researchers have investigated several communications skills and their potential effect on performance. Such abilities as gathering information and asking questions, listening or the lack thereof, and recognizing different communication styles have been advocated as critical to successful buyer-seller interactions.

Lustig and Koester (1993) defined intercultural communication is a symbolic, interpretive, transactional, contextual process in which the degree of difference between people is large and important enough to create dis similar interpretations and expectations about what are regarded as competent behaviours that should be used to create shared meanings. In the negotiation context, intercultural communication occurs when a message from a buyer (seller) from one culture must be processed by a seller (buyer) from another. Research in intercultural communication has uncovered dispositions and skills that can affect buyer-seller interactions. It is posited here that these constructs can be incorporated into a theoretical framework that integrates cultural diversity into buyer-seller relationship management.

Chapter 3

The Impact of Artificial Intelligence

3.1. AI in Global Trade: Opportunities, Challenges, and Multilateral Governance

Artificial intelligence has moved from being largely a research concept to becoming a technology with a significant impact on both economies and societies. As Brynjolfsson and McAfee (2014) argue, digital technologies, and particularly AI, are reshaping productivity and economic structures in unprecedented ways. Its rapid development is closely tied to three mutually reinforcing factors: increasing computational power, advancements in algorithms, and the unprecedented availability of data.

Goodfellow et al. (2016) point out how these factors have allowed AI systems to perform tasks that previously required human cognition, ranging from legal analysis and language translation to self-driving cars and financial decision-making. These systems are changing learning systems. As a result, AI is not just another digital technology, but a general-purpose infrastructure capable of reshaping global production systems, changing the foundations of international trade and redistributing economic power.

This transformation has happened unequally across countries, showing differences in technological capability and legal regulation. Baldwin (2016) notes that digital globalization increases the gaps between advanced economies and developing economies. While technologically advanced economies are already in the phase of data accumulation and algorithmic innovation, less advanced economies act only as users of AI.

This asymmetry contributes to the reshaping of global economic relations, raising concerns about new forms of dependency and inequality. Moreover, regulatory responses to AI differ across jurisdictions, since they are based not only on economic calculations but also on cultural, ethical, and social values. Floridi et al. (2018) reinforce the idea that ethical principles shape AI governance differently in different societies. The
result is a fragmented regulatory landscape that challenges the coherence of existing trade rules.

In this context, international trade governance, particularly within the framework traditionally embodied by the multilateral trading system, faces a set of unprecedented tensions. WTO rules were not designed for data-driven economies. The system was designed in a historical period that did not anticipate technologies capable of autonomously generating content, making decisions, or interacting with the physical environment.

Mitchell and Mishra (2019) emphasize that the distinction between goods and services, for example, is becoming increasingly blurred when digital products incorporate both intangible and tangible elements, or when services are directly integrated into physical devices. The difficulty of classification is particularly evident in the case of AI-based legal tools. Susskind (2019) discusses how technology is transforming the legal profession by automating key tasks. For example, documentation activities and writing assistants challenge traditional definitions of professional services. Their regulatory treatment therefore raises fundamental issues regarding market access, professional standards, and cross-border provision. Abbott (2020) highlights that regulatory frameworks struggle to classify AI legal services consistently. Existing legal frameworks do not easily capture these hybrid forms and attempts to categorize them often lead to inconsistencies and uncertainty. A similar tension emerges in the domain of intellectual property. AI systems are increasingly capable of producing creative outputs such as articles, music, or technical inventions with minimal human intervention.

As wrote by Ginsburg and Budiardjo (2019), this calls into question the requirement for human authorship laid down in copyright law. Whilst some legal systems have introduced flexible approaches that allow for the recognition of non-human contributions, others maintain a strict requirement for human involvement. This divergence creates practical difficulties in the cross-border recognition of rights, leading to fragmented rights and trade friction.

AI is raising regulatory issues deeply rooted in social and ethical values. One of the most striking examples is the design of autonomous decision-making systems, such as self-driving vehicles. The example of unavoidable accidents illustrates how algorithmic decisions reflect each person’s moral judgements. Bonnefon et al. (2016) analyse how ethical dilemmas in autonomous driving reveal cultural differences in moral preferences. These technologies must operate in situations involving ethical trade-offs, where different choices can lead to different consequences and liabilities. However, Awad et al. (2018) discusses that societal preferences regarding such dilemmas vary across cultures, influenced by historical traditions, philosophical beliefs, and legal systems.

As a result, governments may adopt different regulatory standards that encode these values into technological design.

Such divergence, while legitimate from a domestic perspective, can create barriers to trade and complicate international coordination. Trade rules, which traditionally aim at reducing discrimination and promoting market integration, may struggle to accommodate these deeply embedded differences. Attempts to impose uniform standards risk overlooking legitimate diversity, while excessive fragmentation undermines predictability and cooperation. Another dimension of complexity arises from the increasing use of AI in decision-making processes, including in areas traditionally reserved for human judgment. Agrawal et al. (2018) argue that AI reduces the cost of prediction, transforming decision-making processes. Data-driven tools can enhance efficiency, reduce costs, and support complex analytical tasks.

In international economic relations, AI tools improve negotiation processes, assess legal arguments and contribute to the resolution of disputes. Mittelstadt et al. (2016) highlights the ethical risks associated with algorithmic decision-making. Indeed, these benefits raise important questions regarding transparency, accountability and bias. Often, Algorithmic systems operate as opaque structures, making it difficult to understand the process by which decisions are reached.

Burrell (2016) wrote that such opacity can undermine trust, particularly when the results have legal or economic consequences. O'Neil (2016) points out that data-driven approaches can reproduce and amplify existing inequalities, especially if the underlying data reflects historical biases. Delegating decision-making power to such systems therefore raises fundamental questions regarding procedural safeguards.

The gap between the rapid evolution of technology and the slower process of legal compliance is called "*the pacing problem*". In fact, as Marchant et al. (2011) describes, legal systems often lag technological innovation. Legislators and regulators often struggle to anticipate the implications of emerging innovations, causing reactive rather than proactive governance.

At the international level, Ebert and Löffler (2020) wrote that this difficulty is compounded by the need to coordinate between jurisdictions with different mindsets and priorities. As a result, regulatory responses are fragmented and constantly evolving, rather than being consistent and stable. This phenomenon can be called legal pluralism, i.e. the emergence of diversified governance approaches.

Deakin (2019) explained that multiple regulatory regimes can coexist and interact together in a complex context. Countries experiment with different strategies that reflect their specific contexts and objectives rather than converging towards a single global model,

The role of international institutions cannot be limited to the application of uniform rules, on the contrary, they must facilitate dialogue, coordination and mutual understanding between a wide range of stakeholders.

In this era, the role of international institutions cannot be limited to the application of uniform rules. Rather, it must facilitate dialogue, coordination and mutual understanding between different stakeholders. Pauwelyn (2014) stresses the importance of flexible and adaptive international governance. Flexibility becomes a fundamental requirement, allowing governance to adapt to changing circumstances and to integrate new forms of knowledge. At the same time, respect for local diversity is essential, because attempts to impose rigid harmonization could be counterproductive. In fact, incremental and experimental approaches appear particularly suitable in this context.

Sabel and Zeitlin (2012) discuss that experimental governance allows for gradual learning and adaptation. Policymakers can adopt step-by-step strategies that allow for continuous adjustment instead of relying on a complete system and definitive solutions. Furthermore, initiatives involving limited groups of actors can act as a testing ground for new practices. Over time, these models can spread and contribute to broader convergence, without the need for centralized taxation. However, thoses approaches are not without risk.

Differences in technological capacity and access to data reinforce existing disparities between countries, creating new forms of imbalance in the global economy. A UNCTAD Conference on Trade and Development (2021) informs that data concentration could increase global inequalities. States that possess advanced AI capabilities and large data resources are likely to exert more influence by influencing standards and practices in ways that reflect their interests. This dynamic could lead to a reconfiguration of the traditional North-South division, with significant implications for international cooperation.

In conclusion, the interaction between AI and global trade governance requires strong attention. On the one hand, it is necessary to ensure that technological innovation can thrive and contribute to economic development. On the other hand, Floridi et al. (2018) suggest that it is equally important to address the issue of social, ethical and political consequences of these digital transformations. Rather than seeking immediate and definitive answers, as Jasanoff (2003) suggests, governance must rather adapt to uncertainty. In fact, uncertainty is an intrinsic feature of technological change

Therefore, the challenge is not to eliminate the diversity of approaches but to manage it in a way that allows coexistence and cooperation. It is necessary to respect local contexts and encourage the experimentation of new practices.

3.2. Operational Efficiency

Business analytics refers to the use of data analysis techniques to support decision-making and improve organizational performance.

It integrates statistical analysis, predictive modelling, and data visualisation to transform raw data into actionable insights. In today's highly competitive business environment, operational efficiency, defined by Chowdhury (2024) as the capability to deliver products and services at the lowest possible cost while maintaining quality, represents a key objective for organisations striving to achieve a competitive advantage. Business analytics helps organisations identify inefficiencies, anticipate future demand, and improve operational processes. Through data-driven insights, organisations can enhance operational effectiveness, reduce costs, and strengthen overall performance.

Chowdhury (2024) wrote that "*Artificial Intelligence (AI) can be referred to the simulation of human intelligence*" within machines that are programmed to perform tasks typically requiring human cognitive abilities. As organisations generate and store increasing amounts of data, they require more advanced tools to turn that information into useful insights. AI-based technologies, including machine learning, natural language processing (NLP), and predictive analytics have expanded the traditional analytical methods by supporting more sophisticated forms of data processing and interpretation.

Machine learning techniques allow systems to identify patterns, correlations, and behavioural trends that are not immediately visible through conventional statistical approaches. At the same time, natural language processing facilitates the analysis of unstructured information, such as reports, contracts, customer feedback, and social media content, transforming qualitative material into actionable insights. These technologies react more quickly to market developments have changed how organisations use information.

AI has had a noticeable impact on operational efficiency. Research has shown that advanced analytical systems improve supply chain performance through accurate demand forecasting by enhancing inventory management. Machine learning allows firms to reduce excess inventory while limiting the risks associated with stock shortages, in fact models are used to anticipate fluctuations in demand. This allows firms to manage resources more effectively while reducing vulnerability to supply disruptions.

The financial sector has also experienced substantial benefits from the adoption of AI technologies. The capacity of intelligent systems to process large volumes of transactional data in real time has strengthened fraud detection mechanisms and improved risk assessment practices. By identifying anomalies and behavioural patterns that may indicate fraudulent activity, AI-based solutions support more effective monitoring and compliance procedures. Furthermore, predictive models enable institutions to respond more rapidly to emerging risks and market developments.

AI has also transformed customer service operations. Automated systems such as chatbots and virtual assistants have transformed customer service operations by handling routine activities. Those tools provide continuous support and they reduce response times.

These technologies allow organisations to improve service quality while simultaneously reducing operational costs, thereby enhancing customer satisfaction and organisational performance.

In recent years, AI has also become increasingly important in procurement and purchasing. Recent developments in AI-driven procurement have introduced new approaches to supplier management, sourcing decisions, and operational planning. By combining machine learning, natural language processing, and advanced analytical tools, organisations are able to process large quantities of information derived from invoices, procurement records, inventory databases, market data, and external variables such as economic conditions or weather patterns.

Tasks that traditionally required substantial human intervention such as the supplier evaluation, the contract monitoring or the purchase order management can now be partially automated. This increases efficiency and likelihood the possibility of administrative errors. Moreover, predictive analytics improve demand forecasting and purchasing decisions by anticipating future requirements with accuracy.

Now, the evaluation of suppliers incorporates a broad range of performance indicators such as reliability, financial stability, compliance records, sustainability objectives, and environmental, social, and governance (ESG) criteria. Indeed, organizations conduct more comprehensive risk assessments and identify potential vulnerabilities within their supply networks before they materialise those vulnerabilities.

Research generally suggests that AI can improve productivity, reduce costs, and strengthen risk management practices in procurement.

By improving visibility across supply chains and supporting data-driven decision-making, intelligent procurement systems contribute to stronger organisational competitiveness, particularly in increasingly complex and globalised markets. So, procurement is increasingly viewed as a strategic function that contributes directly to business planning and performance.

Cloud technologies help automate procurement activities while making information easier to access and share across the organization. They can also connect with enterprise resource planning (ERP) systems, supplier networks, and other digital platforms, allowing data and processes to flow more smoothly between different stakeholders.

This interoperability allows information to circulate across organisational boundaries, supporting greater transparency and coordination throughout the procurement lifecycle.

Public organisations are also adopting cloud-based solutions to support broader digital transformation efforts. In both public and private organisations, AI-enabled platforms are being employed to support compliance monitoring, financial planning, expenditure analysis, and risk evaluation. These applications contribute to more efficient resource allocation by reducing administrative and operational costs. The ability of AI systems to adapt rapidly to changing regulatory requirements further improves their value in highly regulated environments.

Procurement professionals increasingly rely on analytical tools to identify inefficiencies and anticipate emerging risks. However, organisations must ensure the integration frameworks between the digital ecosystem to interact and to maximise these benefits.

Automated workflows improve process reliability, reduce delays, and facilitate coordination among internal departments and external partners. The combination of intelligent technologies and innovative organisational practices generates value and enhance long-term business performance.

3.2.1 Automation of transactional processes (Procure-to-Pay)

The Procure-to-Pay (P2P) cycle is a key process in manufacturing organisations, linking procurement, logistics, and financial activities.

As outlined by Potla (2023), the process encompasses a sequence of interconnected stages, including purchase requisitioning, purchase order generation, goods receipt, invoice processing, and payment authorization. Despite their functional interdependence, these activities have traditionally been managed through separate systems and organisational structures. Trautmann and Lasch (2020) argue that the fragmentation results in operational inefficiencies and delayed payments.

Moreover, the lack of integration also affects supplier relationships. Vachon and Klassen (2008) observe that fragmented communication channels and inconsistent data exchange mechanisms hind collaboration between buyers and suppliers. Organisations should increasingly adopted supplier collaboration portals by improving their digital transformation strategies. Peltomaa (2021) highlights how these platforms facilitate more structured and transparent interactions by centralising information exchange, reducing manual errors, and improving coordination throughout the procurement process.

In manufacturing, the P2P process depends on close coordination between procurement, finance, and supply chain teams. Given the volume and complexity of transactions involved, organisations have increasingly invested in digital technologies aimed at streamlining operational workflows.

Enterprise Resource Planning (ERP) systems, Electronic Data Interchange (EDI) technologies, and cloud-based supplier networks are key enablers of procurement automation according to Vanjoki (2013).

Schulze et al. (2021) argue that automation contributes to higher data quality and stronger compliance monitoring. These benefits are helpful in manufacturing environments characterised by large purchasing volumes and multiple approval stages. Berg (2020) further notes that automated support adherence to corporate governance requirements and to internal control procedures.

Integrating ERP systems with supplier networks reduces duplicate records and streamline approvals. Moreover, Automated P2P systems aim companies meet compliance requirements by creating clear digital records and standardized documentation.

These platforms allow buyers and suppliers to share information in real time and coordinate procurement activities more easily. Suppliers can receive and confirm purchase orders, update delivery information, and send shipping notices, helping procurement and logistics teams stay aligned.

Supplier portals also increase transparency by giving suppliers direct access to information such as invoices, payment status, communication history, and performance data. This reduces the need for manual communication, and it improves information sharing between buyers and suppliers.

Digital platforms also improve transaction traceability by recording each stage of the procurement process electronically. From purchase order creation to final payment execution, all relevant activities can be documented and audited when necessary. Greater transparency can support compliance efforts while helping buyers and suppliers work more effectively together. Furthermore, the integration of purchase order and ASN data with warehouse management and accounts payable systems supports just-in-time (JIT) manufacturing practices, where accurate shipment visibility is critical for reducing inventory costs and maintaining production continuity.

Digital technologies have transformed invoice processing by reducing the need for manual data entry and document verification. This helps minimize errors, avoid delays, and lower the administrative costs associated with decreasing the inconsistencies between purchase orders, deliveries, and invoices.

Recent advances in Artificial Intelligence (AI) and Machine Learning (ML) have made invoice automation far more effective than traditional rule-based systems.

Intelligent systems are now able to extract data from invoices, validate information, perform three-way matching procedures, and identify anomalies with limited human intervention. As a consequence, organisations can reduce manual processing efforts while increasing both accuracy and processing speed.

AI tools help reduce mistakes by identifying duplicate invoices and inconsistencies in financial data. Machine learning algorithms learn from past transactions and previous user actions. These systems become better at spotting potential issues, making invoice checks faster and more reliable.

Workflow automation can further improve efficiency by reducing manual approval activities. By routing invoices automatically to the appropriate approvers according to predefined organisational rules, these systems reduce approval times and improve process visibility. Automated approval mechanisms also help organisations identify bottlenecks more quickly and accelerate payment cycles.

Many modern invoice management platforms now include predictive analytics features.

By analysing historical expenditure patterns, payment behaviour and financial data, those tools help organizations better manage cash flow to support payment planning and identify potential savings opportunities.

3.2.2 Intelligent spend classification.

Spend classification is a key procurement activity that helps organisations organise and analyse purchasing data more accurately. Through the systematic categorisation of expenditures, firms are able to gain greater visibility over procurement activities, improve supplier management, and identify opportunities for cost canon. By grouping purchases according to common characteristics, organisations can analyse spending patterns more structured and support strategic sourcing decisions.

Mandl (2023) underlines that a well-designed classification framework contributes to supplier development by assessing the areas where improvements in cost efficiency, product quality, and delivery performance can be achieved.

According to Monczka et al. (2016), Spend analysis involves the systematic examination of organisational expenditure with the goal of understanding how financial resources are allocated across different purchasing categories. This process focuses not only on the value and volume of purchases but also on the identification of the goods and services acquired, the suppliers involved and the organisational units responsible for generating demand. Furthermore, companies can identify inefficient purchasing practices and reduce unnecessary supplier duplication by understanding how money is spent.

Tapkan et al. (2016) emphasize the role of data mining techniques in extracting meaningful patterns from large procurement datasets. These techniques reveal patterns in purchasing behaviour and supplier relationships that traditional expenditure reviews might overlook.

In addition to supporting descriptive analysis, advanced analytical methods also contribute to forecasting activities. In fact, examining historical procurement data, organisations anticipate future spending trends, estimate demand fluctuations, and identify new procurement requirements. As noted by Tapkan et al. (2016), predictive techniques reveal hidden associations between purchasing categories.

Additionally, spend analysis can benefit from numerical taxonomic analysis to identify distinctive buyer groups and their information-gathering behaviours. 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. Pellini and Jones (2011) classified that 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. 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.

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. Shaham et al. (2021) wrote that 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. Chaugule and Natu (2021) add that AI's ability to model behaviour dynamics and detect anomalies, such as maverick spends, enhances the precision of spend analysis by identifying non-compliant procurement activities and recommending alternative options. Hoffman and Elm (2006) suggested that 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, which resulted in substantial annual savings.

According to Singh et al. (2005), the use of AI forecasting techniques, for example the support vector machines, improves demand prediction and supports purchasing decisions that are more closely aligned with actual consumption patterns. Therefore, those techniques reduce excess inventory and avoid unnecessary storage and handling costs.

AI applications can also support managerial decisions by providing clearer and more reliable information. Singh et al. (2005) highlight those explainable models, such as multi-criteria ABC classification approaches, provide managers with a clearer understanding of inventory dynamics and product priorities. By combining predictive capabilities with interpretable analytical outputs, these systems support more informed procurement decisions and contribute to more effective inventory control practices. Lastly, AI's dual abilities of automation and smartness can influence suppliers' pricing strategies, ensuring that buyers receive competitive quotes, thereby maximizing procurement value.

3.2.3 Manage of the Contract Principles

A key question in the debate on AI and contract law is whether AI systems should be treated simply as tools or as independent actors in contractual transactions. As observed by Martin-Bariteau and Scassa (2021), the discussion centres on whether AI should be treated merely as an instrument operating on behalf of human actors or whether, under certain circumstances, it could be regarded as an autonomous participant capable of engaging in contractual relations independently.

According to the traditional agency theory, AI is a tool that operates under human control rather than an independent actor. Therefore, legal responsibility for its actions remains with the individual or organization using the system. AI does not possess independent legal capacity but serves as a tool through which contractual intentions are executed.

This view sees AI as a tool that works under human supervision, much like electronic contracting systems. Just as online platforms help people make contracts without changing the basic rules of contract law, AI support contractual activities while responsibility remains with the people or organisations using it.

The autonomy granted to the system is operational rather than legal, since its activities are constrained by predefined objectives, parameters, and governance mechanisms designed to prevent unintended or unauthorised transactions.

A more controversial position emerges when AI is considered capable of making decisions with a high degree of independence. Recent developments in machine learning and autonomous systems have increased the ability of AI applications to process information, adapt to changing environments, and perform complex tasks without continuous human intervention.

These developments raise new legal challenges, especially when AI systems produce outcomes that are difficult to predict. However, AI remains a human-created technology and is still influenced by the data and design choices behind it. While AI can support decision-making, it does not possess human qualities such as intention, moral judgment, or legal responsibility. For this reason, the possibility of recognising AI as an autonomous contracting entity remains a highly debated and largely unexplored issue within legal scholarship. As noted by Solanki (2023), modern contract law has been developed around assumptions concerning human parties and human intentions, making the integration of autonomous AI systems into existing legal doctrines particularly challenging.

The impact of AI extends beyond debates about legal personality, affecting how contracts are managed in practice. Contract law involves a variety of procedural, administrative, and legal requirements that must be satisfied before an agreement becomes valid and enforceable. Many organisations now use AI tools to streamline contract management, allowing legal teams to process complex tasks more quickly.

The contribution of AI is especially evident during the pre-contractual stage. At this phase, organisations often need to process large amounts of information, evaluate contractual risks, conduct due diligence activities, and review extensive documentation. AI systems are useful in analysing large datasets, identifying recurring contractual patterns, detecting anomalies, and extracting relevant information from legal documents. Thus, legal professionals can review documents faster and identify relevant contractual clauses more easily. The use of AI can also simplify activities such as due diligence investigations and contract abstraction. By automating repetitive analytical tasks, legal professionals can devote greater attention to strategic assessments and complex legal issues that require human judgment. For many organisations, AI has become a practical tool that supports legal work rather than simply an emerging technology.

AI can also assist once contracts are in force, helping organisations manage and monitor contractual obligations. Drafting assistance and automated redlining tools can accelerate the preparation and revision of contractual documents while promoting greater consistency across agreements. Furthermore, intelligent systems can continuously monitor contractual provisions, identify potentially problematic clauses, and alert users to compliance risks or contractual inconsistencies before they generate disputes.

AI can also assist once contracts are in force, helping organisations manage and monitor contractual obligations. Advanced systems can examine extensive collections of legislation, judicial decisions, regulatory materials, and legal commentary in a fraction of the time required by traditional research methods.

AI help legal professionals analyses large amounts of legal information such as judicial decisions, and legal precedents making it easier to find relevant cases and support legal decisions. It can also use past court decisions and litigation data to estimate the possible outcome of disputes, helping organisations to plan their legal strategies. However, these predictions are only a support tool and cannot replace professional legal judgment.

Current evidence suggests that AI is more likely to enhance the work of legal professionals than to replace them, particularly by improving the speed and accuracy of contract management activities.
At the same time, the growing sophistication of AI systems continues to raise important legal and theoretical questions concerning responsibility, autonomy, and the future evolution of contractual relationships in increasingly digital environments.

3.3. Governance Implications

Schneider et al. (2022) defined AI governance for business as "*the structure of rules, practices, and processes used to ensure that the organization's AI technology sustains and extends the organization's strategies and objectives*".

Abraham et al. (2019) point out the following six parts of AI governance:

- raising collaboration across functions
- structuring and formalizing AI management through a framework
- focusing on AI as a strategic asset
- defining how and who makes decisions
- developing supporting artifacts (policy, standards, and procedures)
- monitoring compliance.

Russell and Norvig (2020) wrote that Machine Learning can be seen as a branch of AI with the narrower goal of learning from data. Thus, ML denotes the models and processes for building and testing models by learning from data. AI aims at building an AI system consisting of an ML model and typically other components, e.g., graphical user interface and input handling for an AI (software) system or physical elements such as those found for a robot. The ML model might be seen as the brain of the AI, and it is responsible for making decisions.

The term AI differs from the one of ML. It is not only broader regarding its goal but also in terms of the techniques used to achieve intelligent behaviour. Russell and Norvig (2020) wrote that while ML focuses on learning from data, AI includes non-learning, based techniques and logical deduction. From a governance perspective, Schneider et al. (2022) chose to define AI in the following three areas: data, model, and (AI-)system since they relate to existing governance areas. Furthermore, they build on top of each other. AI governance refers to data and IT governance, covering both systems (commonly a large software code basis) and models (typically a small code basis). In contrast, model governance is a new area that comprises the governance of relatively small software codes (compared to traditional software) that contain models and procedures for training, evaluation, and testing.

Businesses can make use of various mechanisms to govern AI. They consist of formal structures connecting business, IT, data, model, ML, and system management functions, formal processes and procedures for decision-making and monitoring, as well as practices supporting the active participation and collaboration among stakeholders. Schneider et al. (2022) employ the separation between structural, procedural, and relational governance mechanisms.

Borgman et al. (2016) wrote that structural governance mechanisms define reporting structures, governance bodies, and accountability. They comprise roles and responsibilities and the allocation of decision-making authority.
Tarafdar et al. (2019) noted that developing AI systems is a multi-disciplinary endeavour. Thus, establishing an interdisciplinary AI governance council that has been advocated for AI in healthcare might be needed to handle the complex interrelation between model outputs, training data, regulatory and business requirements. Executive sponsors also play an essential role because they control and decide on performance goals that might depend on the company's stage of adoption.

Procedural governance mechanisms aim to ensure that AI systems and ML models operate correctly, they are held securely, and their operation meets legal and company internal requirements and policies concerning explainability, fairness, accountability, security, and safety. While ultimately, these goals must be fulfilled for the entire system and the ML model, explainability, fairness, and accountability are primary concerns of ML models. In contrast, safety is a more holistic trait, e.g., while an ML model might be deemed unsafe, safeguards such as non-AI-based backup components providing only reduced functionality might ensure the safety of the entire system. Procedural mechanisms also aim to ensure data, model, and system-relevant traits and targets. Schneider et al. (2022) found for data, model and systems individually and holistically, they comprise a strategy, policies, standards, processes and procedures, contractual agreements, performance measurement, compliance monitoring and issue management.

The strategy denotes high-level guidance of actions based on strategic business objectives. The review by Keding (2020) investigated the interplay of AI and strategic management, focusing on two aspects. The first, the antecedents and data-driven workflows (data value chain and data quality), managerial willingness, and organizational determinants (AI strategy and implementation). The second, the consequences of AI in strategic management on an individual and organizational level (e.g., human-AI collaboration, AI in business models).

AI policies provide high-level guidelines and rules. Organizations use AI policies to communicate key objectives, accountability, roles, and responsibilities. On an organizational level, one source for policies might be best practices. Mishra et al. (2020) discussed aspects of how to measure AI's societal and economic impact and risks and threats of AI systems.

In our framework, standards should ensure that data representations, ML models, and the architecture of AI systems, including their accompanying processes, are consistent and normalized throughout the organization. Mosley et al. (2010) support interoperability within and across organizations and ensure their fitness for purpose.

The concepts of process and procedure play a central role in organisational management and operational governance. The International Organization for Standardization (ISO), within the ISO 9000 framework, describes a process as a group of interrelated activities through which inputs are transformed into outputs, generating value for an organisation or its stakeholders. According to ISO 9000, a process is a set of activities that produces a result, while a procedure defines how those activities should be carried out. In governance systems, both processes and procedures are standardized and repeatable to guarantee consistency and control.

AI processes can be considered a fundamental element of a successful AI governance implementation. Abraham et al. (2019) wrote that they relate to data governance processes and processes tied to ML and AI systems. Similarly, Stoica et al. (2017) develop and enforce model (and system) architectural principles, documentation, and code guidelines with the goal of better composability and maintainability might also be a governance instrument for AI to foster interoperability.

Serban et al. (2020) view the documentation of each feature, including its rationale, as best practice.

Contractual agreements between participating internal departments or external organizations might be related to data but also models and AI systems. Models contain information on the training data that might be extracted and abused in various ways, e.g., by competitors to reduce costs for data labelling. For instance, consider a system that allows uploading an image and obtaining a classification. A competitor might use the system to label her unlabelled data. The competitor might use the resulting dataset to train a novel classifier and offer an "identical" service. Contracts often reduce liability risk by specifying operational boundaries of AI. AI might malfunction under circumstances that are non-intuitive and unexpected for a human. Therefore, operational constraints and limitations require explicit legal notices.

Classical risk management approaches have also been suggested for AI. AI agency risk and the mitigation using business process management have been discussed on a conceptual level.

Compliance monitoring tracks and enforces conformance with regulatory requirements and organizational policies, standards, procedures, and contractual agreements. Prominent regulations include the European General Data Protection Regulation (GDPR), which touches upon data and models, e.g., it grants the right to explanations of model decisions. GDPR is supported by extensive guidelines on compliance. Audits allow for interrogating complex processes to clarify whether these processes adhere to company policy, industry standards, or regulations.

Brundage et al. (2020) discuss AI auditing and emphasize its need due to the complexity of AI. Issue management refers to identifying, managing, and resolving AI-related issues. For data issues, Abraham et al. (2019) include processes for the standardization of data issues and their resolution, the nominating persons for issue resolution, as well as an escalation process. For model and AI systems, little information is available.

Relational governance mechanisms facilitate collaboration between stakeholders. They encompass communication, training, and the coordination of decision-making. Serban et al. (2020) express the need to communicate within an interdisciplinary ML team and suggest utilizing a collaborative development platform. Training procedures for data scientists have been put forward in Biomedicine by Van Horn et al. (2018). They analysed a rich set of training resources and conducted training events on applied projects. Mikalef and Gupta (2021) stated that technical and business skills are essential AI capabilities.

Thus, training employees is critical. While training might often refer to developing skills to leverage AI, it might also refer to training employees whose tasks and responsibilities might be automated or augmented by AI to mitigate negative impacts. Communication might help reduce employees' fear, e.g., by signalling a company's intention to use AI as augmentation of workers rather than a replacement. Overall, little is known for ML models and AI systems governance in contrast to data governance.

Chapter 4

Buyer vs. AI or Buyer with AI? The Analysis

4.1. New Procurement Perspectives

The rapid evolution of digital technologies is progressively changing the role and the scope of procurement in the organizations. Traditionally, procurement has been viewed as an operational function, focus only on activities such as supplier selection, sourcing, contract administration, and purchasing execution. In this perspective, the primary objectives were typically associated with cost containment, process efficiency, and the effective management of transactional activities. Nowadays, however, both the growing availability of organisational data and the easy use of artificial intelligence (AI) have expanded the definition of procurement. Buyers are increasingly involved in strategic decision-making, helping organisations use data more accurately to support broader business goals.

In this context, procurement processes are becoming increasingly complex due to the globalisation of supply chains, the growing number of stakeholders involved, and the need to operate in highly dynamic and uncertain environments.

From a theoretical standpoint, these developments can be interpreted through the lens of Information Processing Theory (IPT). As discussed in the previous section, uncertainty emerges when organisations lack sufficient information to make informed decisions regarding their activities and outcomes. In procurement, such uncertainty is particularly relevant, as firms must deal with heterogeneous suppliers, volatile markets and evolving regulatory and technological contexts. In line with IPT, organisations seek to reduce uncertainty by developing appropriate information processing capabilities, which may be articulated through structural, process-based, and technological mechanisms.

In this evolving scenario, AI-based tools and digital procurement platforms play a key role in supporting organisations in managing increasing information processing needs. These technologies help organisations bring together and analyses large amounts of data, allowing procurement professionals to make decisions more quickly and with a stronger evidence base. At the same time, they contribute to redefining the boundaries between human and technological roles within procurement activities, generating new perspectives on how decisions are made, supported and executed.

More specifically, procurement can be conceptualised as a set of interconnected activities in which information flows across different processes and actors. Within this framework, three domains emerge as particularly relevant for understanding how AI is reshaping procurement practices.

The first domain concerns supplier selection and scouting. While traditional approaches to supplier selection have focused primarily on evaluating a predefined set of suppliers through multi-criteria decision-making models, recent developments highlight the increasing importance of supplier scouting, that is, the identification of new potential suppliers. This activity is inherently characterised by high levels of uncertainty and information requirements, making it particularly suitable for the application of AI-based solutions capable of supporting data collection, analysis and interpretation.

The second domain relates to negotiation processes, where digital technologies are enabling new forms of support for both individual and organisational learning. AI can assist negotiators before, during and after interactions by providing insights based on past performance, real-time feedback and personalised recommendations. Moreover, the introduction of artificial agents and automated systems is expanding the traditional boundaries of negotiation, allowing firms to explore new ways of interacting with suppliers and managing negotiation activities at scale.

The third domain concerns risk management, which represents a critical aspect of procurement because it increases uncertainty and interconnected supply chains. The ability to identify, assess and mitigate different types of risk, such as credit risk, operational risk and compliance risk, has become essential for ensuring organisational resilience. In this context, AI and machine learning techniques enable firms to process large datasets, detect patterns and anomalies and support more proactive and informed risk management practices.

Together, these three areas highlight how procurement is moving beyond its traditional focus on transactions and becoming a more integrated function that relies on data and analysis to support decision-making.

4.1.1 Supplier Selection and Scouting

In recent years, researchers and practitioners have increasingly explored how AI can support decision-making in supply chain management. AI helps firms analyse large datasets, making it easier to detect market trends, anticipate customer needs, and respond more quickly to changing supply chain conditions. A substantial body of research has focused on the application of AI to supplier evaluation and selection, frequently adopting multi-criteria decision-making approaches.

Pitchipoo et al. (2013) developed a hybrid decision-making framework aimed at evaluating and selecting suppliers through the integration of multiple assessment criteria. Similarly, Zair et al. (2019) proposed an agent-based model in which supplier selection and negotiation activities involve both the buying organization and its customers. By incorporating customer preferences into the negotiation process, the model seeks to support the identification of suppliers capable of generating greater value for the supply chain. Scott et al. (2015) addressed the complexity of supplier selection in environments characterized by multiple stakeholders and competing objectives through the integration of the Analytic Hierarchy Process (AHP) and Quality Function Deployment (QFD).

Although these studies provide valuable insights into supplier evaluation and selection, their primary focus remains the assessment of suppliers that have already been identified and shortlisted by the buying firm.

Identifying new suppliers can extend source options and help firms better understand their supply markets. Furthermore, existing evidence suggests that many organizations are still at a relatively early stage of digital transformation, with the capabilities offered by artificial intelligence remaining underutilized across not only several procurement activities (including market scouting supplier discovery), but also other functions.

Guida et al. (2023) defined Information Processing Theory (IPT) to investigate the role of AI in the supplier scouting. As highlighted by Galbraith (1974) and later reinforced by Roßmann et al. (2018), IPT provides a suitable framework for examining organizational responses to technology-driven changes, because is especially useful in contexts where decisions depend on large amounts of information and the ability to interpret it with greater precision.

A central concept that concerns IPT is the uncertainty, which emerges when decision-makers lack sufficient information regarding a given situation or its potential outcomes: in these situations, different sources of uncertainty (including environmental, task-related, and inter-organizational factors) generate Information Processing Needs (IPNs).

Bensaou and Venkatraman (1995) wrote that organizations address these needs through Information Processing Capabilities (IPCs), which can take the form of structural arrangements, organizational processes, or information technology mechanisms. According to IPT, organizations perform in a structured manner when their ability to process information matches the level of information required by their activities.
Guida et al. (2023) suggest that identifying new suppliers is an uncertain process because firms often have limited information when evaluating potential partners.
The process requires the evaluation of numerous variables, the collection of information from diverse sources, and the involvement of multiple organizational stakeholders: all these factors increase the demand for information processing and create specific informational requirements. To cope with such complexity, firms can rely on AI-enabled solutions available through digital procurement platforms and on AI-enabled procurement platforms that help firms identify and assess potential suppliers more by providing access to relevant information and analytical tools. Given those tools, buyers can reduce uncertainty and make sourcing decisions with greater confidence.
The specific mechanisms through which these capabilities operate are summarized in Table 4.1 of the Appendix.

4.1.2 Negotiation

Recent advances in AI are changing how negotiation is taught, analyzed, and practiced, creating new opportunities for more personalized forms of support and learning. Its contribution extends across several interconnected areas, including the enhancement of individual negotiation skills, the dissemination of effective practices within organizations, and the development of autonomous negotiation agents By analyzing negotiation data, AI tools can identify behavioral patterns and provide feedback that helps negotiators learn from their experiences. As a result, AI is changing how negotiators prepare, learn, and make decisions throughout the negotiation process.
Technologies designed to support negotiators are particularly valuable because effective learning depends on structured self-reflection, individualized feedback, and the integration of experience into future practice, as highlighted by Dinnar et al. (2021). Digital platforms can facilitate this process by analysing negotiation data and transforming personal experiences into actionable insights.

Traditional learning techniques, for example journals and post-negotiation reviews, wrote that negotiation become more effective when supported by AI-driven systems capable of processing both structured and unstructured information. AI can provide to buyers written or spoken reflections about the negotiation. If repeated, these platforms may use past negotiation experiences and performance to provide suggestions that reflect each user's strengths, weaknesses, and negotiation style, also real-time using immediate feedback during interactions. AI technologies can analyse vocal indications and conversational dynamics while interactions are taking place, offering suggestions that encourage greater empathy, confidence, clarity, or professionalism of the buyer: at the same time, each user can access aggregated performance information that facilitates coaching, supervision, and organizational learning.

Haring et al. (2019) demonstrate that virtual agents can play a constructive role in conflict mediation and post-task debriefing processes, although their effectiveness depends heavily on thoughtful design and implementation. Related developments in affective computing, a concept introduced by Picard (1997), seek to identify, interpret, and respond to emotional states using computational methods. These systems rely on the analysis of large volumes of data to recognize behavioural and emotional signals, potentially improving communication and negotiation outcomes. Nevertheless, important questions remain regarding the reliability of emotion recognition across different cultural contexts and the possibility that AI systems may reproduce or amplify biases associated with nationality, ethnicity, religion, age, disability, gender, or other social characteristics. The growing collection and analysis of behavioural data raise significant concerns related to privacy, transparency and control over personal information.

When data are shared among colleagues and teams, buyers can practice and and learn more consistently from past negotiations. Contemporary communication technologies make it easier to document, store and distribute negotiation knowledge, while AI systems enhance accessibility by helping users recall relevant insights when preparing for future interactions. Mentors and experts can contribute remotely through digital platforms that facilitate feedback and guidance, meanwhile machine learning algorithms can support personalized debriefing processes based on contextual information.

A further area of development involves negotiation with computer-controlled agents. Human understanding of negotiation can be enhanced not only through interaction with other people but also by autonomous systems capable of negotiating on behalf of organizations. Negotiation bots provide an experiential learning environment in which users can practice negotiating strategies and receive detailed feedback regarding their performance. These systems can model cognitive and behavioural elements commonly associated with negotiation, including preference analysis, strategic reasoning and value creation. Starting by analysing offers, negotiation platforms can evaluate how users identify counterpart interests, manage information disclosure and pursue mutually beneficial outcomes. Some optimization processes may increasingly become automated, allowing systems to recommend adjustments based on accumulated experience. Despite this growing autonomy, human oversight remains essential because he must supervise agent behaviour: this implies that professionals may spend less time conducting routine negotiations themselves but more time overseeing the systems that support or automate these activities.

This transition presents significant opportunities for efficiency and scalability, but it also raises important ethical, strategic, and governance challenges that require careful consideration and responsible implementation (Dinnar et al., 2021; Haring et al., 2019; Picard, 1997).

4.1.3 Risk Management

Aziz and Dowling (2019) examine a range of practical applications of artificial intelligence (AI) and machine learning (ML) within risk management, organizing their analysis according to established risk categories. In the context of procurement and business operations, particular attention is devoted to credit risk, operational risk, and compliance risk.

Aziz and Dowling (2019) wrote that Credit risk can be defined as the possibility of financial loss resulting from a counterparty's inability or unwillingness to meet contractual obligations generated by missed payments, delayed repayments or a deterioration in the borrower's creditworthiness during the life of a transaction. Credit risk assessment relied primarily on traditional statistical methods (for example linear regression, logistic regression and probit models) but the growing complexity of financial markets and the increasing availability of large and heterogeneous datasets have encouraged organizations to explore AI- and ML-based approaches.

A key advantage of machine learning is its ability to analyse large amounts of unstructured data, complementing traditional approaches to credit risk assessment.

This capability has become particularly relevant in markets characterized by high uncertainty, such as the Credit Default Swap (CDS) market, where estimating both the probability of default and the potential loss associated with a credit event remains challenging. Evidence provided by Son et al. (2016), based on daily CDS data across multiple maturities and credit rating categories between January 2001 and February 2014, indicates that deep-learning and other non-parametric machine learning models can outperform traditional benchmark models in forecasting accuracy while also supporting more effective hedging strategies.

The adoption of machine learning is also becoming widespread in consumer and small and medium-sized enterprise (SME) lending, where decision-makers must process large quantities of information.

Khandani et al. (2010) developed a machine-learning framework combining decision trees and Support Vector Machines (SVMs) and demonstrated substantial cost reductions when applied to real-world lending portfolios.

Figini et al. (2017) show that multivariate outlier-detection techniques enhance credit risk evaluation in SME lending by improving the identification of potentially problematic borrowers.

Aziz and Dowling (2019) wrote that Operational risk management concerns the identification, assessment, and mitigation of risks arising from failures in internal processes, human resources, information systems, or external events. Such risks may include fraud, cybersecurity incidents, control deficiencies, procedural errors, and disruptions caused by natural disasters. According to Choi et al. (2017), the increasing volume, diversity, and interconnectedness of operational risk exposures have created favourable conditions for the adoption of AI-driven analytical tools.

AI technologies can support organizations throughout the risk management cycle. Their applications extend from the identification and measurement of risk exposures to the assessment of potential impacts and the selection of appropriate mitigation strategies. Early implementations focused primarily on preventing losses generated by external fraud, particularly in payment systems and credit card transactions, but nowadays the scope of these applications has broadened considerably. AI systems are now routinely employed to analyse extensive document repositories, automate repetitive operational tasks and support anti-money laundering activities through the examination of large-scale datasets.

Financial fraud detection represents one of the most established applications of AI and machine learning in risk management. Financial institutions increasingly rely on advanced analytical methods to strengthen the protection of their systems, data, and customers. AI can improve operational efficiency by automating routine activities, reducing the likelihood of human error and accelerating the analysis of both structured and unstructured information. These capabilities facilitate the identification of adverse news, suspicious transactions and complex relationships among individuals and organizations.

Machine learning methods, such as clustering and classification, enable the creation of behavioural profiles based on trading activity, communication records and transactional data, which help organizations identifying emerging risks, detecting unusual interactions between individuals and prioritizing alerts according to the level of potential threat. Ngai et al. (2011) provided a comprehensive review of AI applications in fraud detection and identify decision trees and neural networks among the most widely adopted techniques in this field.

Regulatory compliance factors are often treated as distinct organizational functions, but they are closely related because they contribute to the identification, monitoring and control of risk exposures. Compliance can be viewed as an integral element of enterprise risk management that, at the same time, intersecting with specific domains such as credit risk and operational risk.

The growing complexity of regulatory frameworks with the continuous increase in the volume and variety of information that organizations must process have encouraged the adoption of AI and machine learning technologies to support compliance activities.

Arner et al. (2016) wrote that AI allows firms to identify potential regulatory breaches at an early stage, supporting a more proactive approach to risk management and reducing the likelihood of non-compliance. Other benefits may be operational efficiency, improved consistency in decision-making processes and reductions in the costs associated with labour-intensive compliance procedures.

Natural Language Processing (NLP) assist organizations in understanding new requirements, evaluating their implications and ensuring consistent implementation across business activities. AI can also be applied to the analysis of communications, transactional records and behavioural data, enabling the detection of anomalies and patterns that may indicate potentially non-compliant conduct.

4.2. Practical Application: Procurement Case Studies

As this study extends Information Processing Theory (IPT) to a research context that has received limited attention in prior literature, a multiple-case study methodology was adopted. Consistent with the approach proposed by Guida et al. (2023), this research design is particularly suitable for exploratory investigations and for the development and refinement of theoretical insights. Empirical data were collected through twelve case studies involving firms operating as IT solution providers and information service providers.

Twelve cases were analysed because this number was considered large enough to identify common patterns across cases, yet small enough to allow a detailed examination of each organisation.

Such a balance is especially important in theory-building research, where both cross-case patterns and case-specific evidence contribute to the development of robust conceptual frameworks.

The choice of focusing on IT and information providers is further supported by their close relevance to the researcher's professional activities as an ICT Buyer. The procurement processes examined in this study closely reflect practical challenges encountered in everyday sourcing activities. Moreover, these organizations represent a particularly appropriate setting for investigating information processing requirements associated with supplier scouting.

First, IT and information providers possess direct knowledge of the information processing needs (IPNs) that emerge during supplier scouting activities. Through their collaboration with buying organizations, they routinely access, analyse, and manage data that support supplier identification and evaluation processes.

Second, these firms offer technological solutions designed to support supplier scouting and supplier discovery activities. Those solutions such as the industry sector, the organizational size and the purchasing categories are adapted to the specific characteristics of client organizations.

Third, solution providers are directly involved in the design and development of the technologies used by buying firms. They develop a deeper understanding of the functionalities, technical capabilities, and limitations of AI-based scouting systems than the organizations that use them.

Because they work with many different clients, technology providers are able to observe a variety of procurement practices and identify approaches that are particularly effective. This experience can help organizations adopt more consistent supplier scouting processes and reduce their reliance on informal or highly company-specific methods. Consequently, the solutions developed by these providers tend to be scalable and adaptable, making advanced AI-supported scouting processes accessible to organizations of different sizes and operating in diverse industries.
To ensure a diverse sample, Guida et al. (2023) included organizations with extensive experience in the use of AI for supplier scouting. Established technology providers were included because their solutions are widely adopted by large, innovation-oriented companies operating in international markets. At the same time, the sample also incorporates start-ups, whose flexibility and innovation-oriented culture often place them at the forefront of developments in digital technologies and artificial intelligence. Since AI applications depend heavily on the availability and quality of data, the sample further includes information providers that supply the data resources necessary to support algorithmic decision-making processes. The final composition of the sample is reported in Table 4.2.

Table 4.2 Sample of Case

Provider	**Type of provider**	**Turnover**	**Number of employees**	**Headquarters**
Provider A	Start-up	€870K in funding over three rounds	11–50	Italy
Provider B	Start-up	$4 million	11–50	Italy
Provider C	Start-up	< €1 million	1–10	Italy
Provider D	Start-up	€2.3 million	20	Italy
Provider E	Established IT provider	€5.4 million	60	Italy
Provider F	Established IT provider	$1.3 billion	2,360	USA
Provider G	Established IT provider	$250 million	1,200	USA

Provider H	Established IT provider	$63 million	300	USA
Provider I	Established IT provider	$1 billion	5,000	USA
Provider J	Information provider	$84.3 million in funding over two rounds	5,000	UK
Provider L	Information provider	$235.8 million in funding over six rounds	721	France
Provider K	Information provider	$1.8 million in funding over three rounds	45	Italy

Source: "*Artificial intelligence for supplier scouting: an information processing theory approach, 2023*"

The discussion proposed by Guida et al. (2023) shows clearly that supplier selection today is no longer a simple activity of searching and choosing new suppliers, but rather a complex and information-heavy process, where companies need to manage a large amount of data, often incomplete, heterogeneous and continuously changing. This complexity is well summarized in Table 4.3 in the Appendix, where different types of uncertainty are identified. What emerges is that companies increasingly operate in contexts where the information required to identify and evaluate suppliers is very detailed and specific: for example, as highlighted by providers such as Provider B and Provider L, firms in highly specialized industries need insights not only about prices and financial conditions, but also about technical capabilities, certifications and compliance requirements, which strongly increases the amount of information to be collected and processed. At the same time, providers like Provider A and Provider C emphasize that regulatory pressure plays a crucial role, since firms must continuously update supplier information to comply with changing regulations, especially in sectors such as energy or manufacturing; this aspect further reinforces the idea that supplier scouting is characterized by high and dynamic information needs.

However, the study also highlights that while the complexity of the environment and the corresponding information needs are growing, many companies are still not adequately equipped to manage them. In fact, as noted by Providers D, E and I, the adoption of AI-based solutions in procurement is still limited, and many organizations lack the

technological maturity and internal competencies required to exploit these tools. This creates a clear mismatch between what firms need and what they are able to do, which is one of the central arguments of this thesis. This gap is also visible in task-related aspects: many organizations do not have structured processes for scouting and behave in a reactive way, as underlined by Providers D and F, looking for new suppliers only when a problem arises rather than continuously monitoring the supply market.
In addition, Providers D and H point out that procurement activities are often divided across different business units, leading to duplicated efforts and inconsistent data. Providers G and I stress the concept of the lack of skills, in fact procurement teams often do not have the capabilities needed to interpret complex data or to use advanced analytics, which means that they are not able to benefit from digital tools.
As shown in Table 4.3, partnership uncertainty is high, and Provider C, K and L report that both buyers and suppliers are reluctant to share sensitive information, due to concerns about confidentiality and competitive risks. The limited level of trust among participants represents a significant barrier to the effective functioning of digital platforms, whose value creation mechanisms depend on the exchange and integration of information. Suppliers may be reluctant to disclose detailed data regarding their competencies, resources, or operational capabilities, while buyers are often uncertain to share information about their existing supplier networks. Those constraints reduce the availability and quality of information, making it more difficult to develop reliable databases. In many cases, they are rooted in organizational practices and inter-organizational relationships, where concerns related to trust, confidentiality, and information governance can substantially influence the effectiveness of digital solutions.
In response to these challenges, Table 4.4 in the Appendix shows how IT and information providers contribute to improving supplier scouting through a set of mechanisms that increase information processing capabilities. The Provider A, C and G help companies to formalize their processes. In many cases, firms initially rely on unstructured approaches, but by adopting AI-based platforms, they can introduce standardized procedures and clear workflows. Digital solutions create value not only through automation but also by introducing greater order and structure to previously fragmented activities.

From a process perspective, providers also act as intermediaries, facilitating the exchange of information between buyers and suppliers. For instance, as explained by Providers F and G, many platforms are designed with layered data structures, where suppliers can

decide which information to share and with whom. This helps balance the need for collaboration with the need to protect sensitive data.
However, providers such as Provider E and Provider H also indicate that these mechanisms are not always sufficient: if suppliers are not willing to actively provide data, or if companies are not fully engaged, the benefits of these platforms remain limited. Following this example, it can be affirmed that technology alone cannot solve the problem, and that human and organizational factors remain critical.
Providers F and I demonstrate advanced capabilities in aggregating and analysing data from multiple sources. By using AI technologies such as natural language processing and recommendation algorithms, organizations can handle large amounts of information and identify suitable suppliers more quickly.
These functionalities improve the quality of sourcing decisions while reducing the effort associated with data-intensive scouting activities.
While some organizations have invested in sophisticated analytical tools and data-processing infrastructures, others operate with more limited functionalities. This is evident among smaller providers, such as Providers C, D, and E, whose solutions offer a lower degree of analytical complexity. So, their ability to support complex supplier scouting activities (for instance extensive data integration, advanced supplier evaluation, the analysis of large and heterogeneous datasets) appears more restricted. These differences suggest that the benefits derived from AI-enabled supplier scouting depend not only on the adoption of digital technologies but also on the maturity and depth of the underlying analytical abilities set in the solutions provided.
This means that not all digital solutions are equally effective, and the choice of provider becomes a key decision for companies.
Another important aspect concerns data quality. Providers B and J emphasize the need to ensure that data are accurate, up-to-date and consistent, often implementing validation procedures and integrating information from trusted external sources. This is crucial because poor data quality can affect the reliability of decisions. In addition, integration with internal systems, especially ERP platforms, is highlighted by Provider A, F and G as a major advantage, since it allows companies to connect supplier scouting with their operational processes and to have a more comprehensive view of their supply base.

Overall, the main implication of the work done by Guida et al. (2023) is that the effectiveness of supplier scouting does not depend simply on adopting AI technologies, but on achieving a proper alignment between information needs and information processing capabilities. When an effective alignment exists between organizational needs and the capabilities offered by digital solutions (as is more frequently observed in firms adopting the services of advanced providers such as Providers F, G, and I) organizations are better positioned to cope with uncertainty, introduce greater structure into supplier scouting activities, and support more informed decision-making. Conversely, when technological and analytical capabilities are less developed, this alignment becomes more difficult to achieve, reducing the extent to which firms can benefit from digital procurement tools.

The successful adoption of AI-enabled scouting solutions depends mostly on the development of complementary organizational resources. Therefore, firms therefore need to strengthen internal competencies, establish robust data management practices, and adapt procurement processes to fully leverage the opportunities offered by digital technologies. In parallel, technology providers increasingly assume a role that extends beyond the traditional functions of software vendors. Rather than merely supplying technological tools, they contribute expertise, methodological support, and strategic guidance that enable organizations to derive greater value from their digital transformation initiatives.

Overall, supplier scouting may be viewed as a process in which outcomes are shaped by the organization's ability to match growing environmental and informational complexity with adequate information-processing capabilities. Within this framework, AI represents an important enabling factor. However, its contribution depends not only on the sophistication of the technology itself, but also on the extent to which it is implanted within organizational processes and decision-making practices.

4.3. The definition of a New Model: the Adoption of Generative Artificial Intelligence (GenAI)

Singh et al. (2025) highlight that Generative Artificial Intelligence (GenAI) is rapidly emerging as a transformative technological paradigm within procurement and supply chain management (SCM). Fundamentally, GenAI can redefine how organizations approach decision-making, operational efficiency and strategic value creation. Unlike traditional artificial intelligence systems, which are typically designed to perform narrowly defined tasks such as demand forecasting or inventory optimization, GenAI introduces an entirely different computational logic based on generativity, probabilistic reasoning and adaptive learning capabilities. Frederico (2023) focuses on this distinction, because GenAI not only processes and analyses data but is also capable of generating new content, simulating complex scenarios and supporting unstructured decision-making processes in highly dynamic environments. As supply chains become more complex and unpredictable, organizations are increasingly using GenAI to support faster and more proactive decision-making. Another advantage is its ability to generate synthetic data, which can help when reliable data is limited or incomplete.

Hacker et al. (2023) wrote that GenAI, by generating high-quality synthetic datasets, supports model training, scenario simulation and sensitivity analysis, thereby enhancing the robustness and reliability of decision-making processes.

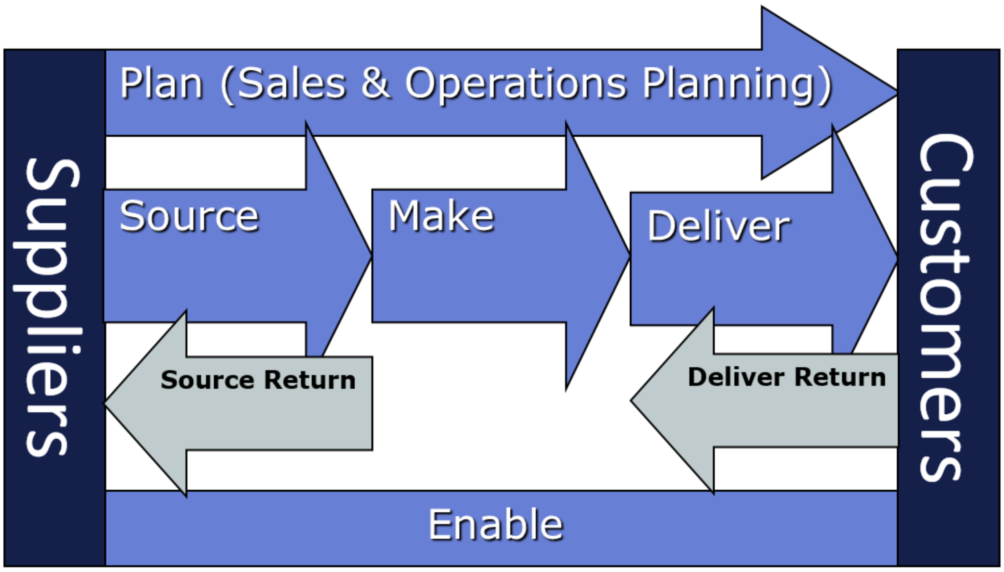
Within procurement, GenAI has demonstrated a significant impact on supplier discovery and qualification processes. As seen in the previous chapters, supplier identification relies on limited internal databases, partnerships and relationships, which may constrain the exploration of new alternative sourcing opportunities. Li et al. (2024) argue that GenAI can support supplier identification by combining information from multiple sources, such as industry reports, online platforms, and social media. This makes it easier for organizations to discover new suppliers and emerging market players that may otherwise be overlooked. Natural language processing further improves this process by allowing users to search using everyday language rather than relying on specific keywords.

GenAI can also support supplier evaluation by applying consistent criteria, including financial performance, compliance requirements, and past supplier records. In addition, real-time data analysis allows companies to continuously monitor supplier performance and update their assessments when new risks or performance issues emerge.

This is particularly useful in supply chains exposed to frequent disruptions, as it helps organizations identify potential problems earlier and adjust sourcing decisions when necessary.

The application of GenAI across supply chain processes can be comprehensively understood through the Supply Chain Operations Reference (SCOR) model, which categorises activities into planning, sourcing, manufacturing, delivery, return and enabling processes (Figure 4.1).

Figure 4.1 Supply Chain Operations Reference (SCOR) model



Source: Adapted from Supply-Chain Council (2003)

In the planning phase, GenAI develops demand forecasting by analyzing large volumes of structured and unstructured data, including historical sales, market trends and external variables. Compared to traditional statistical models, Richey et al. (2023) demonstrate GenAI-based approaches show superior accuracy by identifying complex nonlinear patterns and correlations that are otherwise difficult to detect. GenAI can assist companies not only in forecasting demand but also in planning production activities. By analysing capacity, resource availability and order requirements, it helps develop more efficient production schedules. Its predictive capabilities can also support risk management by identifying potential supply chain issues at an early stage and helping organizations respond more quickly.

Roozkhosh et al. (2024) wrote that organizations can leverage GenAI to simulate potential risk scenarios, assess their impact and develop mitigation strategies in real time, instead of relying on static reporting tools. This capability not only enables more proactive and data-driven decision-making, but also supports greater organizational agility, allowing firms to quickly adapt to demand fluctuations, supply disruptions and changing market conditions, thereby strengthening overall supply chain performance and competitiveness.

In sourcing processes, GenAI enables a shift from traditional transactional approaches to more strategic and value-driven procurement models, supporting more informed decision-making and fostering stronger, long-term supplier relationships. One of the most notable applications is the use of AI-driven negotiation systems, which leverage advanced analytics and real-time data to improve negotiation outcomes, and can autonomously analyze supplier proposals, optimize pricing strategies and even engage in contract negotiations. Additionally, Liu and Luo (2023) stated that GenAI enhances contract management by automating the extraction and analysis of key contractual information, thereby reducing manual effort and increasing accuracy, enabling organizations to identify risks, ensure compliance and optimize contractual terms more accurately, ultimately contributing to greater transparency across the sourcing function.

In manufacturing operations, GenAI contributes to both innovation and efficiency, enabling organizations to simultaneously improve productivity, flexibility and overall operational excellence. Generative AI can support product development by helping engineers explore and compare different design alternatives in a short time. This allows organizations to evaluate a wider range of options before selecting the most suitable solution. As noted by Goswami et al. (2023), combining human expertise with AI capabilities can improve design decisions by bringing together technical knowledge, experience, and data-driven insights.

Generative AI can also support maintenance activities through the analysis of equipment and operational data. According to Stohr et al. (2024), AI systems can detect early signs of equipment failure, allowing companies to intervene before problems occur. This can reduce downtime, lower maintenance costs, and improve the performance and lifespan of critical assets, particularly in industries where equipment availability is essential for operations.

In these contexts, predictive capabilities support more effective maintenance planning, help prevent unexpected interruptions, and allow organizations to allocate resources more productively.

In addition, GenAI can support real-time process optimization by continuously monitoring production parameters and suggesting adjustments to improve quality and efficiency, thereby minimizing waste, reducing defects and ensuring more consistent output levels. Overall, the integration of GenAI in manufacturing not only enhances operational performance but also fosters a more adaptive and resilient production environment, capable of responding quickly to changes in demand, resource availability and external conditions."

Delivery encompasses all logistics and distribution activities required to move products through the supply chain. Effective management of this phase is essential for controlling costs, maintaining operational efficiency, and ensuring a high level of service quality.

Delivery is a critical stage of the supply chain because it directly affects customer satisfaction and service quality. In this area, GenAI can support logistics planning by analysing real-time information such as traffic conditions, weather disruptions, and delivery requirements. This helps companies select more efficient transportation routes, reduce costs, and improve the use of available resources. As highlighted by Subramanian (2024),GenAI can also support international logistics by helping firms analyse tariffs, regulatory requirements, and trade agreements, making it easier to operate in complex global markets .

Reverse logistics is another challenging area of supply chain management**,** as it involves managing returned products efficiently. Moreover, GenAI can help companies estimate future return volumes and improve coordination between forward and reverse logistics activities. GenAI can also support decisions on whether returned products should be refurbished, recycled, resold, or disposed of. In addition, analysing data from multiple sources provides greater visibility over return processes and helps organizations improve efficiency while reducing waste. These capabilities contribute to the development of supply chains that are more efficient, resilient, and environmentally sustainable.

The enabling role of GenAI within supply chains is equally significant, as it enhances data integration, operational visibility and decision-making capabilities, thereby allowing organizations to operate in a more coordinated, transparent and data-driven manner across all supply chain activities. By aggregating and analyzing data from multiple sources, both internal and external, Dubey et al. (2024) noted that GenAI provides real-time insights into inventory levels, order status and logistics operations, facilitating better coordination among supply chain stakeholders, and enabling faster and more accurate responses to changing conditions. This increased visibility aids organizations to identify inefficiencies, optimize resource allocation and respond more effectively to disruptions, while also supporting continuous performance monitoring and process improvement initiatives. Integrating data across different business functions helps improve information sharing and coordination between procurement, production, distribution, and customer service. In addition, Hermann and Puntoni (2024) suggest that GenAI can support more personalised customer interactions by analysing customer preferences and past behaviour. This allows companies to better understand customer needs and provide services that are more closely aligned with their expectations, ultimately strengthening customer relationships.

This personalization capability can be extended across multiple touchpoints, including order management, delivery options and post-sales services, allowing firms to create more tailored and value-added offerings. More generally, the adoption of Generative Artificial Intelligence (GenAI) is fostering the evolution of increasingly intelligent and interconnected supply chain ecosystems. By combining real-time information with advanced analytical capabilities, organizations can support both operational and strategic decision-making more effectively. The availability of real-time information helps organizations react more quickly to market changes, identify potential risks, and spot new business opportunities. As a result, the value of GenAI goes beyond improving individual processes and can support broader digital transformation initiatives.

Despite these benefits, the adoption of GenAI also presents several challenges. One of the main issues is data quality. Many organizations still rely on divided data systems, where information may be incomplete or inconsistent, limiting the accuracy of AI-generated outputs. In addition, older IT systems are often difficult to integrate with modern AI solutions, requiring technical upgrades, organizational changes, and additional investments before GenAI can be effectively implemented.

Another significant barrier is the lack of relevant skills within the workforce. The effective deployment of GenAI requires expertise in data science, machine learning and AI governance, which are not yet widely available in many procurement and supply chain functions. These skills gap not only delays adoption but also limits the ability of organizations to fully exploit the potential of GenAI technologies. In addition, ethical and regulatory considerations play a crucial role, particularly in relation to data privacy, algorithmic bias and decision transparency. For GenAI to be successfully adopted, organizations need to guarantee that its use is transparent, fair, and properly monitored. As AI becomes more integrated into procurement and supply chain activities, it is important that employees and stakeholders understand how decisions are made and they can trust the outputs generated by these systems.

Although GenAI offers significant opportunities, its implementation is not straightforward. Many organizations need to improve data quality, update existing

systems, and invest in technologies that can support AI applications. At the same time, employees need to learn how to work with these tools.
Clear governance structures and ethical guidelines are also important to reduce risks related to bias, accountability, and regulatory compliance. By combining technology investments with strong data management and workforce development, organizations can support the long-term adoption of GenAI.

Critically, the implications of GenAI adoption extend far beyond technological improvements, profoundly reshaping the role of procurement professionals. While GenAI enhances analytical capabilities, automates routine tasks and supports data-driven decision-making, it also redefines the position of the buyer within the organization, shifting it from an operational and transactional function toward a more strategic, interpretative and governance-oriented role.
The growing use of GenAI is changing how procurement decisions are made. Rather than replacing buyers, these tools support their work by providing additional information and analytical insights. Procurement professionals still need to interpret AI-generated recommendations and combine them with their experience, market knowledge and business priorities.
At the same time, the use of GenAI raises several challenges. The quality of the results depends on factors such as data accuracy, model reliability, and the ability to understand how recommendations are generated. For this reason, procurement professionals remain responsible for reviewing AI outputs and ensuring that decisions comply with organizational policies, regulations, and ethical standards.
This is particularly important in supplier selection and performance evaluation, where decisions can have long-term consequences. If AI systems rely on incomplete or biased data, they may produce misleading recommendations or overlook suitable suppliers. Human oversight is therefore essential to verify results, identify potential inconsistencies, and ensure that decisions are made fairly and objectively. Ultimately, the success of GenAI in procurement depends not only on the technology itself but also on the ability of procurement professionals to apply critical judgment when using it.
Another critical implication concerns the evolution of required skill sets. As routine tasks become increasingly automated, buyers must develop new competencies, including data literacy, analytical thinking and a basic understanding of AI systems. At the same time, uniquely human capabilities such as negotiation skills, relationship management and

strategic thinking become even more valuable, as they cannot be fully replicated by AI technologies.
Instead of relying only on past events and historical data, procurement professionals can use AI-generated insights to identify potential risks, monitor market developments, and explore new opportunities at an earlier stage. This allows to broader business objectives.
As procurement becomes more strategic, buyers are expected to do more than manage transactions. They increasingly need to analyse information, compare different options, and support decisions involving multiple stakeholders. AI tools can help by providing faster access to relevant information and supporting more informed evaluations. However, procurement professionals remain responsible for interpreting results and maintaining effective relationships with suppliers and business partners.
For this reason, GenAI should be seen as a tool that supports procurement professionals rather than replaces them. While AI can improve access to information and strengthen analytical capabilities, experience, business knowledge, and professional judgment remain essential for making decisions that are aligned with organizational priorities and long-term goals
The benefits of AI are likely to be greatest when technological capabilities are combined with the experience and judgment of procurement professionals, helping organizations make better decisions and adapt more effectively to supply chain challenges.

Conclusion

In this thesis, I set out to investigate how the interaction between human judgment and Artificial Intelligence is reshaping procurement processes and, more specifically, redefining the role of the Strategic Buyer within contemporary organizations. As an ICT Buyer, I approached procurement as a complex activity characterized by uncertainty, interdependencies. The procurement needs interpretation beyond the analytical reasoning.
In the first chapter, I look at the fundamental principles of procurement within the framework of Supply Chain Management. The analysis highlighted how procurement has traditionally relied on established conceptual models, such as the Kraljic Matrix, Porter's Five Forces and the Balanced Scorecard. These tools have contributed to the formalization and rationalization of procurement decisions, enabling organizations to switch complex market dynamics into manageable variables. However, I also emphasized that procurement decisions cannot be fully reduced to analytical frameworks, since they inherently involve elements of judgment, contextual understanding, and relationship management.
Building on these foundations, the second chapter focused on the role of the buyer, highlighting the evolution from an operational executor to a strategic actor within the organization. I wrote that procurement effectiveness depends on technical competencies, together with interpersonal skills for example communication and cross functional leadership.
In my professional experience, these competencies are particularly important when interacting with internal stakeholders and external suppliers, especially in IT environments characterized by rapid technological change and high levels of specialization. The buyer, therefore, emerges as an interface manager, capable of aligning organizational objectives with market opportunities and constraints.
In the third chapter, I analysed the impact of Artificial Intelligence on procurement processes, focusing on its role in enhancing operational efficiency, data processing capabilities and decision support. AI-based systems, particularly those based on machine learning and natural language processing, are transforming key activities such as spend analysis, supplier evaluation, and risk management. Automation of routine activities, improved data organization, and digital contract management tools allow organizations to handle procurement processes more quickly than traditional approaches. At the same

time, these changes create new challenges related to oversight, responsibility, and the proper use of information.

Based on my experience as a buyer, these technologies do not remove the responsibility of making decisions. Instead, they change the focus of the role, allowing procurement professionals to spend less time collecting information and more time evaluating results, validating information, and supporting business decisions.

The fourth chapter represents the core analytical contribution of this thesis, where I investigated whether procurement is evolving towards a "Buyer versus AI" or a "Buyer with AI" paradigm. Through the application of Information Processing Theory and the analysis of twelve case studies involving IT and information providers, I identified a critical mismatch between increasing information processing needs and the actual capabilities of organizations. Supplier scouting emerges as a highly complex and data-intensive activity, characterized by environmental, task and partnership uncertainty. The empirical evidence shows that, although AI-based solutions significantly enhance the ability to collect, process and analyse data, many organizations still lack the internal competencies, technological maturity and organizational structures required to fully exploit these tools.

From these findings, a key insight emerges: the effectiveness of AI in procurement does not depend solely on technological adoption, but on the alignment between information needs and information processing capabilities.

When this alignment is achieved, AI enables organizations to structure their processes, reduce uncertainty and improve decision-making quality. Conversely, when such alignment is missing, the introduction of AI may even amplify inefficiencies, due to poor data quality, lack of skills, and fragmented processes.

Furthermore, the analysis highlights that technological challenges are closely intertwined with organizational and relational factors. Issues such as lack of trust in data sharing, resistance to change, and low digital culture significantly limit the effectiveness of AI-based platforms. In this context, IT providers play a crucial role not only as technology vendors, but as strategic partners capable of supporting process formalization, data integration and capability development.

The introduction of Generative Artificial Intelligence further reinforces this transformation, extending the potential of traditional AI from analytical support to generative and scenario-based decision making. As highlighted in the final section of the analysis, GenAI enables more proactive, predictive and adaptive procurement strategies across the entire supply chain. However, its adoption also amplifies the need for strong governance frameworks, high-quality data and new skill sets within procurement teams.

From a managerial perspective, the most relevant implication of this thesis is that the role of the buyer is not being replaced by AI, but rather deeply transformed. In my experience as an ICT Buyer, I observe that the increasing reliance on data-driven systems requires a shift towards a more strategic, interpretative and governance-oriented role. The buyer becomes responsible for validating AI outputs, contextualizing insights, and ensuring that decisions remain aligned with organizational objectives and ethical standards. At the same time, uniquely human capabilities, such as negotiation, relationship management and critical thinking, become even more valuable, as they cannot be fully replicated by technological systems.

In conclusion, this thesis argues that the future of procurement lies not in replacing human judgment with artificial intelligence, but by a progressive integration between the two components. The evolution towards a “Buyer with AI” paradigm implies a redefinition of roles, competencies and organizational processes, where technology acts as an enabler of augmented decision-making rather than a substitute for human expertise. Organizations that are able to balance technological capabilities with human judgment, and to align information processing needs with organizational capabilities, will be better positioned to achieve sustainable competitive advantage in increasingly complex and uncertain supply chain environments.

Appendix

Table 4.1 Mapping Uncertainty and Information Processing Mechanisms in Supplier Scouting (pag. 76)

Main Construct		Reference from a seminal work	Findings from sourcing management discourse
Environmental Uncertainty	**Sociopolitical component**	Governmental regulatory control over the industry, the public political attitude towards the industry and its particular product, and the industry's relationship with trade unions that have jurisdiction in the organization (Duncan, 1972)	Buyer firms are subject to both international regulations and pressures from multiple stakeholders such as customers and nongovernmental organizations (Nair et al., 2016). Macro-changes in a buyer firm's environment entail changes to government policies, regulatory norms, cultural ethics and political and social changes (Dubey et al., 2015). Institutional pressures occur in the form of coercive data regulation or normative pressure for excellence, driving information processing interventions for automatic data storage and management in the procurement process (Lorentz et al., 2020)
Environmental Uncertainty	**Environmental dynamism**	Environmental dynamism reflects the need for the organizational design to respond to the general characteristics of external dynamism. It is better defined by the maturity of the underlying technologies, among other things (Bensaou and Venkatraman, 1995)	In the digital procurement domain, the maturity of the underlying technology refers to a company's ability to embrace and use new technological assets. Technological readiness comprises the IT infrastructure that enables digital procurement (Kosmol et al., 2019)
Environmental Uncertainty	**Environmental complexity**	The heterogeneity and range of an organization's activities. From the resource-dependence perspective,	Many different requirements are demanded of potential new suppliers, necessitating a significant amount of input information tailored to the specific requirements of the

		environmental complexity refers to competition in the industry that requires many different inputs or that produces many different outputs (Bensaou and Venkatraman, 1995)	buyer firm. Supplier scouting systems become complex by reflecting user (i.e., buyer firm) requirements for functions or services. Supplier scouting solutions are developed by focusing on the embodiment of functions according to user demand in order to improve and accommodate the buyer's opinions (Lee et al., 2012)
Task Uncertainty	**Organizational personnel component**	Employees' educational and technological background and skills, including previous technological and managerial skills, individual members' involvement and commitment to attaining the system's goals, interpersonal behaviour styles and the availability of manpower for utilization within the system (Duncan, 1972)	The organizational personnel component comprises human resources, including the knowledge and skills to implement digital technologies in the digital procurement domain (Bals et al., 2019; Kosmol et al., 2019) "Top management support denotes the degree to which top managers understand and appreciate the value potential of digital procurement, as well as the degree to which they champion and promote the use of digital technologies and practices in procurement" (Kosmol et al., 2019, p. 5)
Task Uncertainty	**Organizational functional and staff units component**	The technological characteristics of organizational units, the interdependence of organizational units in carrying out their objectives and intra-unit and inter-unit conflict among organizational functional and staff units (Duncan, 1972)	In the digital procurement domain, the organizational functional and staff units component refers to "the roles, responsibilities, and interfaces for the coordination and integration of digital procurement both in the company and with external partners. Coordination and integration of these units 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, p. 5)
Task Uncertainty	**Task analysability**	The extent to which there is a known	The scouting process is not formalized in the literature.

		procedure that specifies the sequence of steps to be followed when performing a task (Bensaou and Venkatraman, 1995)	Market research may be outsourced to external providers such as Beroe (https://www.beroeinc.com/). After data collection, the purchasing team must process and integrate the data to ensure that they are effectively used for scouting activities (Monczka et al., 2016)
Task Uncertainty	**Task variety**	The number of exceptions or the frequency of unanticipated and novel events that require different methods or procedures for doing the job (Bensaou and Venkatraman, 1995)	The process of scouting for new suppliers is different for more strategic components or standardized commodities; each scouting process has its own characteristics. The services operators for industrial firms offering scouting solutions return several different pieces of information about the potential supplier (Bartezzaghi and Ronchi, 2005; Monczka et al., 2016)
Task Uncertainty	**Knowledge intensity**	The extent to which a firm depends on the knowledge inherent in its activities and outputs as a source of competitive advantage (Cegielski et al., 2012)	The whole point of conducting market research is to access knowledge about suppliers, understand prevailing market conditions and ascertain the ability of potential new suppliers to deliver the product or service effectively. Supply market intelligence is a source of competitive advantage (Monczka et al., 2016)
Partnership Uncertainty	**Level of mutual trust**	A factor that can help reduce uncertainty about the opportunistic behaviour of the other partner (Bensaou and Venkatraman, 1995)	When both the buyer and the supplier can objectively trust one another because there are no grounds for opportunism on either side, the development of mutual trust and the collaborative sharing of information between buyers and suppliers become key for the success of the relationship. In all other cases – which we believe to be predominate in business exchanges – such approaches may prove problematic (Cox, 2001)

Partnership Uncertainty	**Supplier's asset specificity**	The extent to which the supply of a good/service requires capabilities and skills unique to a supplier (Bensaou and Venkatraman, 1995)	When a supplier's asset specificity is significant, buyer firms will face high switching costs and high search costs. On the other hand, this makes the supplier's offering relatively unique, increasing the power of the supplier in the negotiation (Cox, 2015)
Structural Mechanisms	**Formalization**	The process of formalizing – in terms of rules and procedures – the information exchange, or the extent to which the information exchange is used for coordination versus control purposes (Bensaou and Venkatraman, 1995)	The level of formalization of the supplier scouting process can vary in terms of activities and procedures to be accomplished, how information flows and how coordination occurs among the involved stakeholders (Spina, 2008)
Structural Mechanisms	**Commitment**	The extent to which there exists an equal bearing of risks, burdens and benefits between the two firms (Bensaou and Venkatraman, 1995)	Digital procurement can provide a basis for exploring capabilities for broader value contribution based on knowledge and market intelligence sharing as well as collaboration and integration (Lorentz et al., 2020). In the present study, the commitment included in value creation involves the buyer firm, the suppliers and the IT provider synergistically delivering the scouting solution
Structural Mechanisms	**Joint action**	The extent to which there exists joint efforts and cooperation between the two companies in terms of long-range planning, product planning, product engineering, process engineering tooling development, technical assistance and training/education	Supply market intelligence acquisition requires discussions and meetings with suppliers, internal and external stakeholder meetings for leads and the maintenance of personal contact networks. In particular, the role of experts in the field is recognized as a way to attain new supply market intelligence (Lorentz et al., 2020). In the present research, joint action is intended as a two-way effort in the relationships between the buyer firm, the suppliers and the

		(Bensaou and Venkatraman, 1995)	IT provider delivering the scouting solution.
Technological Mechanisms	**Compatibility**	The ability to share information across any type of technology platform (Byrd, 2000; Cegielski et al., 2012)	“This parameter may be an appropriate measure for control and coordination of communications among partners in a supply chain. Furthermore, this dimension is particularly apt for assessing the information processing capability of a supply chain member organization because it captures the perspective of an organization’s information systems to adapt to meet the needs of the users throughout the organization as a whole rather than assessing the single usefulness of a specific application or software program to facilitate a specific task”(Cegielskiet al., 2012, p. 189)
Technological Mechanisms	**Data processing capabilities**	A firm’s ability to collect and analyse data to gain critical insights (Agarwal and Dhar, 2014). Analytics capability is the organizational facility with tools, techniques and processes that enable a firm to process, organize, visualize and analyse data, thereby producing insights that enable data-driven operational planning, decision-making and execution. “Analytics capability enables firms to increase their information processing capacity, whereby firms gather data from various sources and analyse it to gain insights for supply chain	In the supply market intelligence context, data processing capability includes a broad range of mechanisms, such as analyses focused on different sources of information commercial databases and sourcing tools, ERP-based supplier scorecards and Internet- based reports. It can also include higher-level features of the system, such as subscription- based newsfeeds. In some cases, this mechanism enables the use of collaborative platforms, and these, as a side effect, also provide intelligence about supply markets. Such platforms have a high capacity for conveying rich information because they may be used to gather data from many different stakeholders, process these data and produce interesting insights for the buyer firm (Lorentz et al., 2020)

		managers" (Srinivasan and Swing 2018, p. 1851)	
Technological Mechanisms	**Data quality**	The degree to which data can be used to process information (Cegielski et al., 2012). "The degree to which data can be used is largely determined by their quality. Poor quality data can have a direct impact on business decisions" (Hazen et al., 2014, p. 72)	In the digital procurement domain, a technology intervention pertains to data quality. This intervention requires combining a high volume, variety and velocity of data from heterogeneous internal and external sources, sharing data with external stakeholders for a specific purpose, and organizing data to ensure the access, quality and use of such data (Lorentz et al., 2020)
Technological Mechanisms	**ERP integration**	The ability to integrate with the organizational ERP package in order to enable real-time information sharing and the integration of business functions (Bag, 2020)	The integration of the ERP in the procurement process proves useful in the adoption of Procurement 4.0 systems (Huang and Handfield, 2015)

Source: "Artificial intelligence for supplier scouting: an information processing theory approach, 2023"

Table 4.3 Uncertainties from the case studies (pag. 85)

Main construct		Quotes from the case studies	Descriptive in vivo code	IPT code value
Environmental Uncertainty	**Environmental complexity: Product level of customization**	"Buyers require the implementation of questionnaires to be submitted to potential suppliers, and the resulting scorecard has to be highly according to the specific service asked for by the buyer". – Provider L "Customers that resort to purchasing platforms to perform the scouting process are typically looking for a very specialized solution tailored to their business needs". – Provider B "AI in supplier scouting helps in channelling specific purchasing requests so the complexity of the AI-based solution is significant. If the buyer has generic requirements for the scouting process, traditional solutions work well". – Provider K. (Guida et al. 2023)	IT provider's level of customization of the supplier scouting solution required by the buyer firm. (Guida et al. 2023)	customized product. (Guida et al. 2023)
Environmental Uncertainty	**Environmental dynamism: Maturity of the underlying technology**	"Companies are craving AI and the innovation it can bring in the scouting process. However, actual implementations are still in an early stage and technology providers are struggling to deliver what they promised, as the technology has yet to reach the maturity stage of adoption". – Provider I "The adoption of AI in procurement is very low; only around 2% of Italian firms use digital platforms	Maturity of the AI technology and maturity of the procurement department in embracing the change suggested by AI. (Guida et al. 2023)	new technology. (Guida et al. 2023)

		for supplier scouting". – Provider D "The maturity of AI application in scouting is still too low to justify massive investments in this kind of solutions, even though it shows a huge potential growth in its adoption rate". – Provider E. (Guida et al. 2023)		
Environmental Uncertainty	**Sociopolitical component: Governmental regulatory control over the industry**	"Firms have to deal with frequent changes in regulations about the management of suppliers' data and the level of control over the supply chain". – Provider C "In highly a regulated industry, such as the oil & gas or energy sectors, the buyer firm is exposed to many regulations that change very quickly over time, so it is necessary to conduct informed scouting activities when a new supplier is required". – Provider A. (Guida et al. 2023)	Requirements and changes in regulatory control over the industry. (Guida et al. 2023)	high regulatory control. (Guida et al. 2023)
Environmental Uncertainty	**Sourcing strategy: Strategic relevance of the purchasing category**	"Having a high strategic relevance, core purchasing categories are a source of uncertainty as you have to define the right approach and the consequent impact on the strategic level of the organization. Scouting for a supplier of an indirect category is different; this kind of supplier is not differential in terms of strategic impact. So, applying AI in scouting for the management of core purchasing category can be considered as	Complexity of data gathering and analysis due to the strategic relevance of the purchasing category. (Guida et al. 2023)	from low to high depending on the category. (Guida et al. 2023)

		relevant at the strategic level". – Provider F. (Guida et al. 2023)		
Task Uncertainty	**Organizational personnel component: Education and technological background and skills**	"The lack of a true digital culture at the buyer firm is a problem for the implementation of AI in supplier scouting: if managers do not understand the value of the tons of data they have, they feed the procurement platform with poor quality data or misinterpret the results". – Provider G "Most buyer miss a proactive approach to scouting, as they scout for new suppliers only when a new purchasing category is required". – Provider D "Companies don't perceive the importance of digitalizing processes, and the involvement in digitalization projects is low. Only after the first applications do they start to understand the benefits of switching to digital and intelligent technologies". – Provider F "Customers are experiencing adoption issues when it comes to AI, mostly due to a lack of appropriate background technological skills". – Provider I. (Guida et al. 2023)	Level of digital competence among the procurement representatives in the buyer firm. (Guida et al. 2023)	Low. (Guida et al. 2023)
Task Uncertainty	**Individual members' involvement and commitment to attaining the system's goals**	"The top management of buying firms rarely has the right amount of commitment in pursuing complex and costly projects, like digitalizing and improving the scouting process, as they tend to look at the costs	Change management, top management endorsement and prioritization of procurement innovation	Low. (Guida et al. 2023)

		more than the potential benefits". – Provider C "Organizations' lack of the culture needed to implement the innovation is a problem of change management: within the firm, every change is always seen as an obstacle, since they do not want to modify the current way of doing things and they do not feel the need to apply the AI". – Provider H. (Guida et al. 2023)	projects. (Guida et al. 2023)	
Task Uncertainty	**Organizational functional and staff units component: Inter-unit conflict among organizational functional and staff units**	"Different organizational units approach purchasing as stand-alone, causing a higher complexity as compared to the case of centralized purchasing requirements for the whole organization". – Provider D "Firms have shown a lack of data consistency within different business units of the same organization, ultimately resulting in internal communication problems and data asymmetries". – Provider H. (Guida et al. 2023)	Centralization of the supplier scouting process and information asymmetries among different units. (Guida et al. 2023)	Low. (Guida et al. 2023)
Task Uncertainty	**Task analysability: Extent to which established practices and procedures are followed in performing the task**	"The scouting process does not follow a structured approach based on the definition of procedures, but every instance is managed differently". – Provider D "The approach to data gathering for the scouting process is typically conducted in a reactive way, as the lack of standard practices and	Standardized procedures for the supplier scouting activities and visibility of the whole process. (Guida et al. 2023)	Low. (Guida et al. 2023)

		procedures for proactively and systematically searching for relevant information prevents buying firms from predictively analysing real-time supplier data". – Provider F. (Guida et al. 2023)		
Task Uncertainty	**Knowledge intensity: Intensity of knowledge required by the processes**	"Suppliers are reluctant to share their data publicly without a guarantee that their data will remain safe and accessible by selected customers". – Provider B "The scouting and qualification of new suppliers require an extensive amount of data. In some countries, the government publishes detailed information about organizations operating in that country (e.g. in the UK). This facilitates the task of collecting data for these countries, but in many other countries (e.g. in Italy), these data are not available". – Provider J "The adoption of AI in the supplier scouting process requires an extensive range of different data, as buying firms are not interested only in the economic data of their suppliers. To build an efficient scouting system, the presence of the right data is mandatory for the training phase of the algorithm". – Provider K. (Guida et al. 2023)	Access to knowledge and insights about the supply network and the industrial context. (Guida et al. 2023)	High. (Guida et al. 2023)
Partnership Uncertainty	**Supplier's asset specificity: Extent to**	"Most customers seek for long-term, strategic partnership, as a more extensive knowledge of	Buyers' search for strategic partnerships and long-term	High. (Guida et al. 2023)

	which the supply of the good/service requires capabilities	supplier data and a greater level of supplier engagement calls for more effective supplier-development projects". – Provider J. (Guida et al. 2023)	relationships. (Guida et al. 2023)	
Partnership Uncertainty	**Mutual trust: Degree of comfort about sharing sensitive information with the provider**	"Customers are not willing to share their data about the supply base with their competitors or other potential suppliers". – Provider C "Suppliers aren't comfortable in sharing their data with every customer on the platform, just with the selected ones". – Provider K "Providers have to protect the confidentiality of data of their customers and their relationship with potential suppliers in order to avoid information spill overs". – Provider L. (Guida et al. 2023)	Willingness of buyer and supplier firms to share data between themselves and with the IT provider. (Guida et al. 2023)	Weak. (Guida et al. 2023)

Source: Artificial intelligence for supplier scouting: an information processing theory approach, 2023

Table 4.4 Mechanisms from case studies (pag. 86)

Main construct		**Quotes from the case studies**	**Descriptive in vivo code**	**IPT code value**
Structural Mechanisms	**Formalization: Extent to which the scouting process is formalized**	"The scouting process requires some sort of formalization to define standard tasks. Considering the complexity of supplier scouting, it cannot be based only on human activities or a simple Google search. Relying on an AI solution could be a good way to formalize	Advisory role of IT providers in the formalization and re-design of the scouting process. (Guida et al. 2023)	high (thanks to the IT provider) low (for Providers C, D, E). (Guida et al. 2023)

		the scouting methodology itself". – Provider K "The IT provider takes control of the customer's whole procurement process, allowing for a higher degree of structure and formalization". – Provider A "The platform takes care of the entire scouting process on behalf of the buyer firm". – Provider C "The adoption of an AI-based platform helps the customer to achieve a greater level of formalization and methodological approach. In some cases, the user needs to be guided during the technological change and the process re-design". – Provider G. (Guida et al. 2023)		
Process Mechanisms	**Commitment: Extent to which there exists an equal sharing of risks, burden and benefits between the two firms**	"Both buyers' and suppliers' data sharing is intermediated by the platform provider that grants the security of the data and does not disclose them without the direct authorization of each buyer or supplier". – Provider G "In many cases, suppliers are more willing to share their data to the IT provider instead of the buyer, as the IT provider is an intermediary and is not interested in sharing sensitive data outside their proprietary platform". – Provider B "The platform has a layered structure, in which every supplier has a public layer with	Intermediation role of IT providers in guaranteeing data security. (Guida et al. 2023)	High. (Guida et al. 2023)

		generic information that can be accessed by every customer in the platform, and a set of more specific layers that allow the supplier to disclose the information they desire of the customer they accept". – Provider F "Supplier data are protected from any spill overs and kept secret, as the closed structure of the platform guarantees that only the entitled customer can view the data from a certain supplier". – Provider H. (Guida et al. 2023)		
Process Mechanisms	**Joint action: Extent to which there exists joint effort and cooperation between the two companies**	"The data gathering process could be improved by a higher level of joint action, especially from the supplier side, as they are not always prompt in providing the right data on the platforms". – Provider E "The system is based on a network of collaboration that provides the buyer firm with more and more information about the potential suppliers to support the supplier scouting process. The network fosters reciprocal and proactive communication on both the supplier and the buyer sides". – Provider F. (Guida et al. 2023)	Effort of buyer and supplier firms in feeding the positive network externality coming from the shared platform. (Guida et al. 2023)	high low (for Providers C, D, E). (Guida et al. 2023)
Technological Mechanisms	**Compatibility: Ability to access systems across platforms**	"The platform is deployed in a cloud, so it is easy to access from every other system of both suppliers and customers". –	Ability to access the supplier scouting solution	High. (Guida et al. 2023)

		Provider B "The solution consists of a single platform where all data are stored and can be accessed effortlessly from any platform". – Provider G "The supplier database can be accessed across different platforms and organizations. Customers may decide to share the information about their suppliers in communities that allow them to exchange relevant information with their peers". – Provider J "Easy-to-read scores and simple user interface allows all the members of the procurement department to easily navigate the system". – Provider K. (Guida et al. 2023)	through different systems. (Guida et al. 2023)	
Technological Mechanisms	**Transparency of interfaces between systems**	"Our AI-based solution consists of a single platform where all data are stored and can be accessed. The buyer firms that are part of the network let the provider access their system to have full visibility on different elements. This kind of transparency is also guaranteed internally to the buyer firm, as all the involved stakeholders in the company can have visibility on the processes of interest". – Provider G "The platform offers several tools for data viewing, and it allows viewers to have a complete and transparent view of all the relevant data, while also	Transparency on the scouting activities and on the whole procurement process. (Guida et al. 2023)	High. (Guida et al. 2023)

		integrating information coming from outside the company". – Provider H "The solution is provided through a collaborative platform where all the procurement team have visibility and access, thanks to the possibility of integrating the solution with ERPs and other procurement tools". – Provider L. (Guida et al. 2023)		
Technological Mechanisms	**Variety of processed data types**	"The platform includes data coming from structured sources only, such as official financial statements". – Provider D "Among the wide variety of processed data, unstructured data represent the vast majority. This data includes news from the main newspapers, industry-specific reports, websites and even O-data, and allows us to gather direct insights on the analysed suppliers". – Provider F. (Guida et al. 2023)	Ability to process data from a variety of sources relevant to supplier scouting. (Guida et al. 2023)	High. (Guida et al. 2023)
Technological Mechanisms	**Data processing capabilities: Analytics capabilities**	"We are able to gather a wide variety of data from different sources, offering the buyers a high degree of knowledge about the suppliers in their database. On the other hand, we lack specific data analytics skills and know that there is still room for improvement". – Provider E "Data coming from multiple sources, particularly in an unstructured form	Capabilities of the IT provider to provide advanced analytics and AI-based solutions supporting supplier scouting. (Guida et al. 2023)	high low (for Providers C, D, E). (Guida et al. 2023)

		(websites and news), is processed through a semantic analysis algorithm that ranks the reliability of the information and collects data about supply risk". – Provider F "The implementation of AI is embedded in a wider platform that combines data processing skills and a managerial approach about the insight given by those data". – Provider I. (Guida et al. 2023)		
Technological Mechanisms	**Data accuracy**	"The accuracy of the provided data is granted with a tier-based approach. First, a check of documents is automatically run via integration with third parties. The second tier is a further control we run to verify the accuracy of the data. Eventually, the third tier consists of audits". – Provider J "All the supplier data in the platform is automatically checked to ensure that it is trustworthy and that certifications are not expired". – Provider B "The database in our solution is fed by our customer. User-generated data does not have any kind of input control. Manual checks are done, but data accuracy is still low". – Provider C "Data are gathered from third-party information providers: their data are certified and can be considered reliable". –	Accuracy of the data used in supplier scouting coming from the buyer and suppliers' database and from external sources. (Guida et al. 2023)	high low (for Providers C, D, E). (Guida et al. 2023)

		Provider D. (Guida et al. 2023)		
Technological Mechanisms	**Data timeliness**	"All data in the platform is real-time updated; alerts are set about the expiration of due documentation". – Provider B "Real-time data are analysed and processed in our solution, as the algorithms do not require data to be stored in a local database". – Provider F. (Guida et al. 2023)	Timeliness of the data used in supplier scouting coming from the buyer and suppliers' database and from external sources. (Guida et al. 2023)	high low (for Providers C, D, E). (Guida et al. 2023)
Technological Mechanisms	**Data consistency**	"Data consistency is enhanced by the fact that the main input data comes from the suppliers who are required to upload them in a certain format". – Provider H "Customers are given the option to choose the most relevant information, and the platform designs the database in accordance with their decisions. This allows for consistent databases where all the information are kept in the same format". – Provider F. (Guida et al. 2023)	Consistency of the data used in supplier scouting coming from the buyer and suppliers' database and from external sources. (Guida et al. 2023)	high low (for Providers C, D, E). (Guida et al. 2023)
Technological Mechanisms	**Data completeness**	"AI algorithms can be applied only if data are complete and significant". – Provider K. (Guida et al. 2023)	Completeness of the data used in supplier scouting coming from the buyer and suppliers' database and from external sources. (Guida et al. 2023)	high low (for Providers C, D, E). (Guida et al. 2023)

Technological Mechanisms	**ERP integration: Capability to integrate with ERP package for daily operation**	"Integrating with the ERP of both buyers and suppliers allows us to respond quickly to the purchasing needs of our customers, directly accessing all the relevant information without any need for intermediation. With the support of AI this goal is easier to reach". – Provider A "The AI-based platform is ERP-native, making it an end-to-end procurement solution. This allows suppliers and buyers to access the broader picture by not focusing only on the scouting, but having a wider platform to make sure that the scouting process is aligned with the whole purchasing process". – Provider F "The integration with the ERP system of the buyer firm and the scouting solution is considered to be a plus that increases the process of data gathering". – Provider G "The solution can be accessed outside of the provider's platform, and it can be directly integrated in the customer's ERP for easier access". – Provider K. (Guida et al. 2023)	Integration of the AI-based supplier solutions with the ERP of the buyer and suppliers' firms. (Guida et al. 2023)	High. (Guida et al. 2023)
Technological Mechanisms	**Integration with information providers: Presence of integrations with information**	"Collaborations with info providers allow the platform to gather descriptive information about suppliers that help the platform in labelling each supplier's purchasing category". – Provider B "In order to	Integration of the AI-based supplier solution with the services offered by information providers to feed the	High. (Guida et al. 2023)

	providers for data gathering	gather more information, depending on the buyer-specific requirements, the IT provider can rely on other information providers”. – Provider K “Integrating with information providers helps to retrieve significant data about the potential suppliers in real time. Thanks to this integration, the IT provider only needs the ID number of the supplier to collect the related data if the supplier is present in the information providers’ databases”. – Provider F “The integration with information providers represents a source of reliable data that are easy to access, allowing users to unlock documents and information that could take a long time to be processed if they are required to be sent directly to suppliers”. – Provider J. (Guida et al. 2023)	algorithms and update the supply market intelligence database. (Guida et al. 2023)	

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Bibliography

Abbott, R. (2020), "*The Reasonable Robot: Artificial Intelligence and the Law*", Cambridge University Press, Cambridge.

Abdolazimi, O., Abraham, A., Salehi Esfandarani, M., Salehi, M. e Shishebori, D. (2021), "*Design of a supply chain network for determining the optimal number of items at the inventory groups based on ABC analysis: a comparison of exact and meta-heuristic methods*", Neural Computing and Applications, 33, pp. 6641-6656.

Abraham, R., Schneider, J. e Vom Brocke, J. (2019), "*Data governance: A conceptual framework, structured review, and research agenda*", International Journal of Information Management, 49, pp. 424-438.

Agrawal, A., Gans, J. e Goldfarb, A. (2018), "*Prediction Machines: The Simple Economics of Artificial Intelligence*", Harvard Business Review Press, Boston.

Ambati, K. C. (2025), "*AI procurement*", *International Journal of Multidisciplinary and Scientific Emerging Research*, 13(2).

Arner, D. W., Barberis, J. N. e Buckley, R. P. (2016), "*The emergence of RegTech 2.0: From know your customer to know your data*", *Journal of Financial Transformation*, 79 (UNSW Law Research Paper No. 17–63).

Awad, E., Dsouza, S., Kim, R., Schulz, J., Henrich, J., Shariff, A., Bonnefon, J.-F. e Rahwan, I. (2018), "*The Moral Machine experiment*", Nature, 563, pp. 59-64.

Aziz, S. e Dowling, M. (2019), "*Machine Learning and AI for Risk Management*", in T. Lynn, G. Mooney, P. Rosati e M. Cummins (a cura di), Disrupting Finance: FinTech and Strategy in the 21st Century, Palgrave Pivot, Cham, pp. 33-50.

Bag, S.W.L. (2020), "*Procurement 4.0 and its implications on business process performance in a circular economy*", Resources, Conservation and Recycling, Vol. 152.

Baldwin, R. (2016), "*The Great Convergence: Information Technology and the New Globalization*", Harvard University Press, Cambridge, MA.

Bals, L., Schulze, H., Kelly, S. and Stek, K. (2019), "*Purchasing and supply management (PSM) competencies: current and future requirements*", Journal of Purchasing and Supply Management, Vol. 25 No. 5, 100572.

Bartezzaghi, E. and Ronchi, S. (2005), "*E-sourcing in a buyer-operator-seller perspective: benefits and criticalities*", Production Planning and Control, Vol. 16 No. 4, pp. 405-412.

Benasaou, B. M. e Venkatraman, N. (1995), "*Configurations of inter-organizational relationships: a comparison between US and Japanese automakers*", Management Science, Vol. 41 No. 9, pp. 1471-1492.

Bonnefon, J.-F., Shariff, A. e Rahwan, I. (2016), "*The social dilemma of autonomous vehicles*", Science, 352(6293), pp. 1573-1576.

Borgman, H., Heier, H., Bahli, B. e Boekamp, T. (2016), "*Dotting the I and crossing out the T in IT governance: new challenges for information governance*", in Proceedings of the Hawaii International Conference on System Sciences (HICSS), pp. 4901-4909.

Borgo, A. (2021), Implementing Automated Procure-to-Pay: Organizational Change and Organization Design, Lappeenranta-Lahti University of Technology LUT, Lappeenranta.

Brundage, M., Avin, S., Wang, J., Belfield, H., Krueger, G., Hadfield, G. et al. (2020), "*Toward trustworthy AI development: Mechanisms for supporting verifiable claims*", arXiv preprint, arXiv:2004.07213.

Brynjolfsson, E. e McAfee, A. (2014), The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies, W.W. Norton & Company, New York.

Burger, P. e Hawkesworth, I. (2013), "*Capital budgeting and procurement practices*", OECD Journal on Budgeting.

Burrell, J. (2016), "*How the machine 'thinks': Understanding opacity in machine learning algorithms*", Big Data & Society, 3(1).

Byrd, T.A. (2000), "*Measuring the flexibility of information technology infrastructure: exploratory analysis of a construct*", *Journal of Management Information Systems*, Vol. 17 No. 1, pp. 167-208.

Cegielski, C., Allison Jones-Farmer, L., Wu, Y. and Hazen, B. (2012), "*Adoption of cloud computing technologies in supply chains: an organizational information processing theory approach*", International Journal of Logistics Management, Vol. 23 No. 2, pp. 184-211.

Chaugule, A. e Natu, M. (2021), "*Mining Mavericks – Data-driven approach to detect spend leakage*", in 2021 IEEE 8th International Conference on Data Science and Advanced Analytics (DSAA), IEEE, pp. 1-2.

Chen, Y., Li, K. W., Kilgour, D. M. e Hipel, K. W. (2008), "*A case-based distance model for multiple criteria ABC analysis*", Computers & Operations Research, 35, pp. 776-796.

Choi, T. M., Wallace, S. W. e Wang, Y. (2018), "*Big data analytics in operations management*", *European Journal of Operational Research*, 271(3), pp. 558-569.

Chowdhury, R. H. (2024), "*AI-driven business analytics for operational efficiency*", *World Journal of Advanced Engineering Technology and Sciences*, 12(2), pp. 535-543.

Conner, K. R. e Prahalad, C. K. (1996), "*A resource-based theory of the firm: knowledge versus opportunism*", Organization Science, 7(5), pp. 477-500.

Cox, A. (2001), "*The power perspective in procurement and supply management*", *Journal of Supply Chain Management*, No, Vol. 4, pp. 4-7.

Cox, A. (2015), "*Sourcing portfolio analysis and power positioning: towards a 'paradigm shift' in category management and strategic sourcing*", *Supply Chain Management: An International Journal*, Vol. 20 No. 6, pp. 717-736.

Deakin, S. (2019), "*The Future of Work – Artificial Intelligence and Labour Law*", in The Future of Work – Artificial Intelligence and Labour Law, Working Paper, Hans-Böckler-Stiftung, Düsseldorf.

Dinnar, S., Dede, C., Johnson, E., Straub, C. e Korjus, K. (2021), "*Artificial intelligence and technology in teaching negotiation*", Negotiation Journal, 37(1), pp. 65-82.

Doz, Y. L. e Hamel, G. (1998), Alliance Advantage, Harvard Business School Press, Boston.

Dubey, R., Gunasekaran, A. e Papadopoulos, T. (2024), "*Benchmarking operations and supply chain management practices using generative AI: towards a theoretical framework*", Transportation Research Part E: Logistics and Transportation Review, Vol. 189, p. 103689.

Dubey, R., Singh, T. and Gupta, O. (2015), "*Impact of agility, adaptability and alignment on humanitarian logistics performance: mediating effect of leadership*", Global Business Review, Vol. 16 No. 5, pp. 812-831.

Duncan, R.B. (1972), "*Characteristics of organizational environments and perceived environmental uncertainty*", Administrative Science Quarterly, Vol. 17 No. 3, pp. 313-327.

Ebert, N. e Löffler, M. (2021), "*The impact of artificial intelligence on the labour market*", OECD Social, Employment and Migration Working Papers, No. 265, OECD Publishing, Paris.

Fachrie, Y. e Arviansyah, A. (2020), "*Supplier evaluation in industrial power services: A case study in gas-turbine maintenance, repair, and overhaul*", in E3S Web of Conferences, 202, 13002.

Figini, S., Bonelli, F. e Giovannini, E. (2017), "*Solvency prediction for small and medium enterprises in banking*", Decision Support Systems, 102, pp. 91-97.

Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., Luetge, C., Madelin, R., Pagallo, U., Rossi, F., Schafer, B. e Valcke, P. (2018), "*AI4People — An Ethical Framework for a Good AI Society: Opportunities, Risks, Principles, and Recommendations*", Minds and Machines, 28, pp. 689-707.

Frederico, G. F. (2023), "*ChatGPT in supply chains: initial evidence of applications and potential research agenda*", Logistics, Vol. 7 No. 2, p. 26.

Galbraith, J. R. (1974), "*Organization design: an information processing view*", Interfaces, Vol. 4 No. 3, pp. 28-36.

Gadde, L.-E. e Snehota, I. (2000), "*Making the most of supplier relationships*", Industrial Marketing Management, 29(4), pp. 305-316.

Gelderman, C. J. e Van Weele, A. J. (2003), "*Handling measurement issues and strategic directions in Kraljic's purchasing portfolio model*", *Journal of Purchasing and Supply Management*, 9(5), pp. 207-216.

Glöckner, H.-H., Pieters, R. e de Rooij, W. (2005), "*Importance of the Kraljic Matrix as a strategic tool for modern purchasing*", report, Hochschule Bremen.

Ginsburg, J. C. e Budiardjo, L. (2019), "*Authors and Machines*", Berkeley Technology Law Journal, 34, pp. 343-419.

Goodfellow, I., Bengio, Y. e Courville, A. (2016), Deep Learning, MIT Press, Cambridge, MA.

Goswami, L., Deka, M. K. e Roy, M. (2023), "*Artificial intelligence in material engineering: a review on applications of artificial intelligence in material engineering*", Advanced Engineering Materials, Vol. 25 No. 13, p. 2300104.

Guida, M., Caniato, F., Moretto, A. e Ronchi, S. (2023), "*Artificial intelligence for supplier scouting: an information processing theory approach*", *International Journal of Physical Distribution & Logistics Management*, 53(4), pp. 387-423.

Guida, M., Caniato, F. e Moretto, A. (2025), "*AI meets spend classification: A new frontier in information processing*", *Journal of Purchasing and Supply Management*, 31, art. 100993.

Habib, F., Bastl, M. e Pilbeam, C. (2015), "*Strategic responses to power dominance in buyer-supplier relationships",* International Journal of Physical Distribution & Logistics Management, 45(1/2), pp. 182-203.

Hacker, P., Engel, A. e Mauer, M. (2023), "*Regulating ChatGPT and other large generative AI models*", arXiv, preprint, arXiv:2302.02337.

Haring, K. S., Tobias, J., Waligora, J., Phillips, E., Tenhundfeld, N. L., Lucas, G., de Visser, E. J., Gratch, J. e Tossel, C. (2019), "*Conflict mediation in human–machine teaming: Using a virtual agent to support mission planning and debriefing*", New Delhi, India

Hazen, B.T., Boone, C.A., Ezell, J.D. and Jones-Farmer, L.A. (2014), "*Data quality for data science, predictive analytics, and big data in supply chain management: an introduction to the problem and suggestions for research and applications", International Journal Production Economics*, Vol. 154, pp. 72-80.

Hermann, E. e Puntoni, S. (2024), "*Artificial intelligence and consumer behavior: from predictive to generative AI*", *Journal of Business Research*, Vol. 180, p. 114720.

Hoffman, R. R. e Elm, W. C. (2006), "*HCC implications for the procurement process*", IEEE Intelligent Systems, 21(1), pp. 74-81.

Huang, Y. and Handfield, R. (2015), "*Measuring the benefits of ERP on supply management maturity model: a 'big data' method*", *International Journal of Operations* *and Production Management*, Vol. 35 No. 1, pp. 2-25, doi: 10.1108/IJOPM-07-2013-0341.

Hutton, J. P. e Ruocco, A. (2000), "*Can tax progression raise employment*?", Centro Studi Confindustria, Working Paper No. 24.

Jasanoff, S. (2003), "*Technologies of Humility: Citizen Participation in Governing Science*", Minerva, 41, pp. 223-244.

Kawa, A. e Koczkodaj, W. W. (2015), "*Supplier Evaluation Process by Pairwise Comparisons*", Mathematical Problems in Engineering, 2015, art. 976742.

Khandani, A. E., Kim, A. J. e Lo, A. W. (2010), "*Consumer credit-risk models via machine-learning algorithms*", Journal of Banking & Finance, 34(11), pp. 2767–2787.

Kosmol, T., Reimann, F. and Kaufmann, L. (2019), "*You'll never walk alone: why we need a supply chain practice view on digital procurement*", Journal of Purchasing and Supply Management, Vol. 25 No. 4, doi: 10.1016/j.pursup.2019.100553.

Kraljic, P. (1983), "*Purchasing must become supply management*", Harvard Business Review, 61(5), pp. 109-117.

Kshetri, N. (2018), "*Big data's role in expanding access to financial services in developing countries*", Journal of Business Research, 91, pp. 60-71.

Lee, S., Ryu, K., Kurniadi, K.A. and Park, Y. (2012), *Framework and System for Supplier Scouting Enabling Web-Based Collaboration*, World Academy of Science, Engineering and Technology.

Li, L., Liu, Y., Jin, Y., Cheng, T. C. E. e Zhang, Q. (2024), "*Generative AI-enabled supply chain management: the critical role of coordination and dynamism*", International Journal of Production Economics, Vol. 277, p. 109388.

Li, W., Li, X. e Liu, Y. (2020), "*Machine learning for inventory management: A case study*", European Journal of Operational Research, 283(3), pp. 764-775.

Liu, H.-W. e Lin, C.-F. (2020), "*Artificial Intelligence and Global Trade Governance: A Pluralist Agenda*", Harvard International Law Journal, 61(2), pp. 301-344.

Liu, S. e Luo, Z. (2023), *"On-demand delivery from stores: dynamic dispatching and routing with random demand*", Manufacturing and Service Operations Management, Vol. 25 No. 2, pp. 595-612.

Lorentz, H., Aminoff, A., Kaipia, R., Pihlajamaa, M., Ehtamo, J. and Tanskanen, K. (2020), "*Acquisition of supply market intelligence– an information processing perspective*", Journal of Purchasing and Supply Management, Vol. 26 No. 5, doi: 10.1016/j.pursup.2020.100649.

Lustig, M. e Koester, J. (1993), Intercultural Competence, HarperCollins, New York.

Mandl, C. (2023), "*Data-driven spend management*", in Procurement Analytics, Springer Series in Supply Chain Management, vol. 22, Springer, Cham.

Marchant, G. E., Allenby, B. R. e Herkert, J. R. (a cura di) (2011), The Growing Gap Between Emerging Technologies and Legal-Ethical Oversight: The Pacing Problem, Springer, Dordrecht.

Mikalef, P. e Gupta, M. (2021), "*Artificial intelligence capability: conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance*", Information & Management, 58(3), 103434.

Mishra, S., Clark, J. e Perrault, C. R. (2020), "*Measurement in AI policy: opportunities and challenges*", arXiv preprint, arXiv:2009.09071.

Mitchell, M. e Mishra, N. (2019), "*The Future of AI Ethics*", in The Oxford Handbook of Ethics of AI, Oxford University Press, Oxford.

Mittelstadt, B. D., Allo, P., Taddeo, M., Wachter, S. e Floridi, L. (2016), "*The ethics of algorithms: Mapping the debate*", Big Data & Society, 3(2).

Mohr, J. e Nevin, J. R. (1990), "*Communication strategies in marketing channels: A theoretical perspective*", Journal of Marketing, 54, pp. 36-51.

Monczka, R. M., Handfield, R. B., Giunipero, L. C. e Patterson, J. L. (2016), *Purchasing and Supply Chain Management* (6a ed.), Cengage Learning, Boston.

Mosley, M., Brackett, M., Earley, S. e Henderson, D. (2010), The DAMA Guide to the Data Management Body of Knowledge (1a ed.), Technics Publications LLC.

Mujiya Ulkhaq, M. e Nagris Pratiwi, T. (2024), "*Formulating purchasing strategies with Kraljic portfolio matrix: A case study in an investment management company*", Jurnal Sistem dan Manajemen Industri, 8(2), pp. 119-128.

Nair, A., Yan, T., Ro, Y., Oke, A., Chiles, T. and Lee, S. (2016), "*How environmental innovations emerge and proliferate in supply networks: a complex adaptive systems perspective*", Journal of Supply Chain Management, Vol. 52 No. 2, pp. 66-86

Ngai, E. W., Hu, Y., Wong, Y. H., Chen, Y. e Sun, X. (2011), "*The application of data mining techniques in financial fraud detection: A classification framework and an academic review of literature*", Decision Support Systems, 50(3), pp. 559–569.

Olsen, R. F. e Ellram, L. M. (1997), "*A portfolio approach to supplier relationships*", Industrial Marketing Management, 26(2), pp. 101-113.

O'Neil, C. (2016), Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy, Crown, New York.

Pauwelyn, J. (2014), "*Rule-Based Trade 2.0? The Rise of Informal Rules and International Standards and How They May Outcompete WTO Treaties*", Journal of International Economic Law, 17, pp. 739-751.

Payne, J. W., Bettman, J. R. e Johnson, E. J. (1993), The Adaptive Decision Maker, Cambridge University Press, Cambridge.

Peltomaa, T. (2021), Implementing Automated Procure-to-Pay: Organizational Change and Organization Design, master's thesis, Lappeenranta-Lahti University of Technology LUT, Lappeenranta.

Pellini, A. e Jones, H. (2011), Knowledge Taxonomies – A Literature Review, Overseas Development Institute, London.

Perante, W. J. A., Dacuyan, J. Z., Hombid, M. P. e Magallanes, R. T. (2025), "*Cloud-based: purchase order and inspection and acceptance report management system*", bachelor's thesis, Eastern Visayas State University, Ormoc City.

Picard, R. W. (1997), Affective computing, The MIT Press, Cambridge, MA.

Pitchipoo, P., Venkumar, P. e Rajakarunakaran, S. (2013), "*Fuzzy hybrid decision model for supplier evaluation and selection*", International Journal of Production Research, Vol. 51 No. 13, pp. 3903-3919.

Porter, R. e Samovar, L. (1991), "*Basic principles of intercultural communication*", in L. Samovar e R. Porter (a cura di), Intercultural Communication, Wadsworth, Belmont, CA, pp. 5-22.

Potla, R. B. (2023), "*Supplier collaboration portals for component manufacturers: procure-to-pay automation and working-capital outcomes*", ISCSITR – International Journal of Artificial Intelligence, 4(1), pp. 16-40.

Ramabodu, M. S. (2014), Procurement guidelines for project success in cost planning of construction projects, PhD thesis, University of the Free State.

Richey, R. G., Chowdhury, S., Davis-Sramek, B., Giannakis, M. e Dwivedi, Y. K. (2023), "*Artificial intelligence in logistics and supply chain management: a primer and roadmap for research*", Journal of Business Logistics, Vol. 44 No. 4, pp. 532-549.

Roozkhosh, P., Pooya, A., Modares, A. e Bafandegan Emroozi, V. (2024), "*Exploring the adoption and long-term effects of ChatGPT in a sustainable supply chain*", Flexible Services and Manufacturing Journal, Vol. 36 No. 4, pp. 1-37.

Roßmann, B., Canzaniello, A., von der Gracht, H. e 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, Vol. 130, pp. 135-149.

Russell, S. e Norvig, P. (2020), Artificial Intelligence: A Modern Approach (4a ed.), Pearson, Harlow.

Sabel, C. F. e Zeitlin, J. (2012), "*Experimentalist governance*", in The Oxford Handbook of Governance, Oxford University Press, Oxford.

Schneider, J., Abraham, R., Meske, C. e vom Brocke, J. (2022), "*Artificial intelligence governance for businesses*", Information Systems Management, 39(2), pp. 126-146.

Scott, J., Ho, W., Dey, P. K. e Talluri, S. (2015), "*A decision support system for supplier selection and order allocation in stochastic, multi-stakeholder and multi-criteria environments*", International Journal of Production Economics, Vol. 166, pp. 226-237.

Schulze, M., Schröder, M., Jilek, C., Albers, T., Maus, H. e Dengel, A. (2021), "*P2P-O: a purchase-to-pay ontology for enabling semantic invoices*", in European Semantic Web Conference, pp. 647-663.

Serban, A., van der Blom, K., Hoos, H. e Visser, J. (2020), "*Adoption and effects of software engineering best practices in machine learning*", in Proceedings of the 14th ACM/IEEE International Symposium on Empirical Software Engineering and Measurement (ESEM), pp. 1-12.

Shaham, E., Westerski, A., Kanagasabai, R., Narayanan, A., Ong, S., Wong, J. e Singh, M. (2021), "*Using unsupervised learning for data-driven procurement demand* *aggregation*", Proceedings of the AAAI Conference on Artificial Intelligence, 35(17), pp. 15175-15184.

Singh, V., Hughes, L., Albashrawi, M. A., Jeon, I. e Dwivedi, Y. K. (2025), "*Generative artificial intelligence (GenAI) in procurement and supply chain management: applications, opportunities and challenges*", Journal of Systems and Information Technology, 28(1), doi: 10.1108/JSIT-03-2025-0139.

Solanki, K. (2023), "*Artificial Intelligence in Contract Law*", Journal of Legal Research and Juridical Sciences, 2(3).

Son, Y., Byun, H. e Lee, J. (2016), "*Nonparametric machine learning models for predicting the credit default swaps: An empirical study*", Expert Systems with Applications, 58, pp. 210–220.

Spina, G. (2008), "*La gestione dell'impresa*", *Organizzazione, processi decisionali, marketing, acquisti e supply chain*, 2nd ed., ETAS Management., 8845314251, 9788845314254.

Srinivasan, R. and Swink, M. (2018), "*An investigation of visibility and flexibility as complements to supply chain analytics: an organizational information processing theory perspective*", Production and Operations Management, Vol. 27 No. 10, pp. 1849-1867, doi: 10.1111/poms.12746.

Stohr, A., Ollig, P., Keller, R. e Rieger, A. (2024), "*Generative mechanisms of AI implementation: a critical realist perspective on predictive maintenance*", Information and Organization, Vol. 34 No. 2, p. 100503.

Stoica, I., Song, D., Popa, R. A., Patterson, D., Mahoney, M. W., Katz, R., Joseph, A. D., Jordan, M., Hellerstein, J. M., Gonzalez, J. e Goldberg, K. (2017), "*A Berkeley view of systems challenges for AI*", arXiv preprint, arXiv:1712.05855.

Subramanian, S. (2024), Large Language Model-Based Solutions: How to Deliver Value with Cost-Effective Generative AI Applications, John Wiley and Sons, Hoboken, NJ.

Supply-Chain Council (2003), Supply chain operations reference model version 6.0: Quick reference.

Susskind, R. (2019), Online Courts and the Future of Justice, Oxford University Press, Oxford.

Tapkan, P., Özbakır, L., Kulluk, S. e Baykasoğlu, A. (2016), "*A cost-sensitive classification algorithm: BEE-Miner*", Knowledge-Based Systems, 95, pp. 99-113.

Tarafdar, M., Beath, C. M. e Ross, J. W. (2019), "*Using AI to enhance business operations*", MIT Sloan Management Review, 60(4), pp. 37-44.

Trautmann, L. e Lasch, R. (2020), "*Smart contracts in the context of procure-to-pay*", in Smart and Sustainable Supply Chain and Logistics – Trends, Challenges, Methods and Best Practices: Volume 1, Springer International Publishing, Cham, pp. 3-23.

UNCTAD (2021), Digital Economy Report 2021: Cross-border data flows and development, United Nations Conference on Trade and Development, Geneva.

Vachon, S. e Klassen, R. D. (2008), "*Environmental management and manufacturing performance: The role of collaboration in the supply chain*", International Journal of Production Economics, 111(2), pp. 299-315.

Van Horn, J. D., Fierro, L., Kamdar, J., Gordon, J., Stewart, C., Bhattrai, A., Abe, S., Lei, X., O'Driscoll, C., Sinha, A., Jain, P., Burns, G., Lerman, K. e Ambite, J. L. (2018), "*Democratizing data science through data science training*", Pacific Symposium on Biocomputing, 23, pp. 292-303.

Vanjoki, V. (2013), Automated Purchase to Pay Process Value Modeling and Comparative Process Speeds, master's thesis, Aalto University School of Business, Helsinki.

Volberda, H. W. (1996), "*Toward the flexible form: how to remain vital in hypercompetitive environments*", Organization Science, 7(4), pp. 359-374.
Weigel, U. e Ruecker, M. (2017), The Strategic Procurement Practice Guide: Know-how, Tools and Techniques for Global Buyers, Springer, Cham.

Williams, K. C. e Spiro, R. L. (1985), "*Communication style in the salesperson-customer dyad*", Journal of Marketing Research, 22, pp. 434-442.

Wilson, E. J., Lilien, G. L., Wilson, D. T. e Spekman, R. (2001), "*How buyers frame problems: revisited*", Journal of the Academy of Marketing Science, 29(3), pp. 297-313.

Zair, F., Nejma, M., Fourka, M. e Cherkaoui, A. (2019), "*Conceptual architecture for agent-based modelling of supplier selection conducted by a supply chain dyad*", International Journal of Supply Chain Management, Vol. 8 No. 2, pp. 483-492.

Webography

ABC Analysis (80/20 Rule) in Inventory Management – MRPeasy https://publication.sipmm.edu.sg/essential-soft-skills-procurement-leadership/

Art of Procurement. "*Learn Porter's Five Forces in Procurement*", https://artofprocurement.com/blog/learn-porters-five-forces-in-procurement.

Essential Soft Skills for Procurement Leadership – SIPMM Publications https://publication.sipmm.edu.sg/essential-soft-skills-procurement-leadership/

GEP Blog. "*RFI, RFQ, RFP in Procurement & Supply Chain - Meaning & Key Differences*", https://www.gep.com/blog/strategy/rfi-rfq-rfp-differences-procurement.

GEP Blog. "*Key Steps for Successful Purchase Order (PO) Processing*", https://www.gep.com/blog/strategy/steps-for-successful-purchase-order-processing.

Holyk, M. (2024), "*AI in procurement: Applications, Challenges, and Mitigation Strategies*", https://precoro.com/blog/ai-in-procurement/.

Ideson, P. (2025), "*Procurement Orchestration Explained: All You Need To Know*", https://artofprocurement.com/blog/procurement-orchestration-explained/.

Procurement Tactics. "*Kraljic Matrix — Everything You Should Know*", https://procurementtactics.com/kraljic-matrix/.

Supplier ABC Analysis – Accelerated Insight https://www.accelerated-insight.com/spend-analysis/what-is-spend-analysis-abc

TIBA Group. "*Incoterms 2020*", https://www.tibagroup.com/international-trade/regulations/incoterms-2020.