2024

Perceived Benefits of Adopting Artificial Intelligence Technologies in Purchasing Processes

François Constant

Max Berre

Perceived Benefits of Adopting Artificial Intelligence Technologies in Purchasing Processes

François CONSTANT
Associate Professor, Audencia Business School, fconstant@audencia.com
Maxens BERRE
Nyenrode Business University, m.berre@nyenrode.nl

Abstract
This paper examines the benefits of Artificial Intelligence (AI) technologies in purchasing processes. It examines four different types of AI-based technology and their impact on nine typical benefits that purchasing could derive from them. We found out that the adoption of AI is perceived to have a strong impact only on specific activities of the purchasing process (spend analysis, contract management), as well as data quality. Our findings highlighted also the weak perceived influence of AI-based technologies directly on cost savings and risks mitigation. These findings open large avenues for future research relatively to purchasing digital transformation and AI. This paper the first paper to investigate benefits of AI in purchasing, building on a deductive approach. It extends research on purchasing digital transformation by shifting from the focus on technology-centric outcomes, such as information system usage, to understanding the outcomes of AI on purchasing process.

Keywords: Purchasing, Digital transformation, Artificial Intelligence

Introduction
Artificial intelligence (AI) is transforming every facet of business, and hence purchasing as key strategic function is not an exception (Cui *et al.*, 2021). The rapid development of digital transformation during the last years has enabled massive changes and shift in the value chain dynamics of many organizations. To keep up with the change that is happening all around, purchasing departments are embracing this digitalization process and looking to AI technology as a way to untangle purchasing complexity.
AI is usually defined as a machine that is capable of imitating and performing intelligent human behavior (Surya, 2018). The underlying assumption of AI is that intelligence can be mathematically modeled with highly sophisticated algorithms that facilitate the replication of the subtle nuances of human thinking. This attribute has attracted many companies and increased the level of investments in this technology. Because of AI's ability to boost organizational performance and deliver true value (Wamba-Taguimdje *et al.*, 2020), it is not surprising that top executives across industries cite AI as vitally important to the future of their businesses and are planning to increase investments on it. Globally, despite the COVID-19 pandemic, worldwide investments in AI are growing fast (Tricot, 2021).
This surge in AI technologies has amplified the need for more studies and investigations, as AI technologies are becoming increasingly practically and academically relevant. Whilst academic and practitioner literatures provide many examples of AI adoption and benefits in different departments, such as marketing (Vlačić *et al.*, 2021), finance (Mhlanga, 2020), human resources (Zehir *et al.*, 2020) and supply chain (Calatayud *et al.*, 2018), relatively little research has been conducted on the real benefits that purchasing can afford from AI adoption. Literature reports that the adoption of AI in purchasing could have an impact on purchasing process in different ways: increasing the overall purchasing visibility (Modgil *et al.*, 2021), guiding purchasers into the right sourcing decision (Allal-Chérif *et al.*, 2021), reducing risk exposure (Baryannis *et al.*, 2019), improving demand prediction (Dash *et al.*, 2019). Thus, accommodating AI into purchasing can enhance business benefits (Chopra, 2019).
However, in these papers, we noticed that the concept of AI is often seen as an umbrella term, which is used without distinguishing the different types of AI technologies. AI technologies incorporates various degrees of automation (Batin *et al.*, 2017), uses different structure of data, and contains specific implementation forms. This heterogeneity forces researchers to consider a higher level of granularity in their studies. The literature often treats AI as a macro-concept, while AI technologies must be differentiated to better understand the benefit they respectively. In this paper, we investigated four different types of AI-based technologies. We first explored the benefit of each of them taken individually on the purchasing processes, as if to replicate the company's investment in each single technology. Then, we captured the benefits of implementing all these technologies simultaneously on the firm's purchasing process, to replicate the scenario of a company investing heavily in these technologies at the same time.
Purchasing professionals are still involved in many time consuming clerical activities (Seyedghorban *et al.*, 2020), but they not always perceive how AI could impact the business in any strategic way. Perceptions influence how companies fear implementing AI in purchasing and more particularly when it comes to replacing human jobs. Too often AI is

perceived as it is in dystopian fiction, as an overlord, when it's actually more like a workhorse, and a highly effective one. We realized that empirical investigation of the perception of the benefits of AI on purchasing process is currently lacking. We also highlighted that most recent publications investigated procurement processes and activities taken as a whole, without considering specific process stages. Few papers highlighted the benefits of using AI for specific activities, or treated these activities as isolated from other stages of the purchasing process.

To fill in these gaps, we explored *how the different types of AI-based technologies are perceived to have an impact on purchasing processes.* Using the academic literature, we designed a conceptual framework including 4 different types of AI technologies, to understand which of the identified technologies is more influential than the others. We also focused on 9 typical purchasing processes which are expected to be impacted by the adoption of one or several of these technologies.

Literature review

Artificial intelligence – forms of implementation

AI is seen as the ability of a system to interpret and learn from external data to achieve goals (Nikitas *et al.*, 2020). But the absence of a standard interpretation of AI complicates the policy making process (Wang, 2016), leaving room for confused implementations.

Though businesses have implemented different forms of AI, we identified mainly four, which are robotic process automation (RPA), chatbots, bigdata and weak AI (neural networks, deep learning, and prescriptive analytics). First, RPA is considered as the first step in AI implementations (Cui *et al.*, 2021). It deploys algorithms that transform traditional automation (Flechsig, 2021) as a workflow automation toolbox, by efficiently performing repetitive, structured tasks (Syed *et al.*, 2020), ultimately reducing time spent on unproductive clerical tasks. Second, chatbots are infused with AI to respond like a human when conversed with (Khanna et al., 2015). Chatbots can automate customer services in firms to respond to customers' queries. Third, AI relies on bigdata which is a collection of large sets of data that are characterized by volume, velocity, variety, value and variability: bigdata usually involves predictive analytics based on machine learning algorithms to deliver valuable insights (Gandomi and Haider, 2015). Fourth, AI leans on the deployment of weak AI that uses deep learning or neural networks, leading to prescriptive analytics. Natural language processing (NLP) and image processing are major forms of weak AI that improve accuracy and to reduce error rates (Bashar, 2019).

AI in purchasing processes

In the IS literature, it is well established that information technologies have an important influence on the firm's performance (Rehman *et al.*, 2020). The "AI phenomenon" is prompting the purchasing function to undergo a revolutionary transformation, too (Tripathi and Gupta, 2020) and additionally because digitalization can have a profound impact on the improvement of efficiency and optimization in purchasing (Hallikas *et al.*, 2021), we posit that adoption of AI will provide benefits on purchasing process.

Indeed, the four AI technologies listed above are touted to enable business intelligence, helping procurement managers take better decisions (Rane and Narvel, 2021) while AI is expected to create major incremental value in spend analytics and procurement (Chui et al., 2018). As a result, digitally transformed purchasing organizations, utilizing AI and data analytics are more efficient in their operations (Niyazbekova et al., 2021). We scrutinized the literature to find links between specific purchasing processes and the perceived benefits of AI. We classified these benefits taking inspiration from the typical set of purchasing performance management systems (Caniato et al., 2014).

- ***Cost savings***: Cost reductions are expected through RPA (Allal-Chérif *et al.*, 2021) due to reduced maverick buying and transaction costs and due to better spend monitoring (Radell and Schannon, 2018). Chatbots are used in negotiations to give lowest bids (Flechsig, 2021), Neural networks and big data analytics are deployed in cost estimations during negotiations (Biazzin and Castro-Carvalho, 2019) and auctions (Bodendorf *et al.*, 2021) to reach lowest bids. In the auctions process, several AI algorithms are also proposed targeting purchasing cost reduction (García Rodríguez et al., 2020; Jung-sik Hong et al., 2018).
- ***Supplier relationship management (SRM)***: bigdata improves supplier management through supplier selection models (Brintrup *et al.*, 2022; Lamba *et al.*, 2019) and buyer-supplier relationships (Moretto et al., 2017). Yarlagadda (2021) posits that chatbots better respond to supplier queries and place purchase orders efficiently while other scholars argue automation improves supplier communication (Flechsig, 2021). During sourcing process, AI can support bidding process, supplier identification, supplier evaluation (Jahani et al., 2021) or supplier matching (Allal-Chérif et al., 2021).
- ***Data Quality***: RPA can digitalize invoice data without errors, thus increasing data quality manyfold (Sobczak and Ziora, 2021; Viale and Zouari, 2020). Intelligent process automation bots (IPA) enhances processing of unstructured data, resulting in improved data quality (Flechsig, 2021). Cui et al., (2021) presented the impact of AI aided chatbots in the RFI process, improving the quality of supplier data. Literature also suggests that chatbots can negotiate with

humans and fellow bots, to provide the necessary information while also contacting suppliers to request RFIs (Allal-Chérif et al., 2021).

- ***Tasks automation***: Chatbots reduces labor costs while eliminating preliminary interactions in supplier negotiations (Cui *et al*., 2021) or repetitive, low-value added tasks. Radell and Schannon (2018) posits that automation of tasks have reduced in user intervention in resolving blocked invoices.
- ***Contract management***: Natural language processing (NLP) standardizes key terms in contracts drafting and can notify stakeholders over key contract dates (Garg et al., 2021). RPA can monitor ongoing contracts for compliance, also managing changes in them (Anagnoste, 2017). Through big data, contract issues are easily detected while reducing costs for manual contract analysis (Moretto et al., 2017). Ovsyannikova and Domashova (2020) presented a neural network-based risk detection method, to detect risky contracts.
- ***Process optimization***: RPA reduces resolution time of blocked invoices from 32 minutes to 90 seconds (Radell and Schannon, 2018), while also reducing cycle time and can optimize resource usages (Bag et al., 2020). As per Kiefer et al. (2019), neural networks lead to accurate parts cost estimation Finally, real time product performance feedback through big data that can be used by vendors to improve their products (Rejeb et al., 2018). RPA is helpful to buyers since process efficiencies play large role in automating and simplifying purchasing (Yu et al., 2008). Deep learning is further used in anomaly detection in IT purchasing (Domingos et al., 2016).
- ***Internal customer satisfaction***: AI decision making systems deems to produce 90% better customer satisfaction (Kashiwagi and Byfield, 2002). As per Yarlagadda (2018), RPA automation works better than humans in high risk environments, creating customer satisfaction. Papadopoulos et al. (2017) posits that in data driven supply chains, customer satisfaction remains higher due to improved flexibility, reduced costs, improved quality.
- ***Risk management and supply reliability:*** Garg *et al.* (2021) posits that NLP can identify risky contract clauses, while also identifying risk in supply chain by reviewing news materials. As per Hartley and Sawaya (2019), big data with machine learning helps analyze risks in the procurement process. In sourcing risk management, an anti-bid rigging algorithm was proposed by Imhof and Wallimann (2021) based on machine learning. A corruption detection model using machine learning, by analysis of contracts was presented by Gallego et al., (2021).
- ***Spend analysis and categorization:*** Modgil *et al.* (2021) says that use of AI increases spend visibility of firms, helping decision making with classified spend data. As per Wang et al (2016), big data can analyze spends to help managers in making informed decisions.

Through these studies, we can see that the implementation of AI technologies in various purchasing processes start becoming a true reality. However, none of these studies propose a comprehensive understanding of the perceived benefits of these technologies for procurement professionals.

Framework development

Our proposed conceptual framework is presented in Figure 1. It aims to test the benefits of the four technologies RPA, chatbots, big data, and weak AI (hereafter summarized as “AI”) on the nine purchasing activities.

Academics need proper empirical materials to further study the future endeavors of AI adoption in procurement. Thus, we have studied this problem in the light of 9 potential benefits found in academic literature. Thus, validating these benefits will be reassuring to the procurement managers interested in aiming into investing in AI while helping researchers. The ultimate objective of our research is twofold: first, we aim to examine direct causal effects linking each of the four AI technologies to the 9 specific purchasing benefits. Second, we want to investigate the perceived benefits of the four AI technologies, when implemented together, on purchasing processes.

Methodology

Research design and data collection

Almost all purchasing organizations around the world are concerned about digitalization and all purchasers have a perception of what AI can bring to his/her daily activities. This context makes the availability of data very high, making the choice of a quantitative approach obvious. We use survey data to assess the organization-level perception to implement AI technologies in purchasing. The design of our survey greatly benefited from our literature review but was also enriched by case studies published by professional providers and consulting companies. The questionnaire used for the survey listed 14 questions and was designed to capture three views: the motivations, the perceived benefits, and the potential barriers of AI technologies implementation in organizations. We also asked questions about the description of the firm (size, sector, turn over, etc.), the respondent (position, seniority, etc.) to benefit from control variables. The full questionnaire is available from the authors upon request, as well as respondent details.

The survey questionnaire was initially tested with 8 respondents (four purchasing directors and four consultants) to test its accuracy and fine-tune the usage of certain terms. Once corrected, we distributed the survey to the 400 customers of a consulting firm working in the field of purchasing. Target respondents are experienced purchasing professionals, working at senior executive level, have a visionary view of the current purchasing context.

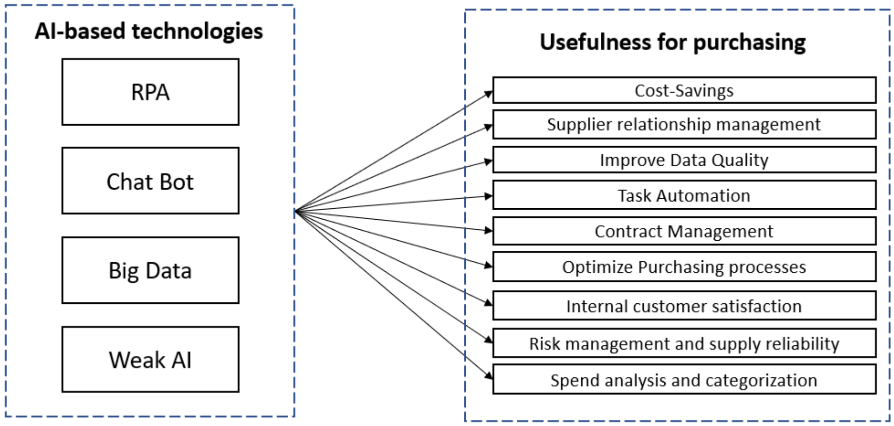

Figure 1 – Conceptual framework (Source: Authors)

Enriching survey data with interviews

Interviews with subject matter experts have been done to enrich the empirical data initially collected through a survey. We proceeded with 8 interviews. The way we conducted the interviews was supposed to get perceptions from the interviewees about the survey data analysis. Indeed, we presented to them the descriptive data and we asked questions about the results found.

Construction of the regression variables

We worked on the construction of indices and variable to organize our data in a consistent and information-rich manner. To empirically examine the benefits of AI on procurement processes, it is necessary to construct information-dense variables, which represent concentrated explanatory power. Index construction can support the increase of information density of both dependent and independent variables via the multivariate combination of existing variables. We have created a series of indices and variables (available upon request).

Data analysis

We received 83 responses to the survey. Answers were then coded and extensively checked for validity. Answers whose validity seemed dubious were discarded. Ultimately, 50 questionnaires were considered for the purpose of this paper. Subsequently, formal verification ensured that the respondents possessed the necessary knowledge and the required experience to discuss their company's practices in relation to AI projects and their outcomes. Nonresponse bias was assessed by confirming that early and late respondents did not differ significantly in their answers.

The data were analyzed using regression methods, with all scales were judged as reliable, with Cronbach alphas greater than or equal to .70. Data analysis was performed using Stata 12. This study primarily makes use of Ordinary Least Squares (OLS) regressions to analyze our key variables. Additionally, our approach in influenced by the partial least squares structural equation modeling (PLS-SEM) approach, in that we make extensive use of path diagrams to model and explain the main causal relationships governing the use of artificial intelligence technologies and the resultant associated benefits. A major advantage of this approach is that complex direct relationships can be expressed simply and flexibly and is able to work well with relatively small sample sizes. Moreover, our approach mirrors the PLS-SEM approach in that few restrictions exist on data distribution and normality and has several advantages in terms of the estimation of interaction effects (Gefen et al., 2000). Analysis tables, like multi-collinearity test, are available upon request.

Research validity

Overall, while sources differ on viable minimum regression sample-sizes for the OLS approach to avoid overfitting due to small sample size, Mason and Perreault (1991) recommend a minimum sample-size of 30 observations. Meanwhile, while Peduzzi et al. (1996) outline 10 to 15 observations per regression variable (ie, the so-called one-in-ten rule), more recent methodological studies, such as Vittinghoff and McCulloch (2010), outline that as few as five observations per predictive variable can be supported. If the Vittinghoff and McCulloch view is considered, this means that a study sample of 50 observations can support as many as 10 regression variables. Lastly Jenkins and Quintana-Ascencio (2020) recommend an N > 25. Taken together, the existing literature explicitly outlines that a sample-size of 50 would support multivariate regressions as large as five regression-parameters. Furthermore, the similarity of regression results between single-significance and joint-significance regressions is indicative that the inclusion of control variables to both single significance and joint-significance regressions does not give rise to model overfitting in our case.

Findings

The findings are presented in two separate sections: single-significance, where we examined direct causal effects linking AI technologies to specific areas of purchasing benefits, and joint-significance, which examined direct causal effects, controlling for the impact of other competing AI technologies. In all regressions we control for sectoral beta, firm size, and firm revenues. Inclusion of these control variables captures the impact on industry-specific risk and firm-specific scale-effects on the effects and impacts of AI technology adoption. Overall, we found that the adoption of heterogeneous AI technologies, has its impacts on a wide selection of business efficiencies and benefits. In general, data quality appears to be the business benefit which is impacted by the broadest range of AI technologies.

Single significance

The single significance here reflects the degree of perceived impact that each of the four AI technologies can have on the purchasing process benefits, taken individually. For instance, it tests our hypothesis that RPA will bring benefits to Contract Management. This perspective provides an interesting view of the benefits provided by one single technology when it is implemented solely, but not the others. Single significance results are presented in Figure 2.

Contract management is impacted by all AI-based technologies, among which RPA and AI show strong significance (resp. 0,6346** and 0,7383***). Both can help classifying contract clauses, searching specific clauses, facilitating the management of contract indexation. They are in many ways faster than traditional “manual” processes. The two others, chatbots and bigdata show moderate significance (resp 0,3473** and 0,4529**). Chatbots can help managing un-structured data (text messages, vocal and / or visual, emails), whereas bigdata is perceived as being a cornerstone of any contract management system, for instance to analyze and classify invoices with orders and contracts, to identify deviations in the execution of the contract. Our study shows that these technologies are not yet widely deployed in most organizations because they still require a better understanding of AI contribution to contract management.

Supplier relationship management is perceived to be strongly facilitated by bigdata and AI, although RPA appears to have moderate significance (resp. 0,6531***, 0,5817***, 0,4183*). Only chatbots technology is not perceived to have an impact on SRM. Industrialization, standardization, and automation of some tasks are major issues for many of the organizations surveyed, convinced that the value of their employees lies in decision-making, in relationship with suppliers or even with action plans implementation, which require human skills. The link between AI-based technologies and SRM is not direct, in a sense that the relation with the suppliers will not be improved because of the technologies (like chatbots). But automation of non-added value tasks helps purchasers to focus more on human relations, especially with suppliers.

Data quality is enhanced by AI and RPA (resp. significance 0,5563*** and 0,5937***). Bigdata appears to have fairly moderate significance (0,3959**) while chatbots are not perceived to have any benefit. Our study emphasizes the importance of data quality, which is still very pregnant topic in many organizations. Purchasers define quality data as available, in large quantities, cleaned and structured (e.g. ready to use). Ultimately, if companies manage to improve the quality of their data and other challenges, they will enjoy a wealth of indirect benefits related to AI. For instance, the implementation of a chatbot acting as an advisor (guided buying) with prescribers can facilitate the usage of request for information (RFI) process and improve the quality of the information collected from suppliers.

Spend analysis and categorization can be broadly facilitated by bigdata (significance 0,6345***) whereas RPA and AI can help with relatively strong influence (resp. 0,4853** and 0,4081**). Chat Bots is not perceived to be useful to deal with spend analysis. The spend analysis and particularly the spend categorization is a pitfall frequently encountered by purchasing managers. They use multiple databases, multiple ERPs, making the unification of data very difficult particularly in international organizations. These large volumes of data come from transactions, orders, or invoices, and are structured, making the need to analyze the spend precisely, both in terms of accuracy and granularity. Our study suggests that AI technologies makes it possible to process, analyze and classify a large volume of data, mainly through the usage of big data analytics, and RPA. In fact, the use of AI algorithms to compare and reconcile the items with the master data allows the fast classification of data, the identification of business actions to renegotiate prices, adjust contracts.

Risks management and supply reliability can be improved through AI and RPA (both significances reach 0,4529**). Practitioners reported that one major motivation for integrating AI is to mitigate supply risks. Indeed, implementing AI-based technologies can increase the knowledge of the supply base, the accuracy of the transportation data, the political risks, the financial risks, etc. Our respondents emphasize that AI and RPA can drive predictive analysis of the risks. However, bigdata appears to have moderate significance on risks management (0,3427*), which can be perceived as contradicting former academic results. It is quite paradoxical to see that the bigdata is being asked to improve the way manage risks whereas a good AI model is precisely based on specific, relevant data. From this statement, we deduct that AI helps to mitigate risks only when related to data reliability.

Tasks automation is strongly related to RPA, bigdata and AI (resp. significances 0,6851***, 0,6124*** and 0,6851***). This is aligned with respondents' views that automation can reduce human exposure to non-value-added tasks. They consider that complex processes can also be automated, if there is a certain degree of repetitiveness in the tasks concerned. RPA appears to have high significance, as it is supposed to be the most efficient technology to automatize processes with reduced human assistance, through the usage of a robot. RPA solutions requires structured, large, repetitive, and data-intensive processes. Implementing RPA is feasible when processes are standardized, with limited exceptions. Last, chatbots is not perceived to have an impact on tasks automation.

Internal customer satisfaction is not perceived to be strongly influenced by any AI technology. Only weak AI and chatbots show potential correlations with internal customer satisfaction (resp. 0,4538** and 0,3675**). Indeed, technology can facilitate communication and purchasing's awareness of internal ecosystems, thus can support purchasing's integration to other departments, resulting in a better internal customer satisfaction. The two other variables bigdata and RPA seem to have almost no impact on internal customer satisfaction.

Purchasing process optimization has average correlations with AI and RPA (resp 0,2758* and 0,3076**). Indeed, new technologies could have a role to play in the reduction of low added value activities, at management level or operational tasks, reduction of repetitive tasks, or other time-consuming activities. The variable bigdata appears to have moderate significance, with 0,2764*, which can be explained by the typology of our respondents, focused on process efficiency through managerial actions more than using technology or data mining. Last, chatbots is not perceived to have an impact on purchasing process optimization.

Cost savings is strongly influenced by AI (0,5124***). We saw that new technologies have an important role to play in the abandonment of low added value activities, like in the management of daily tasks, reduction of repetitive tasks, or other time-consuming activities. These gains can be translated into cost savings for the firm. That is also seen in the assessment of the impact of the two other variables RPA and chatbots, as they show moderate correlations with cost savings (0,4649** and 0,3019**). Surprisingly, bigdata is surprisingly not perceived as a driver of cost savings, which contradicts the fact that data analytics is correlated with efficiency and performance. This could be explained by a lower understanding of the benefits of predictive or prescriptive analytics, than more ambiguous terms like AI.

Joint significance

The joint significance reflects the degree of impact that each technology, when implemented all together, can have on the purchasing process benefits, as well as their interaction-effects. This perspective provides an interesting view of the benefits if all technologies are implemented *simultaneously*. Figure 2 shows the degrees of significance, after calculating the joint significances. Figure 2 also highlights that the most reported benefit is data quality, which is impacted by three of the four technologies examined. This is followed by spend analysis and categorization, which is improved by both big data and RPA technologies. This result indicates that spend analysis and categorization depends on substantial of data-quantity and process quantity to realize qualitative improvement. Meanwhile, task automation and contract management are significantly impacted by AI, while supplier management is significantly impacted by bigdata. Lastly, nether purchasing process optimization nor risk management and supply-reliability are influenced by anything we have data for.

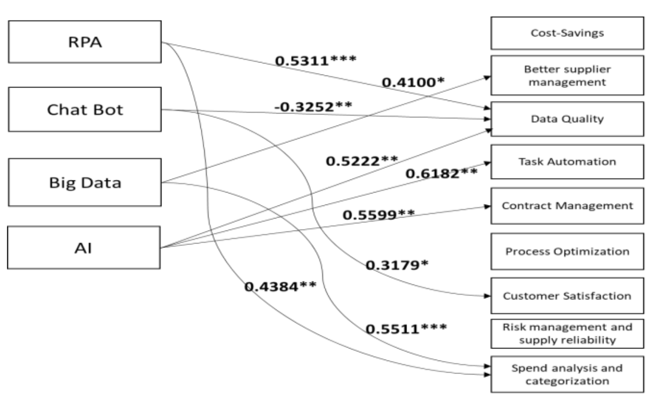

Figure 2: joint significance results

Overall, Figure 2 describes AI as the most influential technology examined in this study, while chat bots are the least influential technology examined in this study, influencing only data quality. It demonstrates also that purchasing process optimization as well as risk management and supply-reliability are impacted by big data, AI, and RPA technologies. In principle, this may indicate that while purchasing process optimization as well as risk management are lightly impacted by several technologies, the impact might be insufficient to demonstrate that any one technology has an impact that outweighs that of another relevant technology.

We performed a measure of multicollinearity among the independent variables (Variance in between factors test, VIF). Detecting multicollinearity is important because it shows potential linear relationship, or correlation, between one or more of the independent variables. In principle, testing positive for multicollinearity in this case would indicate the existence of correlation between the impacts of the key technologies that this study focuses on. In our research, the VIF test delivers VIF scores below 2.70 (calculation available upon request), indicating very mild multicollinearity among the independent variables.

Discussion

On a list of nine topics representing the benefits of AI for purchasing, those perceived as very important for this function are those impacting the focus on "high value-added tasks" and avoiding purchasing to be involved into repetitive tasks. Among the 2 most important benefits according to our respondents, we found: data quality and spend analysis.

Beyond the expected productivity gains, the quality of data is a major issue for buyers and purchasing professionals (Sobczak and Ziora, 2021). Indeed, bad or weak data quality will tend to generate wrong recommendations, behaviors, or incorrect cognitive assumptions. And ultimately, mislead a buyer at the time of the decision making. Our research suggests that the highest benefit of implementing AI-based technologies in purchasing lies in the improvement of data quality. RPA, chatbots and various typical applications like neural networks, deep learning based weak AI have strong impact on data quality. Moreover, if production data differs from training data, AI performance may drift or deteriorate. It is necessary to ensure the structure and volume of the data available, and that there is no bias in the data to avoid producing erroneous predictions. While the data quality improvement is intuitive from AI technologies in general, it should be noted that big data deals with dimensionality and data-quantity moreso than its quality. Moreover, our study shows that RPA and chat bots strongly impact data quality, which is aligned with other recent publications in purchasing field (Flechsig, 2021). Our interviews highlighted that quality of data is critically important:

> *"At the foundations of AI is the exploitation of data: available, in large quantities, structured or unstructured and quality. The relevance and performance of AI is based on data. It is the volume and the quality of data that will allow AI to be precise in its analyses, its proposals, and the automation it offers." PS*
>
> *"Ultimately, if companies manage to improve the quality of their data and other challenges, they will enjoy a host of benefits related to AI. Indeed, bad or weak data quality will tend to generate wrong recommendations, inadequate behaviors, or incorrect cognitive assumptions. And ultimately, mislead a buyer at the time of decision making." DK*
>
> *"Expenditure mapping, supplier risk analysis, or simpler processes such as the calculation of a cost breakdown require irreproachable quality of purchasing data, and this is even more true where AI is involved." JG*

Spend analysis is the second most important benefit of AI technologies, perceived by purchasing professionals. Our study suggests that big data analytics and RPA provide strong benefits to purchasing processes. This is quite an intuitive finding, already promoted by various other publications (Modgil et al., 2021; Wang et al., 2016). Indeed, AI-based technologies makes it possible to process, analyze and classify a large volume of data automatically, providing better visibility on spend and foster decision making in purchasing. Several interviewees report that spend analysis benefit widely from AI:

> *"Spend analysis and spend categorization is a pitfall frequently encountered by Purchasers. This is particularly true in an international firm, hosting multiple ERP systems and whose repositories are not necessarily unified. Behind these large volumes of data transactions referring to orders or invoices, structured, linked to quotes or contracts hides the need for classification of expenses, both in terms of comprehensiveness and granularity. Artificial Intelligence makes it possible to process, analyze and classify a large volume of data in an automatic way." VM*
>
> *"We have experienced AI-powered spend analysis tool which allows to proceed to multiple tasks in the most efficient way. For instance, the identification of all sources of expenses, the design of a classification model and definition of product families or categories, the classification of expenses. It even allows to predict a draft of budget based on last year's spends." SN*

In the same vein, interviewees suggest that low value-added activities will benefit more from the digitalization of the entire purchasing process than complex tasks. For instance, implementing RPA-based tools allows to automate certain tasks, while the usage of a chatbot makes th buyer's life easier. Contracting process is positively affected, too:

> *"The innovative combination of RPA Engine and Machine Learning delivers optimal performance of low value-added tasks automatization. The RPA engine is composed of many specialized business algorithms which proceed to the reconciliation between a payment and its invoice" VM*

"The implementation of a chatbot acting as an advisor to buyers facilitates the purchase request process using natural language processing. The bot's value contribution is to redirect the buyer from a purchase outside the catalog or outside the contract to a purchase using negotiated elements when possible. The bot can even submit to the buyer prescribers or buyers alternative supply solutions in compliance with the deployed purchasing policy." JG

"AI make it possible to share, within more or less open ecosystems, all the contracts with suppliers, to automate certain transactions (smart contracts), to materialize transfers of responsibility or to support a reliable audit trail in B2B relationships" LB

What is more surprising in our findings is that purchasing professionals do not perceive predictive/prescriptive analytics, machine learning and deep learning as key drivers of spend analytics, which contradicts recent pieces of literature (Wang et al (2016). This might be explained by the lack of knowledge CPOs have on the usage of these technologies and their effects on the quick, reliable, and industrialized classification of purchases, on the identification of spend improvement through a better spend categorization, or on implementation of business actions built on a better spend visibility.

"The development of AO requires a scientific base to manipulate the algorithms. This requires transformations and developments in the purchasing skills and competencies. Not saying that we need to turn a buyer into a data scientist or a python expert, but good for knowing what AI can bring, making him/her understand how AI operates and what can derive from it. Otherwise, technical terms will repulse most buyers." JM

The most unexpected revelation of our study is the observation that, even if AI is among the most important trends for future business environments and purchasing, revealed by the literature, no actual AI-based technology is showing significance to "Cost savings" and "Process optimization". In other terms, IA-based technology do not *directly* facilitate the reduction of costs, neither process optimization. As a first read, this could contradict seminal literature arguing that AI can have positive impact on cost savings (Radell and Schannon, 2018; Flechsig, 2021; Bodendorf et al., 2021). However, as said above, our study focuses on the direct impact between technologies and benefits, but suggests also that indirect benefits may occur. Indeed, having AI-based technologies impacting data quality or spend analysis will obviously positively affect cost savings, as an indirect benefit. Also, the idea that digital technologies such as "AI" are predicted to enable more evidenced-based decision-making or process optimization is supported by recent studies published in the purchasing field (Allal-Cherif et al., 2021). But we suggest that AI-based technologies and the related tools are only seen as enablers for successful process optimization, but not necessarily as something the technology must provide as a unique benefit itself for procurement.

"Efficiency of AI implementation depends on the maturity of the purchasing department. Indeed, everyone is confronted with the increase in the mass of data available. Less mature purchasing departments often have multiple information systems multiple, split and siloed. They expect AI to bring marginal gains of productivity. Instead, they cannot track even a single euro of productivity. Savings come in a second stage, when the entire process is well structured and the data are cleaned." AM

We also need to discuss another interesting finding of that empirical study. It concerns the difference between implementing one single AI-based technology to address one specific purchasing issue, versus implementing all existing AI-based technologies in the same time to address indistinctly all the activities of the purchasing process. This kind of suggestion is already available in IS field, which encompass various studies about IS implementation strategies (Yeow et al., 2018; Kwilinski, 2018). From a practitioner's perspective, this reflects a company's strategic decision to invest in digitizing their entire purchasing organization with AI-based technologies, or to select specific technologies to solve problems one by one. For instance, we found that implementing all AI-based technologies in the same time will end up with almost no impact on risk management performance and supply reliability. A combination of several technologies is feasible, this has also been suggested by various interviewees:

"The great strength of the combination of the several technologies, for instance RPA + machine learning, lies in the ability to absorb a large volume of data without impacting application performance. It integrates perfectly with market-leading ERPs allowing a smooth integration of accounting entries." VM

Conclusion

Academics still have a confusing perception of the role that AI can play in a purchasing process. If a large number of CPOs consider that AI technologies are essential to improve procurement performance and for generating value, the adoption of these technologies is however at an early, often experimental stage, also in academia. Many procurement departments are still at the beginning of their transformation journey and still uncertain of the business case or return on investment due to the immaturity of applications. Moreover, there's a lot of buzzword and market noise around the use of AI which is creating more confusion for procurement professionals and academics. This situation suggests that AI vendor marketing is far more advanced than real capabilities of AI solutions and perhaps explains why some organizations are not ready of ceding control to AI different steps of procurement processes.

The process of implementing AI-based technologies in purchasing is complex. While often hailed as a way to make purchasing saving costs and increasing efficiency, recent research do not distinguish the real impacts these technologies have on specific purchasing processes. This research illustrates a contingent relationship between the implementation of AI-based technologies and emerging theoretical linkages between AI and purchasing processes. In particular, our research contributes to a better granularity in the understanding of how 4 different AI-based technologies can benefit 9 typical purchasing outcomes. We first investigated each individual technology and its impact on each respective purchasing activity, then we investigated the impact of all AI-based technology taken together, on the whole purchasing process.

Although researchers and practitioners perceive AI-based technologies aimed at increasing the overall firm's performance, this research underscored the importance of going beyond only a technical analysis of process requirements and functionality to a deeper analysis of the impact that AI-based technologies is likely to have on the day-today activities of the purchasing process. Our findings suggest that the influence of AI-based technologies may be more complex than previously thought, at least if we consider each of these technologies taken separately, and impacting each stage of the purchasing process taken also separately.

Our results provide strong managerial implications: it suggests that managers should not only consider AI-based technologies as an important technological artifact in the organization, but also view it as a key driver of functional and strategic efficiency. It highlights also the limitations of several AI-based technologies, in respect of specific purchasing process stages. It shows how important it is to listen carefully (e.g. with discernment) to vendors trying to sell AI-powered tools, because they often over-estimate the benefits of their solutions: adopting a better granularity in the assessment of the promised benefits is a key driver of any investment decision.

Lastly, we believe that the impact of AI-based technologies on cost savings should be deeper explored, because in this study we have not investigated indirect benefits of AI on cost savings. That perspective could become an immense contribution either academically, or for practitioners. Main limitation of this research comes from the sample size, and future research is likely to build on larger numbers. Last, a longitudinal study could be interesting to perform, as most recent events like COVID-19 and war in Ukraine are likely to have a strong impact on how purchasing organizations take risk management, local sourcing and reshoring, price volatility into account. AI-powered tools could lend immense support to all these challenges, putting academics at the forefront of fascinating research.

Bibliography:

Allal-Chérif, O., Simón-Moya, V., & Ballester, A. C. C. (2021a). Intelligent purchasing: How artificial intelligence can redefine the purchasing function. Journal of Business Research, 124, 69–76.

Anagnoste, S. (2017). Robotic Automation Process-The next major revolution in terms of back-office operations improvement. Proceedings of the International Conference on Business Excellence, 11(1), 676–686.

Bag, S., Wood, L. C., Mangla, S. K., & Luthra, S. (2020). Procurement 4.0 and its implications on business process performance in a circular economy. Resources, Conservation and Recycling, 152, 104502.

Baryannis, G., Validi, S., Dani, S., & Antoniou, G. (2019). Supply chain risk management and artificial intelligence: State of the art and future research directions. International Journal of Production Research, 57(7), 2179–2202.

Bashar, A. (2019). Survey on evolving deep learning neural network architectures. Journal of Artificial Intelligence, 1(02), 73–82.

Batin, M., Turchin, A., Sergey, M., Zhila, A., & Denkenberger, D. (2017). Artificial intelligence in life extension: from deep learning to superintelligence. Informatica, 41(4).

Biazzin, C., & Castro-Carvalho, L. (2019). Big data in procurement: the role of people behavior and organization alignment. Dimensión Empresarial, 17(4), 10-28.

Bodendorf, F., Merkl, P., & Franke, J. (2021). Intelligent cost estimation by machine learning in supply management: A structured literature review. Computers & Industrial Engineering, 160, 107601.

Brintrup, A., Kosasih, E. E., MacCarthy, B. L., & Demirel, G. (2022). Digital supply chain surveillance: concepts, challenges, and frameworks. In The Digital Supply Chain (pp. 379-396). Elsevier.

Calatayud, A., Mangan, J., & Christopher, M. (2018). The self-thinking supply chain. Supply Chain Management: An International Journal.

Caniato, F., Luzzini, D., & Ronchi, S. (2014). Purchasing performance management systems: an empirical investigation. Production Planning & Control, 25(7), 616-635.

Chopra, A. (2019). AI in supply & procurement. 2019 Amity International Conference on Artificial Intelligence (AICAI), 308–316.

Chui, M., Manyika, J., Miremadi, M., Henke, N., Chung, R., Nel, P., & Malhotra, S. (2018). Notes from the AI frontier: Insights from hundreds of use cases. McKinsey Global Institute.

Cui, R., Li, M., & Zhang, S. (2021). AI and Procurement. Manufacturing & Service Operations Management.

Dash, R., McMurtrey, M., Rebman, C., & Kar, U. K. (2019). Application of artificial intelligence in automation of supply chain management. Journal of Strategic Innovation and Sustainability, 14(3), 43–53.
Domingos, S. L., Carvalho, R. N., Carvalho, R. S., & Ramos, G. N. (2016). Identifying IT Purchases Anomalies in the Brazilian Government Procurement System Using Deep Learning. 2016 15th IEEE International Conference on Machine Learning and Applications (ICMLA), 722–727.
Flechsig, C. (2021). The Impact of Intelligent Process Automation on Purchasing and Supply Management – Initial Insights from a Multiple Case Study. In Logistics Management (pp. 67–89). Springer International Publishing.
Gallego, J., Rivero, G., & Martínez, J. (2021). Preventing rather than punishing: An early warning model of malfeasance in public procurement. International Journal of Forecasting, 37(1), 360-377.
Gandomi, A., & Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. International Journal of Information Management, 35(2), 137–144.
García Rodríguez, M. J., Rodríguez Montequín, V., Ortega Fernández, F., & Villanueva Balsera, J. M. (2020). Bidders Recommender for Public Procurement Auctions Using Machine Learning: Data Analysis, Algorithm, and Case Study with Tenders from Spain. Complexity, 1–20. edb.
Garg, R., Kiwelekar, A. W., Netak, L. D., & Bhate, S. S. (2021). Potential Use-Cases of Natural Language Processing for a Logistics Organization. In V. K. Gunjan & J. M. Zurada (Eds.), Modern Approaches in Machine Learning and Cognitive Science: A Walkthrough: Latest Trends in AI, Volume 2 (pp. 157–191). Springer International Publishing.
Gefen, D., Straub, D., & Boudreau, M. C. (2000). Structural equation modeling and regression: Guidelines for research practice. Communications of the association for information systems, 4(1), 7.
Hallikas, J., Immonen, M., & Brax, S. (2021). Digitalizing procurement: The impact of data analytics on supply chain performance. Supply Chain Management: An International Journal, 26(5), 629–646.
Imhof, D., & Wallimann, H. (2021). Detecting bid-rigging coalitions in different countries and auction formats. International Review of Law and Economics, 68, 106016.
Jahani, N., Sepehri, A., Vandchali, H. R., & Tirkolaee, E. B. (2021). Application of Industry 4.0 in the Procurement Processes of Supply Chains: A Systematic Literature Review. Sustainability, 13(14), 7520.
Jenkins, D. G., & Quintana-Ascencio, P. F. (2020). A solution to minimum sample size for regressions. PloS one, 15(2), e0229345.
Jung-sik Hong, Hyeongyu Yeo, Nam-Wook Cho, & Taeuk Ahn. (2018). Identification of Core Suppliers Based on E-Invoice Data Using Supervised Machine Learning. Journal of Risk & Financial Management, 11(4), 1–13. edb.
Kashiwagi, D. T., & Byfield, R. (2002). Testing of Minimization of Subjectivity in Best Value Procurement by Using Artificial Intelligence Systems in State of Utah Procurement. Journal of Construction Engineering and Management, 128(6), 496–502.
Khanna, A., Pandey, B., Vashishta, K., Kalia, K., Bhale, P., & Das, T. (2015). A Study of Today's A.I. through Chatbots and Rediscovery of Machine Intelligence. International Journal of U- and e-Service, Science and Technology, 8, 277–284.
Kiefer, D., Ulmer, A., & van Dinther, C. (2019). Application of Artificial Intelligence to optimize forecasting capability in procurement (p. 80).
Kwilinski, A. (2018). Mechanism of formation of industrial enterprise development strategy in the information economy. Virtual Economics, 1(1), 7-25.
Lamba, K., Singh, S. P., & Mishra, N. (2019). Integrated decisions for supplier selection and lot-sizing considering different carbon emission regulations in Big Data environment. Computers & Industrial Engineering, 128, 1052–1062.
Mason, C. H., & Perreault Jr, W. D. (1991). Collinearity, power, and interpretation of multiple regression analysis. Journal of marketing research, 28(3), 268-280.
Mhlanga, D. (2020). Industry 4.0 in Finance: The Impact of Artificial Intelligence (AI) on Digital Financial Inclusion. International Journal of Financial Studies, 8(3), 45. https://doi.org/10.3390/ijfs8030045
Modgil, S., Singh, R. K., & Hannibal, C. (2021). Artificial intelligence for supply chain resilience: Learning from Covid-19. The International Journal of Logistics Management.
Moretto, A., Ronchi, S., & Patrucco, A. S. (2017). Increasing the effectiveness of procurement decisions: The value of big data in the procurement process. International Journal of RF Technologies, 8(3), 79–103.
Nikitas, A., Michalakopoulou, K., Njoya, E. T., & Karampatzakis, D. (2020). Artificial Intelligence, Transport and the Smart City: Definitions and Dimensions of a New Mobility Era. Sustainability, 12(7), 2789.
Niyazbekova, S. U., Kurmankulova, R. Zh., Anzorova, S. P., Goigova, M. G., & Yessymkhanova, Z. K. (2021). Digital Transformation of Government Procurement on the Level of State Governance. In E. G. Popkova, V. N.

Ostrovskaya, & A. V. Bogoviz (Eds.), Socio-economic Systems: Paradigms for the Future (pp. 663–667). Springer International Publishing.
Ovsyannikova, A., & Domashova, J. (2020). Identification of public procurement contracts with a high risk of non-performance based on neural networks. Procedia Computer Science, 169, 795–799. edselp.
Papadopoulos, T., Gunasekaran, A., Dubey, R., & Fosso Wamba, S. (2017). Big data and analytics in operations and supply chain management: Managerial aspects and practical challenges. Production Planning & Control, 28(11–12), 873–876.
Peduzzi, P., Concato, J., Kemper, E., Holford, T. R., & Feinstein, A. R. (1996). A simulation study of the number of events per variable in logistic regression analysis. Journal of clinical epidemiology, 49(12), 1373-1379.
Radell, C., & Schannon, D. (n.d.). Digital Procurement: The Benefits Go Far Beyond Efficiency. 20.
Rane, S. B., & Narvel, Y. A. M. (2021). Leveraging the industry 4.0 technologies for improving agility of project procurement management processes. International Journal of System Assurance Engineering and Management, 12(6), 1146–1172.
Rehman, N., Razaq, S., Farooq, A., Zohaib, N. M., & Nazri, M. (2020). Information technology and firm performance: Mediation role of absorptive capacity and corporate entrepreneurship in manufacturing SMEs. Technology Analysis & Strategic Management, 32(9), 1049–1065
Rejeb, A., Sűle, E., & G. Keogh, J. (2018). Exploring New Technologies in Procurement (SSRN Scholarly Paper ID 3319424). Social Science Research Network.
Seyedghorban, Z., Samson, D., & Tahernejad, H. (2020). Digitalization opportunities for the procurement function: Pathways to maturity. International Journal of Operations & Production Management, 40(11), 1685–1693.
Sobczak, A., & Ziora, L. (2021). The Use of Robotic Process Automation (RPA) as an Element of Smart City Implementation: A Case Study of Electricity Billing Document Management at Bydgoszcz City Hall. Energies, 14(16), 5191.
Surya, L. (2018). Streamlining Cloud Application with AI Technology. International Journal of Innovations in Engineering Research and Technology [IJIERT] ISSN, 2394–3696.
Syed, R., Suriadi, S., Adams, M., Bandara, W., Leemans, S. J. J., Ouyang, C., ter Hofstede, A. H. M., van de Weerd, I., Wynn, M. T., & Reijers, H. A. (2020). Robotic Process Automation: Contemporary themes and challenges. Computers in Industry, 115, 103162.
Tricot, R. (2021). Venture capital investments in artificial intelligence: Analysing trends in VC in AI companies from 2012 through 2020 (OECD Digital Economy Papers No. 319; OECD Digital Economy Papers, Vol. 319).
Tripathi, S., & Gupta, M. (2020). A framework for procurement process re-engineering in Industry 4.0. Business Process Management Journal, 27(2), 439–458.
Viale, L., & Zouari, D. (2020). Impact of digitalization on procurement: The case of robotic process automation. Supply Chain Forum: An International Journal, 21(3), 185–195.
Vittinghoff, E., & McCulloch, C. E. (2007). Relaxing the rule of ten events per variable in logistic and Cox regression. American journal of epidemiology, 165(6), 710-718.
Vlačić, B., Corbo, L., Costa e Silva, S., & Dabić, M. (2021). The evolving role of artificial intelligence in marketing: A review and research agenda. Journal of Business Research, 128, 187–203.
Wamba-Taguimdje, S.-L., Fosso Wamba, S., Kala Kamdjoug, J. R., & Tchatchouang Wanko, C. E. (2020). Influence of artificial intelligence (AI) on firm performance: The business value of AI-based transformation projects. Business Process Management Journal, 26(7), 1893–1924.
Wang, G., Gunasekaran, A., Ngai, E. W. T., & Papadopoulos, T. (2016). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. International Journal of Production Economics, 176, 98–110.
Yarlagadda, R. T. (2018). The RPA and AI Automation. International Journal of Creative Research Thoughts (IJCRT), ISSN, 2320–2882.
Yeow, A., Soh, C., & Hansen, R. (2018). Aligning with new digital strategy: A dynamic capabilities approach. The Journal of Strategic Information Systems, 27(1), 43-58.
Yu, Y., Yu, H.-C., Itoga, H., & Lin, T.-R. (2008). Decision-making factors for effective industrial e-procurement. Technology in Society, 30(2), 163–169.
Zehir, C., Karaboğa, T., & Başar, D. (2020). The transformation of human resource management and its impact on overall business performance: Big data analytics and AI technologies in strategic HRM. In Digital business strategies in blockchain ecosystems (pp. 265–279). Springer.