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Purchasing Information Systems based on Artificial Intelligence: Exploring the Drivers for their Adoption

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Abstract
The rapid development of artificial intelligence (AI) has augmented the functionalities of information systems for purchasing. Many researchers have applied technology acceptance theories to study the adoption of these new tools but have not focused on individual or organizational level. This study aims to determine what drives the adoption of such systems, by gathering the views of the three main stakeholders involved in successful IS adoption: users (buyers), IS consultants, and IS vendors. We report on a series of factors, categorized as ease of usage, functional coverage, and technology strategy. This study provides valuable extensions to technology acceptance models in the context of the purchasing function, and a clear set of criteria for practitioners to consider before investing in an AI-based information system for purchasing.

Keywords: e-procurement, information systems, adoption drivers

Introduction
Recent decades show how the introduction of Information Systems (IS) in purchasing and supply management (PSM) caused dramatic changes in all stages of the purchasing process and usages. The acceleration of information, immediacy, risks, and the increase of corporate social responsibility regulations is changing the usages of IS. At the same time, purchasing is continuing to professionalize and automate its business processes building on IS (Nandankar and Sachan, 2020; Ramkumar et al., 2019). The survivors of the purchasing IS of the 2000s have become large software suites, struggling to reinvent their user experience and tending to copy B2C functionalities at least for occasional users, becoming progressively a compulsory resource for purchasing. The emergence of artificial intelligence (AI) technology has further enhanced the features of these systems so that, when properly implemented and used, they can directly connect organizations and their business processes to multiple data from external stakeholders, while managing the interactions that occur between the parties (Spreitzenbarth et al., 2024; Allal-Cherif et al., 2021).

Among the various challenges, literature on IS stresses that the adoption and usage of IS by users pose several problems (Ain et al., 2019; Markus, 1983). Adoption is a dichotomous decision to fully utilize an invention (Rogers, 2003) also called initial implementation (Ramkumar et al., 2019), reflecting "the decision-making process of an individual unit of adoption, such as an organization, business unit, department or individual." (Woodside and Biemans, 2005, p.285). Adoption is different from assimilation which concerns the effectiveness of the collective usage by individuals and departments within the organization over time (Vaidya and Campbell, 2016). Although this topic has been already researched in the field of PSM (Kehayov et al., 2022; Yang et al., 2021; Nandankar and Sachan, 2020), our paper explores the adoption phase, going deeper in the nature of the drivers and focusing specifically on IS based on AI. It relates to the pre-investment phase of such systems, when purchasing decision makers investigate the relevance of the IS for their own needs before investing.

Purchasing is not exempt from the challenges of adopting digital technology either (Bienhaus and Haddud, 2018). Literature suggests that the adoption of IS in purchasing depends on the profile of the adopter (Min and Galle, 2003). Adoption is often slow, even if buyers are aware of the potential efficiency gains (Henriksen and Mahnke, 2005). The special feature of purchasing IS based on AI make assimilation even more challenging because they add complexity to the purchasing process, requiring developed analytical skills to utilize the system and a supporting environment (Ain et al., 2019). IS users tend to be systematically skeptical about the adoption of AI-based systems, due to many critical issues with AI technology in general (Venkatesh, 2022), but reasons for this resistance are not entirely clear yet, which justifies exploring this perspective.

Drawing on a synthetic framework inspired by AI-based IS adoption models (Sohn and Kwon, 2020), but also on valuable PSM research on IS adoption in procurement, this article aims to better understand what criteria drive procurement to adopt AI-based IS from an individual and organizational perspective. This research is exploratory in nature and its originality stems from the way in which the data was collected: we combined the perspective of multiple stakeholders involved in the IS adoption (e.g. IS vendors, integrators and purchasers), investigating how they perceived and experienced different forms of resistance and drivers. Therefore, we adopted a qualitative approach, following the recommendations of Nandankar and Sachan (2020). We got the insights of 39 people who are directly involved in the process of IS adoption in purchasing.

We present our findings in a form of a framework inspired from the IS adoption theories, including three dimensions: ease of usage and integration, IS functional coverage, and IS technological strategy. Each dimension is populated with specific sub-drivers derived from the emerging codes we found during the data analysis. We also found that the dimension of artificial intelligence and the degree of technology embedded in the system is becoming a driver of adoption. Last, we suggest that the expected performance and the expected effort to integrate the system can in fact become insignificant in the case of intense and successful usage. We assume these findings can support purchasing organizations to either choose an IS or to proactively assess the potential degree of adoption of the IS by the users.

Literature review

Latest developments in the usages and benefits of purchasing IS.

IS for purchasing are internet-based software aiming to increase purchasing's efficiency (Davila et al., 2003). Other terms appear also in the literature like e-procurement tools (Knudsen, 2003), electronic procurement (Nandankar and Sachan, 2020), digital procurement solutions (Srai and Lorentz, 2019; Viale and Zouari, 2020), having a very similar meaning. The systems themselves are often software suites connected to the enterprise resource planning (ERP) through a series of bridges enabling the data sharing. IS can also be used as services for very specific purchasing tasks like supplier scouting (Allal-Cherif et al., 2021); in that case we don't name them suites but best-of-breed solutions.

PSM literature reveals various usages of IS in a purchasing context, such as the bidding process (Masudin et al., 2021), e-tendering, e-catalogues and marketplaces (Vaidya and Campbell, 2016) or business intelligence activities (Bharadiya, 2023). Evidence abounds in relation to the benefits of IS in purchasing with diverse studies identifying the distinct forms of e-procurement employed in purchasing operations. Toktaş-Palut et al. (2014) found that the most dominant benefit was integrated information sharing.

More recently, purchasing IS have incorporated AI engines to further develop IS functionalities (Meyer and Henke, 2023). AI can augment purchasing function (Guida et al., 2023), AI-based systems can boost supplier matching, supplier relationship management or process automation (Allal-Cherif et al., 2021). They can also facilitate automated negotiations (Schulze-Horn et al., 2020), cost analysis (Bodendorf et al., 2022), can affect how procurement organizations are designed and governed, how purchasers are hired, trained (Guida et al., 2023). We noted that these studies examined the benefits and opportunities of AI in procurement but did not explore the success factors for adopting this technology in procurement.

Elaborating a theoretical frame for AI-baserd IS adoption in purchasing.

Many studies, drawing heavily on the literature on innovation adoption and deriving from behavioral psychology theories, have attempted to model the drivers of IS adoption in an organizational context (Davis, 1989) and in the specific context of purchasing (Nadankar and Sachan, 2020; Brandon-Jones and Kauppi, 2018; Oh et al, 2014; Dooley, 2006; Davila et al., 2003). Nadankar and Sachan (2020) reported that the frameworks frequently used in purchasing are the technology acceptance model TAM (Venkatesh et al., 2008) and the technology-organization-environment framework TOE (Tornatzky and Fleischer, 1990). Both introduce key drivers which can be taken as primary codes for our research: usefulness and ease of usage (Kamhi and Salahddine, 2020), perceived relative advantage, organizational context and innovation features (Frambach and Schillewaert, 2002), user experiences and voluntary use (Venkatesh et al., 2008), technological, organizational and environmental context (Teo et al., 2009). Other models, like IS success model (DeLone and McLean, 2016), the Unified Theory of Acceptance and Use of Technology model UTAUT (Venkatesh et al. 2007), the Task-Technology Fit model (Diar et al, 2018) are complementing the set of interesting drivers.

But these models have limitations: almost 60% of the Authors investigating IS adoption in PSM literature develop their own model (Nadankar and Sachan, 2020), which demonstrates that the constructs offered by the frameworks established in IS field cannot be taken for granted for PSM research. For instance, TAM model is limited to support the understanding of IS adoption problems, human behavior during user experience, user satisfaction, etc. An interesting example is shown by DeLone and McLean (2016) who built on established models but broadened with sub-dimensions that fit with purchasing context, taking various constructs from the existing PSM literature. DeLone and McLean (2016) recommended that other researchers further develop and empirically validate established models in other contexts, specific sectors.

Moreover, the dimension of AI as a driver of adoption is rarely available in these models. Only recently, the latest update of the UTAUT model added AI as a driver of adoption (Venkatesh, 2022). UTAUT initially suggests that

the expected performance of the system; the effort to deploy it the social influence (norms, image) and facilitating conditions (organizational and technical infrastructure support the use of the system are drive the adoption (Venkatesh, 2007). Thus, in 2022, Venkatesh proposed a new research agenda for UTAUT model, by defining four main directions research for which the links where the predictors or moderating factors of intention are still to be explored, as well as the application to specific functions.
In sum, although we can get inspired by these models and find interesting drivers in the literature, none of them adopt specific drivers for understanding IS adoption by purchasing, even less when AI-based systems are involved. The following section report on what drives adoption of AI-based IS in purchasing in the current literature.

Searching for the drivers of adoption of AI-based IS in purchasing.
To start establishing our coding tree, we built on the three most common codes found in IS grand theories, as reported by Nadankar and Sachan (2020): IS ease of usage and integration, IS technological strategy, and IS functional coverage. Then we screened existing PSM literature to find the drivers of IS adoption in purchasing, among which several papers focus on the relationships between these drivers (Alomar and Visscher, 2017). Last, we completed with codes that are more specific to AI-based IS (Venkatesh, 2022).
The first dimension is "ease of usage and integration", which includes drivers like platform features and mobility (Schoenherr, 2016), perceived user experience when using the IS, easiness of IS implementation in the organization (Panda and Sahu, 2012) and services to host the IS. The second dimension "IS technological strategy" incorporates data quality (e.g. system data facilitating purchasing tasks, see Schoenherr, 2016), the type of data analytics (Toktaş-Palut et al., 2014), and the level of automation (Viale and Zouari, 2020). The third dimension of the IS, "functional coverage", bridges with purchasing tasks and operations: it concerns strategic purchasing (Moretto et al., 2017), spend categorization (Zou et al., 2020), supplier relationship management (including negotiation, see Schulze-Horn, 2020), procure-to-pay process (Toktaş-Palut et al., 2014), supply risk management (Ivanov and Dolgui, 2021), performance and reporting, contract management, and sourcing (Allal-Cherif et al., 2021).
We noticed that all these studies remained at a macro-level, e.g. did not report on individual level, did not explore the nature of the systems (AI-based or not, IS functionalities), and rarely bridge AI features with purchasing perceived benefits. We believe that, to get clear granularity of adoption drivers, we must investigate IS adoption at each level of the decision-making process and focus on the most recent functionalities that augment IS through AI algorithms.

RQ1: how decision-makers perceive and experience the various forms of drivers for adopting an AI-based information system in purchasing?

Moreover, many papers investigate the organizational context of the IS implementation, following the "organizational context" of the TOE model (Tornatzky and Fleischer, 1990). Authors suggest that adoption could depend on the organizations' digital procurement readiness and maturity (Flechsig et al., 2022), IT infrastructure (Padhi and Mohapatra, 2010; Son and Benbasat, 2007). It also requires purchasing function to develop new skills and competencies to adopt technological advancements (Beske-Janssen et al., 2023). But to the best of our knowledge, there is no publication reporting on specific organizational design facilitating the adoption of AI-based IS in purchasing.

RQ2: how does the organizational context drives the adoption of IS in purchasing?

In the next sections, we present the methodology chosen for addressing the two research questions, our findings, and we discuss the results in light of existing literature.

Methodology

Research strategy
For this study, we took inspiration from existing theory. Because the TAM and UTAUT models were developed for a similar purpose but not specifically for purchasing, we decided not to force our study into an existing framework, remaining exploratory. We positioned our work as theory elaboration (Ketokivi and Choi, 2014), so rather than present a priori propositions we posed open research questions and allowed themes to emerge. Our aim was to develop a specific adoption model for AI-based IS adoption in purchasing. In practice, we moved between theory and the data over time, thus using an abductive process (Dubois and Gadde, 2002).
Studying an emerging practice – adoption of IS in purchasing – lends itself to multiple case research (Voss, 2010) to gain broad insights into procurement's adoption of IS and understand the adoption context. Our ambition was not to generalize but to develop a mapping of critical drivers of adoption.

Cases selection
In the aim to match research strategy to theory elaboration activities, we searched for focused case studies (Stuart et al., 2002). Our study's cases needed to be exemplar, e.g. reflecting adoption of AI-based IS in a purchasing

context. We decided to explore the three main stakeholders of the implementation of purchasing IS: the user of the IS (the purchaser), the IS provider (the vendor of IS), and the consultant in charge of providing services during the IS selection and implementation phase (the integrator). Our goal was to gain insights from 'a broad spectrum of people regarding their roles within the company and their experiences' (Dubois and Araujo, 2007, p. 175).
To select our cases, we identified several key requirements. First, the IS should be built on AI algorithms, as our study focused on this innovation-intensive technology. IS provider must be well established in the market, to demonstrate a certain relevance to users. Requirements for buyers were not limited to function membership, but users had to have contributed to the initial selection of the IS itself, to the final decision of investment, and have sufficient experience to share an opinion about what drove its adoption in the organization. Last, the IS integrators had to demonstrate a clear consulting expertise in the field of IS for purchasing, and a large knowledge in the relationship with IS users as well as adoption problems. Table 1 shows the list of interviewees.

Type of company	Nb of interviews conducted	Total interview duration (hour:min)	Interviewee's position
Consulting firms, providing services of purchasing IS integration for business clients	9	10h45	Consultant in IS, Director of consulting firm in the field of purchasing, Principal Associate of a consulting firm, AI laboratory Director.
Large providers of IS for purchasing (nb employees >400)	6	05h50	Sales direcors, product managers, software engineers.
Small and medium sized providers of IS for purchasing (30<nb employees<400)	17	18h25	CEO, sales representatives, product managers, software engineers.
Start-up providers of IS for purchasing (max. 30 employees, established for less than 3 years)	3	04h30	Funders, sales representatives, product managers, software engineers.
IS users (purchasing and IT functions)	5	06h00	Purchasers, purchasing Director, purchasing excellence managers, IT managers.
		TOTAL 45h30	

Table 1 - Interviews conducted.

Data collection

We adopted a sequential process to build up our data collection progressively over two years. First, we conducted 9 interviews with experts in IS integration to get a broad picture of the drivers from experts in the field. The interviews were semi-structured with a fixed topic and relatively broad scope, focusing on the variables of adoption of the IS by purchasing. We got deep insights about the context purchasers face when selecting and implementing the IS, which helped us to validate first-order codes and to collect second-order codes.
We then interviewed 26 IS providers. In most of the cases, our respondents were the sales and product managers. As our unit of analysis was the procurement function and not the provider itself, instead of focusing too deeply into specific technical features of the system, we asked for customer project examples as we went along. We asked evidence related to ease of usage, to technological strategy and to the system features. With these data, we completed the second-order codes. We also collected secondary data from IS provider websites, demos, corporate documents introducing the IS.
Finally, we showed the second-order codes to five IS users in a series of interviews, to gather their impressions and comments on the factors we had found. This step was very useful for determining the relevance of our results and for challenging our set of drivers by considering experienced buyers.

Data analysis

All interviews were recorded, transcribed, and cleaned, resulting in about 250 pages of exploitable text. We then implemented a manual data coding process (DeCuir-Gunby et al., 2011), which is more precise and relevant than automatized coding systems. Indeed, taking a human look at the transcribed text provides a perspective and a depth of knowledge that computer software cannot offer. Our coding method followed Ragin (1997), using data-driven codes to account for context. These were then categorized theoretically into three coding structures related to ease of usage and integration, embedded technology strategy, functional coverage. We organized the codes into a large matrix structure representing multiple interviewees in columns and codes in lines to identify emerging patterns and facilitate similarity and difference detection. We kept a log of representative quotes from the interviews to illustrate these aspects. Finally, we analyzed emerging themes that we bridged back to the themes from the literature, and we drew the coding tree (figure 2).

Research validity

Our goal was to explore a phenomenon in its specific context, not empirically generalize based on several cases. We ensured validity by interviewing multiple expert profiles in the field, as well as users. We complemented interview data with documentary evidence, including IS web sites, online webinars, system demos, and sectorial data. To increase validity, we returned reports to interviewees to obtain confirmations and clarifications and collected multiple sources of evidence, e.g. reports and organization charts.

Findings

We present the coding tree in Appendix 1. This figure reflects the constructs which were found in the literature, combined with those which emerged from the first round of data analysis. We also report on interesting quotes below to illustrate our findings.

Findings related to RQ1: how decision-makers perceive and experience the various forms of drivers for adopting an AI-based information system in purchasing?

a) Ease of use and integration

Respondents are unanimous and perceive AI as a potential driver for deciding to adopt an IS: according to them, AI can improve the user experience, because it can eliminate tedious tasks like data crunching, repetitive tasks, re-entries, data centralization and cleaning. AI-based tools often offer an extended search engine, guided usage and facilitate data visualization.

> *Procurement folks crave simplicity. They want all the data and insights they need presented in one place, preferably on a dashboard they can customize. Data visualization is key, and I promote only purchasing IS that are making complex data easy to digest. AI is a game changer, which speeds up decision-making.* (Consultant 1).

Other factors favoring adoption are linked to a system interface (the platform) accessible to other internal users, in which AI helps to achieve data conciseness. Adoption is also facilitated by mobile applications: IS apps allow purchasers to react very fast when facing multiple situations, whereas AI augment the reporting speed or a more in-depth analysis. AI helps to balance between conciseness and depth and to keep workflows efficient. Data centralization also facilitate the adoption:

> *We know purchasers often deal with scattered data, which is a real pain. Teams want a single hub where they can access information from all their sources. We have built on AI and bots to present everything in one spot, which ensures purchasers don't miss any critical details*. **(**IS provider 1).

Several consultants emphasize that system implementation can be broadly smoothened when IS offer AI features: AI facilitates the supplier onboarding and support, the integration with existing ERPs, and the ability to connect with third party data providers (like Ecovadis, Duns&Bradstreet, Creditsafe, etc), who are also themselves built on AI algorithms. IS Integration is therefore critically important for purchasing:

> *Purchasing IS can sometimes be complex to integrate, or even to use. To add to the complexity, purchasing departments are now faced with a plethora of tools based on AI, whose heterogeneity makes it difficult to choose the most appropriate one for a given situation. So, we must consider how fast is the integration of a new system, before all other criteria.* (Purch. Director 1).

However, hosting and services are less concerned by AI features, although a few interviewees highlighted that AI can bring more data security and accuracy, in case of guided system usage and multi-tenant platforms (one platform design common among multiple users).

b) Functional coverage

A significant proportion of the IS providers we interviewed have developed partnership strategies with other IS vendors. Many of them voluntarily opt for reduced functional coverage but greater depth with specific functionalities and therefore potentially greater value with AI features ("best of breed" strategy). They can offer their customers a solution with the widest possible functional scope by integrating functionalities from their partnerships. A typical example is supplier relationship management, more precisely negotiation:

> *I perceive AI as an augmented negotiation power: armed with data, I can negotiate from a position of strength, reduce my preparation time, and rush the negotiation outcomes. I chose a best of breed solution only for machine-to-machine negotiation, connected with a larger suite. Now, it is even faster to let machines negotiate together than organizing e-auctions.* (Purchaser Director 2).

Other functionalities are perceived as being much more effective if they are designed around AI modules. The automation of the procure to pay process thanks to AI is now taken for granted: it allows instantly data extraction from purchase orders, automatic invoice recognition, purchase requisitions, orders and receiving management. In brief: AI is seen as reducing overhead costs. Optical characters recognition has been one of the first application of AI, now it allows many more tasks like legal and accounting compliance check, contracts lifecycle management and invoice payment automation. Sourcing emerged also as a powerful adoption driver, especially when access to supplier data are concerned:

The most impressive AI feature we promote those days is the scenario-based sourcing. Indeed, AI can help to design precise sourcing scenarios which include extended sourcing criteria. You can track CSR practices in your value chain, thanks to risk mapping and therefore adapt your sourcing risks with full knowledge of facts and weak signals. (IS provider 2).

Finally, all the consultants we interviewed emphasized the advantages of AI in the diagnosis phase: high-performance systems make it possible to carry out comparative spend analysis, help to define the purchasing plan, track expenditure, and put it into perspective. Sometimes, AI make possible the cross-sectorial comparison of savings on a specific purchasing category.

c) Technology strategy

Vendors of purchasing IS follow their own technology strategy, reflecting the type and the degree of technological innovation integrated into the IS. It was unexpected to discover that IS technology strategy could be a factor in adoption for buyer-users, while they are supposed to be more concerned with IS functionality.

In a constantly evolving environment (regulatory, technological…), Purchasing IS must differentiate themselves by an ambitious and clear technological roadmap. Now that software as a service model became the norm, and that agile methods are embedded into each IS, buyers expect IS vendors to deliver significant improvements in each of their releases, mostly related to AI. (Consultant 2).

Throughout our interviews, we identified three main technology strategies. The first is related to data management, e.g. whether the IS has a structured data lake "in house", and whether this data lake is fed with outside data collected with AI. For instance, half of the IS providers we interviewed offer a data lake made of structured data, completed with services of data scouting, cleaning, and structuring using an AI algorithm. Buyers aren't necessarily concerned about where their data are stored, but they do have a high expectation of reliable, clean and plentiful data in order to make day-to-day decisions.

We have a pretty good idea of what reference data we need. We often have a single source of data, but we have difficulties with unstructured data because it sometimes has quality flaws. What we expect from the system is to provide reliable data sources, and even more importantly data cleaning functionalities. I think AI-based IS are going to change all that. (Purchasing excellence manager).

The second technology strategy which drive the adoption is the ability of the IS to facilitate the automation of the purchasing tasks. Automating repetitive, structured and rules-based processes that are time-consuming and monotonous for humans to manage, allows to reduce errors.

Being guaranteed that supplier payments will be made on time, that contracts will not exceed their expiry date and that buyers will not have to spend a huge amount of time repeating order entry procedures is a key factor in selecting an IS. Our customers can no longer afford this, as they are concentrating their purchasing resources on analytical or strategic activities. (IS provider 3).

Last, we found a third technology strategy which drive the adoption: it is about data analytics, e.g. the predictive and prescriptive capabilities of the IS. Purchasers need to exploit their historical data to predict likely future events. The system must offer data analytics to be used to anticipate supply needs, optimize purchasing operation, and make relevant strategic decisions.

We need to master the dynamics of the supply market every time we take a strategic decision on sourcing. It's a question of business intelligence. But markets evolve so quickly that we have difficulty keeping up with trends. Our system needs to offer this kind of functionality, and AI can facilitate this constant monitoring and alert us whenever a risk appears. It should even advise us proactively by proposing urgent actions. (Purchaser 2).

Findings related to RQ2: how does the organizational context drives the adoption of IS in purchasing?

With the technological environment and the purchasing IS market evolving so rapidly, the benefits of AI are not always clear to buyers. However, those who have experimented with these AI-based IS have positive feedback, while noting that a new organization is likely to emerge as a result of these new systems.

Before Covid-19, I was moving towards digitizing my dashboards with traditional KPIs, but three years later I can use tools capable to reinforce risk management functionalities: that is critically important given the current global context. These tools have even changed the way we are organized in our department: the IS has influenced our processes. AI has definitely augmented our capabilities, but it requires organization adaptations. (Purchaser 1).

Several respondents highlighted the need of adapting the purchasing skills and competencies. It seems essential to have a team capable of understanding and managing these new technologies, but who are not technical experts.

Emotional and relational intelligence, combined with specific technical skills and strategic vision, will represent the future cornerstones of the purchasing profession. This relates to skills like relational skills, teamwork/collaboration and influence, creativity/innovation and flexibility/adaptability. AI will not replace this, but yes for sure will reduce the needs of sills related to data collection and analysis, market research, and even communication and part of leadership skills! (Consultant 3).

Also, modifying the way data management is considered internally is a key driver of success. Those interviewed stressed that the way in which the company's management views data management can be affected by AI-based tools. This includes internal data (activity data specific to the purchasing function, data structured by the company such as price indices or currencies, ERP metadata), and external data (from third parties, collected from suppliers, open data).

The digital transformation of purchasing is already in its second stage: during the first stage 2000 to 2020, purchasers equipped themselves with software suites, offering functionalities for managing purchasing and supply activities, structuring purchasing processes and professionalizing the function. Since 2020, purchasing departments need to feed their systems with reliable data, in sufficient quantity, and above all to process this data efficiently. This new phase reinforces the idea that purchasing data is strategic. (Consultant 4).

Last, interviewees emphasized that ethics and confidentiality, if well managed, are facilitating conditions: the use of AI raises questions about data protection and the ethics of automated decisions. Indeed, they report that the fear of being overwhelmed by the complexity of AI exists, as well as the feeling that their decision-making power is threatened. Despite this, they also advocated that this is an irrational fear, totally psychological in nature. Our respondent often focused on benefits of data sharing, and less on risks:

Purchasing solutions using AI and integrating supplier data shared by their customers, enable users to improve visibility of quality, risk and benchmarking and benchmark metrics throughout the procurement process. When problems are reported by one of the users, the IS offers prescriptive suggestions to all other customer-users, to reduce the likelihood that they will encounter the same problems. (IS provider 4).

Conclusion

The emergence of new IS based on AI is disrupting possibilities. The trend of “everything mobile”, the cloud and “always-on” connectivity is becoming the norm. By simplifying processes, consolidating information, and providing actionable insights, these systems aim to boost efficiency and drive better results in everyday purchasing activities. In theory, buyers have access to numerous and diversified data, with predictive and even prescriptive capabilities reducing sourcing risks, costs, time lost on non-strategic activities. There is no doubt that purchasers have understood the stakes and can seize the opportunities offered by new AI-based IS. However, these new tools also bring their share of constraints and limits, reducing the chances of successful adoption. Although they are sometimes supported by IT department, purchasing directors struggle to exploit the most of the IS market.

This research explored the drivers of adoption of AI-based information systems, focusing not just on the technological dimension, but examining the individual and organizational drivers of adoption. It highlighted the importance of ease of use and integration, user experience, technology strategy and functional coverage. For instance, it suggests that AI-based IS user experience completely renews the experience of man-machine interaction: with data and the use of AI mechanisms at the heart of software, the system proposes, recommends, adapts and even suggests. Our findings also revealed that the procurement organization needs to adapt to the implementation of new information systems: new skills and competencies, new processes, particularly for communicating and collaborating with other functions, and a new way of considering data.

From a theoretical perspective, this study provides valuable extensions to established technology acceptance model in the context of the purchasing function (Sohn and Kwon, 2020). It also complements existing research about IS adoption in the field of PSM (Nandankar and Sachan, 2020; Ramkumar et al., 2019). Among other contributions, it elaborates on the TAM and the UTAUT models and populates the existing adoption criteria with function-specific dimensions. It extends the set of factors driving the adoption of AI-based tools (Venkatesh, 2022; Sohn and Kwon, 2020), focusing on purchasing function. For instance, it develops the “facilitating conditions” which were introduced in the UTAUT model (Venkatesh et al. 2007), suggesting that skills and competencies, firm’s data strategy, ethics management and confidentiality are factors facilitating the adoption of AI-based systems in purchasing.

Last, this research also suggests a clear set of criteria for practitioners to consider before investing in an AI-based information system for purchasing.

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APPENDIX 1: Coding tree