The Promise of AI in Public Bid Management: A Transaction Cost Perspective

A Qualitative Study on AI Adoption in Public Procurement Bidding

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Abstract

As the global economy experiences increasing pressure, reducing additional transaction costs becomes more valuable. The public procurement market is no exception, as the additional protocols necessary to maximise public benefit and ensure fair competition can lead to suppliers incurring significant expenses. At the same time, recent innovations in generative artificial intelligence technology and the advent of large language models have allowed businesses to streamline many time-consuming processes. The authors of this paper aimed to find out whether and how firms selling to the public sector could use generative AI to reduce their transaction costs in the bidding process, as well as map out potential challenges in doing so. A qualitative research project was conducted, collecting data from various actors involved in bidding processes through semi-structured, in-depth interviews. The findings suggest that the current state of artificial intelligence technology allows for significant efficiency gains in the early phases of the bidding process, namely in the screening and qualification of relevant tenders and as an organisational knowledge management tool. However, the technology at the present moment is not mature enough to create bids on its own. The main challenges of implementing artificial intelligence come from the need for transparency in AI outputs and proper data control systems, as well as obstacles related to employee skills, culture, and trust. Being ahead of the competition is also a source of advantage. The authors find indications of potential long-term secondary effects of widespread AI adoption that create uncertainties about AI impact on transaction costs going forward.

Acronyms

AI - Artificial Intelligence

GenAI - Generative Artificial Intelligence

LLM - Large Language Model

LOU - Lagen om offentlig upphandling

NLP - Natural Language Processing

RFI - Request for Information

TCE - Transaction Cost Economics

TED - Tenders Electronic Daily

TOE - Technology-Organisation-Environment Framework

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1. Introduction & Background

As the global economy continues to face ever harsher challenges, the role of public authorities to keep delivering to citizens while simultaneously working with the private sector becomes increasingly crucial. This is made evident by the example of the 2022 public procurement expenditure in Sweden, which, even when limited to larger-sum contracts that require tenders, went up to 921 billion crowns, corresponding to around 18 per cent of the country's gross domestic product (Upphandlingsmyndigheten, 2024). With this level of responsibility comes a high need for intention and efficiency, not just in what services and goods authorities choose to purchase but also in how they do so. Public procurement has a complex structure to ensure fair competition and a maximally beneficial deal for the public (European Commission, 2024). Therefore, there will naturally be a significant degree of resource and time investment to ensure that. In the case of more complex services, these transaction-related costs have been shown to surge as high as 7.6 per cent of the total contract value (Petersen et al., 2019). According to the European Commission, a 1 per cent gain in the efficiency of public procurement could yield savings of 20 billion euros of public funding per year (European Commission, 2024). Therefore, a significant reduction in a major source of such inefficiencies, in the form of transaction costs, would benefit society.

Just like the side of the contracting authority, existing and potential supplying companies also experience the problems of dealing with high transaction costs. Research has shown that firms estimate the cost of selling to governments to be around 34 per cent higher than selling to private sector actors (Potoski, 2023). The consequences of these expenses, both time and money, can lead to a general decrease in interest in the public market for some firms. Additionally, these costs can be compensated for by being calculated into the bid offer. This is a significant drawback considering public buyers' intense focus on price as the sole decisive factor for evaluating most submissions (Potoski, 2023; Rönnbäck, 2012). Lowering suppliers' required effort and costs associated with public procurement would incentivise participation in tenders.

Over the past two years, a prominent emerging phenomenon in the business world has been the accelerating adoption of artificial intelligence technologies. Although the field has seen much research and developments for decades (Russell and Norvig, 2020), the current boom has come due to recent breakthroughs, with Generative AI receiving particular attention. According to a 2024 report by McKinsey & Company, the adoption rate of such tools has risen to sixty-five per cent among surveyed organisations, close to twice the rate measured less than a year prior. This is because of the tangible benefits and diverse use cases these technologies can provide for businesses (Brühl, 2024).

While AI has shown promising results in increasing the efficiency of business processes, its effect on transaction costs still needs to be mapped out. Additionally, although AI's potential has been thoroughly explored by literature in many different contexts, there have been limited studies on how suppliers can utilise it to support their work handling bids. This paper aims to inspect how large language models and their various applications affect transaction costs for suppliers in the public tender bidding process. It will also examine the various enablers and challenges connected to adopting AI in the context of this work.

Given the significant economic impact of transaction costs in public procurement and the transformative potential of AI technologies, this study addresses two research questions:

RQ1: How does the implementation of large language models reduce transaction costs for suppliers in public procurement processes?

RQ2: What enablers and challenges are associated with large language model implementation from a private and public view?

To address the research questions, the study employs a qualitative multiple-case study approach, combining theoretical analysis with empirical investigation of AI implementation in Swedish public procurement. The study utilises two complementary theoretical frameworks: Transaction Cost Economics (TCE) provides the lens for analysing how AI affects different categories of transaction costs (Williamson, 1979), while the Technology-Organization-Environment (TOE) framework helps identify key factors influencing AI adoption (Tornatzky & Fleischer, 1990).

The authors aim to contribute to the theoretical understanding of AI's role in public procurement and provide practical insights for suppliers in AI adoption. As public procurement has such a substantial economic impact, and the rapid evolution of AI has the potential to reduce transaction costs significantly, both public and private stakeholders are interested in understanding how to integrate these technologies into the procurement process while keeping its integrity.

2. Literature review

2.1 Artificial Intelligence

2.1.1 AI Definition

Despite having been an important field of research for decades, there is still no universally accepted, exact definition of Artificial Intelligence. (Loureiro et al., 2021; Wirtz et al., 2019). This definitional ambiguity represents a fundamental problem in understanding AI in its entirety, necessitating the development of an integrated definition that considers both the concept of "intelligence" - defined as the ability to interact, learn, adapt, and resort to information from experiences, as well as deal with uncertainty - and "artificial" - meaning a replica produced by humans (Wirtz et al., 2019).

Russell and Norvig's seminal 1995 book Artificial Intelligence: A Modern Approach and its subsequent editions are the most common sources from which papers attempt to outline the concept of artificial intelligence. This work attempts to create a comprehensive definition of technologies that are widely considered AI, by breaking down how its components are defined differently across literature and including these definitions in a model.

Firstly, the concept of intelligence can be understood either as acting rationally (meaning doing the correct thing) or acting in a way that is faithful to human performance. Another axis is that of thought and behaviour, whether the emphasis is on having the correct reasoning behind a decision or on getting the right decision in the end (Loureiro et al., 2021). From organising definitions systematically, the four categories that arise are systems that act humanly (Turing Test approach), systems that think humanly (cognitive modelling approach), systems that think rationally (laws of thought approach), and systems that act rationally (rational agents) (Russell and Norvig, 2020).

Although this is the most comprehensive definition which is extremely useful to the theory of artificial intelligence as a whole, this study is much more limited and practically oriented. As such, the authors will be focusing on examining the nature of the technologies that have experienced breakthroughs and a surge in implementation since 2022 (McKinsey & Company, 2024), namely Generative Artificial Intelligence (GenAI) and Large Language Models (LLMs), investigating their functioning, capabilities, and effects on the broader organisational context.

These technologies significantly evolved from earlier AI systems, transitioning from narrow, task-specific applications to more general-purpose capabilities (Russell & Norvig, 2020). Early AI systems were highly specialised with simple reflex-based approaches that could only handle fully observable, deterministic environments with complete prior knowledge. The field then evolved toward more sophisticated methods, moving from simple reflex agents to model-based agents capable of handling partial observability and maintaining internal models of how the world works. This was followed by the development of goal-based agents that could plan action sequences and utility-based agents able to handle complex tradeoffs between competing objectives. Furthermore, integrating learning mechanisms allowed agents to improve performance over time in previously unseen environments, thus reducing reliance on hand-coded knowledge. While these developments show a clear path toward more general AI capabilities through increasingly complex architectures, it remains far from achieving human-level general intelligence, with current AI still primarily focusing on specific domains rather than truly general capabilities (Russell & Norvig, 2020).

2.1.2 AI Technologies

Perhaps the largest breakthrough of the past few years is the major improvement in the capacity of AI to perform Natural Language Processing. Liddy (2001, p. 3) defines these technologies as a "range of computational techniques for analysing and representing naturally occurring texts at one or more levels of linguistic analysis to achieve human-like language processing for a range of tasks or applications." This technology has evolved through three key capabilities:

Language Processing: The ability to analyse and interpret human language, converting it into digital representations that computers can process (Lauriola et al., 2021).

Language Generation: The capacity to translate computational outputs into coherent human language, enabling natural communication between machines and users (Chen et al., 2020).

Natural Language Understanding: The advanced capability to comprehend context, form conclusions, and extract meaningful information from text (Khurana et al., 2023).

The development of LLMs represents a leap in capabilities over previous iterations of NLPs. LLMs are trained on vast datasets drawn from the internet, teaching them to process and generate language with high sophistication and relevance in various topics and styles. This evolution from earlier language models to current LLMs enables more complex and nuanced applications such as modern AI tools - GPT-based AI chatbots (Floridi & Chiriatti, 2020). The result of these significant improvements in this capability is what led to the proliferation of LLMs. While earlier technologies, such as pre-trained Language Models, focused on natural language processing in smaller, more controlled environments, LLMs present a vast improvement over previous iterations (Teubner et al., 2023).

At their core, LLMs function like sophisticated pattern recognition systems. The breakthrough that made modern LLMs possible came from Vaswani et al.'s (2017) introduction of the "transformer" architecture, which allows these systems to process language in a way that mimics how humans understand context in conversations. Just as humans pay attention to different parts of a sentence to understand its meaning, LLMs use a mechanism called "attention" to weigh the importance of different words in relation to each other. The combination of context awareness and training allows LLMs to mimic human responses, execute requested tasks, and engage in coherent discussions on many topics.

While LLMs offer powerful capabilities for businesses, they are not without a cost. For instance, OpenAI's ChatGPT Plus subscription costs $20 per month for individual users, while their Team plan is priced at $25-30 per user per month. Microsoft's Copilot for business users is even more expensive at $30 per user per month with an annual subscription requirement (OpenAI, 2024; Microsoft, 2024).

An alternative option is self-hosting LLMs on owned hardware or renting it on the cloud. While it can offer more control, data safety, and potentially lower long-term costs than solutions based on API technology, the infrastructure requirements that would have to be involved are substantial, making it a significant financial decision. According to an analysis by Andreessen Horowitz, organisations need to consider costs related to computing resources, storage, and specialised hardware like GPUs for efficient model inference. This, coupled with the technical expertise required for deployment and maintenance, can make it challenging for smaller organisations to maintain in-house LLM infrastructure (Bornstein & Radovanovic, 2023).

2.1.3 AI Capabilities and Applications

LLM breakthroughs have since resulted in considerable improvements in Generative Artificial Intelligence, which focuses on creating a range of outputs for requests across very different functions and mediums (Dang et al., 2022). The potential application range of these technologies, especially those with language output, is extensive in the everyday life of many organisations, as they possess almost universally useful functions across many different fields. These include generating simple texts, summarising long chunks of text, correcting minor mistakes, and quickly pulling information from external sources, all activities many workers would otherwise spend a significant amount of time on. With tools such as ChatGPT or its different iterations, these work tasks become simplified and even trivialised to a great extent (Brühl, 2024; Batubara et al., 2024). In addition to the benefits it brings by saving time, well-prompted writing generated by AI tends to excel at generating texts with rigid, formulaic structures and can avoid simple mistakes like grammatical errors, thereby potentially surpassing what employees unfamiliar with the desired output could create on their own (Casal & Kessler, 2023). Outside of everyday text-related matters, less all-encompassing tasks such as interpreting unstructured data, drafting documents, creating images and illustrations, providing customer support, or even transcending language barriers become readily available without highly complex skills or resources (Singh, 2023).

Despite these promising capabilities, the reliability of AI systems remains a critical concern that organisations must consider during implementation. As (Hong et al., 2023) emphasise, AI reliability is particularly complex because it is influenced primarily by software systems rather than hardware and is affected by three key factors: operating environment, data quality, and model selection. In the context of business applications, reliability issues can arise when AI systems encounter situations outside their training data (out-of-distribution samples), face data quality issues, or experience adversarial attacks.

The success of AI implementation depends heavily on the organisation's ability to integrate it into existing workflows while maintaining appropriate human oversight. Organisations must know AI's strengths and limitations and combine them effectively with human abilities. This is supported by research indicating that organisations that achieve the highest return on AI investment focus on augmenting rather than replacing human capabilities (Brynjolfsson & McAfee, 2017). This is confirmed by Loureiro et al. (2021), who argue that when AI tools enhance professional judgment rather than substitute for it, they improve efficiency while maintaining service quality and professional standards.

Implementing AI capabilities across different business functions represents varying levels of complexity and organisational readiness. While some applications, such as basic content generation and data analysis, can be implemented with relatively minimal disruption to existing processes, others require significant organisational adaptation and careful consideration of ethical implications (Davenport & Ronanki, 2018).

AI applications can enhance public sector operations through process automation and intelligent systems, potentially reducing administrative burdens and improving service delivery efficiency (Wirtz et al., 2019). In the context of public administration, AI-based process automation systems can "perform formal logical tasks with unpredictable conditions in consistent quality" and support "complex human action processes," which can enhance workflow processing and data management in public organisations (Wirtz et al., 2019, p. 600). As (Reis et al., 2019) note, AI-enabled decision support systems are becoming increasingly important for public administrators to "effectively operate" and "analyse large amounts of data." However, implementation requires careful consideration of challenges around privacy, trust, and ethics.

2.1.4 AI Impact

The introduction of AI technologies in workplaces is forecasted to affect not only the workflows and day-to-day tasks of individual workers but also organisations and society at large (Crafts, 2021). The boom in AI does not affect every type of role equally. Jobs that mainly tackle cognitively-intensive tasks have a higher likelihood of their day-to-day work being affected (Cazzaniga et al., 2024). However, AI adoption will not just mean an increased productivity rate for every role it interacts with. In fact, as AI keeps improving and becoming more reliable, there is predicted to be a large degree of job displacement as entire jobs could be replaced with technology (Gruetzemacher et al., 2020). Although this could imply that more manually-focused jobs are not subjected to job displacement risks from AI, it also means that they will not get the same level of benefit (Cazzaniga et al., 2024).

AI adoption in an organisation comes with several barriers that must be overcome. Haleem et al. (2022) highlight three primary challenges associated with AI adoption: (1) competency gaps in the workforce, (2) trust issues stemming from a limited understanding of AI, and (3) data quality concerns and unreliability of results. Arrieta et al. (2019) highlight another challenge, namely that AI systems often lack transparency and explainility in their decision-making process. This "black-box" problem is particularly concerning when AI decisions must be checked and justified. This creates practical limitations in areas where AI can be easily deployed and can create trust issues among users and stakeholders. These highlighted challenges mean that AI implementation often requires human oversight and validation, which can offset the efficiency gains from automation.

2.2 Public Procurement

2.2.1 What is Public Procurement?

Public procurement is the process by which governments and other public authorities purchase goods and services from the private sector. This occurs due to public bodies' obligation to perform their work for themselves and society, which requires resources and competencies they do not possess (Baldus & Hatton, 2020). To this end, contracts are established as agreements which allow private organisations to supply the public sector with the necessary offerings. Due to the need to make the use of this budget maximally beneficial for the public and ensure fair competition, contracts of significant value are only awarded through an open tender process (European Commission, 2024). In addition to this, The public sector also carries a lot of responsibility to shape the markets as a whole, with procurements representing a large part of the economic activity in any given economy, as the over 900 billion SEK sum of tender-mandated public procurements have shown (Upphandlingsmyndigheten, 2024). With this level of purchasing power, public organisations' tasks extend beyond only providing the best value for the public in a given contract but also include such challenges as having to stimulate certain parts of the economy, acting in the country's strategic interests or instilling new priorities like sustainability in the wider market (Upphandlingsmyndigheten, 2024).

The estimated purchase value is decisive in determining whether a procurement tender is necessary. Purchases below this threshold fall under the category of direct awards in the Swedish system and are usually limited to the category of everyday, low-stakes goods and services generally considered to be of smaller individual importance to the public or occur in rare exceptional circumstances (Konkurrensverket, 2017). The buying authority must go through the procurement tender process for procurements above the decided line. To decide how this will take place, the member countries of the European Union are subject to federal legislation, most recently in the form of the 2004 Directive and later modifications, which provide general guidelines designed to be adapted into national law (EUR-Lex, retrieved 2024). The open procedure is the most common method of public tendering (Your Europe, 2024). Under these rules, any actor from the private sector may participate in bidding, with the one deemed the best along a list of criteria (usually emphasising the lowest price). Under Swedish regulation, namely Lagen om offentlig upphandling (LOU), this is a long process, with many important steps involved before, during and after the starting and closing deadline of the tender.

The first step on the path to a public procurement contract is the preparation stage. During this, the authority allocates necessary time and resources, maps out the market for needs and risks, and conducts an analysis to prepare everything for the procedure. Following this, the procurement phase begins with a formulation and announcement of the tender. The authority constructs a list of requirements and decision criteria and publishes the documents to a publicly accessible source. Then, the tender period opens, allowing suppliers to put together and hand in their bids. After the final deadline, the buying authority evaluates all submissions using a point system along the pre-defined criteria. The contract is awarded based on the highest number of points, closing the process. Finally, the realisation phase consists of the work with implementation and a continuous performance review until the completion of the project or end of the contract period, finishing the process. Additionally, alternative laws, such as LUFS and LUK, apply to specific scenarios, such as military procurements and concessions. (Upphandlingsmyndigheten, retrieved 2024)

2.2.2 The Swedish Public Market

To understand the current state of the Swedish public procurement market, it is crucial to look at the trends of recent years. Due to various economic and geopolitical factors, purchasing authorities have faced several major challenges, as summarised by the report Utvecklingen på upphandlingsområdet 2023, published in 2024. The stark increase in inflation, combined with increasing costs, has made the goods and services needed by the public sector more expensive. Additionally, the weakness of the Swedish crown has resulted in additional costs for transactions done in other currencies, such as the euro. Put together, these effects significantly decreased the purchasing power of public authorities, which was made worse by the decreased rate of tax funding growth. This has necessitated stricter budgeting, as well as alternative approaches to allocate public funding more effectively, which the somewhat decreased number of advertised tenders may be an indication of.

To make matters worse, most buying organisations announce very few tenders (around 1 to 5 annually), as a proportionally small number stand behind the major shares of all procurements announced. The worsening economic trends have similarly harsh effects on suppliers. The year 2023 has seen the highest number of bankruptcies since the turn of the millennium, reaching its highest victim count in the construction industry. Furthermore, there has been an unfortunate slow decline in the average number of participants in tenders observable from year to year over the past decade, which the 2014 EU Directive attempting to increase competition seemingly has not been able to turn around. Today, the most common number of bidders for a contract is two, with 60% getting three or fewer, signalling a lack of sufficient competition in many cases. Finally, the increased national security concerns resulting from the current geopolitical climate have emphasised the need for support and tools to check who owns and controls suppliers and subcontractors for critical or sensitive goods and services. (Upphandlingsmyndigheten, 2024)

The public sector has turned to a list of measures to counteract many major problems, from altering legislation to creating new incentives. One such initiative proposed was a series of regulatory alterations concerning the possibility for certain suppliers to have pre-reserved participation in tenders, a form of positive discrimination. These opportunities were previously limited to only a handful of categories, mainly actors within certain social service-related areas, but now extend to services not connected to primary healthcare. Furthermore, the Armed Forces received the right to make purchases exempt from the general procurement process if necessary for national security. Lastly, the government has begun re-examining and revising the overarching national procurement strategy from 2016 to make the public market more attractive and increase supplier diversity. (Upphandlingsmyndigheten, 2024) However, the various transaction costs related to purchases are a major source of the burden on the public procurement budgets and workload in any market (Petersen et al. 2019). Given the immense amount of public funding savings that could result from small boosts to efficiency (European Commission, 2024), efforts to reduce these expenses and time spent could counteract much of the hardship currently faced by the market on both the purchasing authorities' and the supplier organisations' side.

2.3 Transaction Costs:

Public and private sector entities often engage in similar procurement activities when acquiring goods and services (Potoski et al., 2023; Tadelis, 2012). This is especially true for standardised items such as basic office supplies, computers, and widely used software. Handling these kinds of procurements follows a similar set of steps, starting with requesting bids, choosing a winning bid, negotiating, delivering the products, and closing with an evaluation of quality. However, public and private institutions often differ significantly in their process of procuring customised goods and services, such as buildings, consulting services or IT systems (Tadelis, 2012). This is due to public purchasing occurring under complex purchasing policies and regulations, which may raise transaction cost expenditures.

A comprehensive study by Petersen et al. (2019) of 72 contracts across 47 Danish local governments found substantial variations in ex-ante transaction cost spending across different types of procurement. Their research revealed that these costs ranged from just 0.2 per cent of contract value for standardised services like dental care to 7.6 per cent for complex services like information technology systems. The study, which provided one of the first detailed analyses of actual transaction costs across a broad portfolio of government purchases, found that ex-ante costs were consistently higher for more complex services.

Purchasing activities done by the public sector are conducted in long and complex processes, requiring substantial resource investments from both sides of the transaction. This can include workers specialising in different areas, such as buyers with the expertise necessary to create specifications, lawyers to work out terms and draft legal documents, and experts to conduct performance evaluations. These additional expenses then increase the overall transaction costs, a significant hindrance in public purchasing (Lindholst et al., 2018).

When certain elements increase the likelihood that one or both parties might not receive complete value from a transaction, mutually win-win agreements become more challenging to attain (Akerlof, 1970; Hart & Moore, 1999; Romzek & Johnston, 2002; Wathne & Heide, 2000) Such elements of products and markets are called transaction cost attributes as noted by Williamson (1999). Transaction cost attributes create contracting risks that need to be addressed by both buyers and sellers. When such transaction cost factors are more substantial, both parties need to allocate more resources to exchange activities for preparing, negotiating, executing, and managing the exchange, or they increase the possibility of lost value or a failed exchange (Anguelov, 2020; Bowen & Jones, 1986; Geyskens et al., 2006). For buyers, a priority is ensuring they obtain optimal value from their purchase. Sellers, likewise engage in exchange activities to ensure that they benefit by receiving compensation greater than their costs (Petersen et al., 2021; Williamson, 1996)

Akerlof's (1970) work on quality and uncertainty in markets highlights the negative consequences of information asymmetry between buyers and sellers. He argues that when sellers have more knowledge about product quality than buyers, it can lead to a decline in overall market quality. Using the used car market as an example, he shows that a destructive pattern emerges when sellers know more about product quality than buyers. Since buyers cannot verify quality before purchasing, they must base their request on the probability of getting a good or bad product. For instance, if a buyer believes there's an equal chance of getting a good car (worth $2,000) or a bad car (worth $1,000), they will only offer around $1,500. This pricing mechanism creates two problems: owners of high-quality goods cannot get fair value and withdraw from the market. In contrast, sellers of low-quality goods ("lemons") are incentivised to participate since they receive more than their products are worth. This creates a problem for sellers of high-quality goods, as they cannot command the actual value of their products. Conversely, sellers of low-quality goods benefit from this situation, as they receive a higher price than their products warrant.

Building on this concept, Brown et al. (2016) suggest strategies to improve outcomes in complex contracting situations through a combination of approaches. They propose that carefully designed governance rules (such as performance incentives and third-party monitoring), relationship-building through repeated interactions, and mutual understanding between parties can help increase the likelihood of cooperative behaviour and achieve win-win scenarios. The authors note that effective governance becomes more costly as product uncertainty increases, creating a tradeoff between reducing information asymmetry and maintaining cost-effective oversight.

Effective contract management aims to allocate resources cost-effectively to mitigate risks and enhance contract value, which depends on the specifics of products and contractual circumstances (Williamson, 1996). Hart and Moore (1999) provided the foundation of the analysis of incomplete contracts. They argue that it is impossible or prohibitively costly to account for all contingencies, which in turn leaves gaps in contracts. This incompleteness comes from situational complexity, bounded rationality and difficulty verifying certain performance aspects. This, in turn, often necessitates ex-post renegotiation, resulting in inefficiencies.

When building business relationships, it is important to assess the risk of opportunistic behaviour occurring due to its potential to deteriorate the mutually beneficial nature of collaboration. This phenomenon is analysed in-depth by Wathne & Heide (2000), who emphasise the risk of opportunism becoming a problem in the relationships between firms and the consequences this can lead to. These risks could lead to strict monitoring systems or exhaustive contracts to prevent opportunism from manifesting, making exchanges more expensive.

Win-win exchanges are more difficult to achieve in the presence of factors that increase the risk that one or both parties fail to receive full value, particularly in situations where it is hard to quantify and explicitly state the product's worth in a contractual agreement (Romzek & Johnston, 2002). This challenge is exacerbated when product or service specifics make verifying the quality and effectiveness more challenging, especially for complex or long-term contracts.

There are multiple theoretical approaches to analysing interaction costs between two parties. These include transaction costs, management costs, and coordination costs (Bowen & Jones, 1986; Geyskens et al., 2006; Romzek & Johnston, 2002; Williamson, 1979). Financial and operational problems stemming from the interaction of the two parties are collectively referred to as coordination costs. According to Gulati & Singh (1998), it is the complicated nature of allocating responsibilities between the different partners and managing the activities undertaken together across organisational barriers that give rise to these costs. They also include not only direct expenses but also indirect ones, such as the effort necessary to maintain good communication, the management of relationships between various stakeholders and aiding decision-making processes. Management costs represent a significant component of organisational expenses, particularly in contexts where ownership and control are separated. As Jensen & Meckling (1976) explain, these costs encompass agency costs that arise from the divergence of interests between principals (such as shareholders) and agents (such as managers), including monitoring costs, bonding costs, and residual loss. The need for monitoring and control mechanisms generates additional expenses for overseeing managerial actions and performance to ensure alignment with organisational objectives (Fama & Jensen, 1983). Williamson (1985) also recommends that organisations invest in establishing structures and processes that promote effective management and prevent a large part of agency-related problems from occurring, which further adds to management costs.

Transaction Cost Economics (TCE) provides a valuable lens of analysis for economic exchanges. Williamson (1979) provided the foundation of TCE, arguing that exchanges involve costs more than just the price of goods or services. There are costs related to searching for information, negotiating exchange terms, monitoring performance and enforcing contracts. Factors such as asset specificity, transaction frequency and uncertainty should be considered when choosing a governance structure for a given procurement.

Transaction costs associated with exchanges can vary in magnitude and timing throughout the process (Dyer & Chu, 2003; O. H. Petersen et al., 2019). These costs are typically categorised into two main phases: ex-ante and ex-post. Ex-ante costs are associated with activities before the contract is signed, including search and negotiating activities.

Conversely, ex-post costs are incurred after the contract is signed and involve activities such as monitoring compliance and enforcing contracts. This classification of transaction costs into ex-ante and ex-post categories provides a framework for understanding the different stages at which higher expenditures may occur during a transaction (Dyer, 1997; Potoski et al., 2023).

The ex-ante phase of transactions involves costs that arise before the contract has been signed. Such costs are important for laying the groundwork for successful future exchanges and will greatly impact the total transaction costs that come from a deal. Search costs represent the resources expended to identify and evaluate potential partners (Barthélemy & Quélin, 2006). These costs include screening markets, gathering information to identify and assess potential trading partners, and assembling bid teams (Dyer, 1997; Potoski et al., 2023).

Negotiation or contracting costs are the resources expended to agree on exchange terms, such as price and quality, and to transfer resources between parties (Barthélemy & Quélin, 2006; Dyer, 1997). These costs involve several activities, including reading product specifications, drafting proposals, negotiating exchange terms, verifying and signing contracts, identifying contingencies and negotiating how to handle them (Potoski et al., 2023; Wuyts & Geyskens, 2005).

The ex-post phase of transactions involves costs that arise after the contract has been signed and the exchange has begun. Monitoring costs represent the resources expended to verify whether the product or service meets the terms of the agreement and to ensure that each party fulfils its predetermined set of obligations (Anguelov, 2020; Dyer, 1997; Romzek & Johnston, 2002). Monitoring activities involve but are not exclusive to assessing product quality, producing and supplying performance information, and general relationship management and improving relational capital between the parties (Potoski et al., 2023; Villena et al., 2011).

Enforcement costs are the resources expended to rectify any deficiencies in the contract relationship and to address issues arising after the agreement, which could include ex-post bargaining and penalising the partner (Dyer, 1997; Melese et al., 2007 Wynstra et al., 2018). Potoski et al. (2023) provide a more detailed breakdown of enforcement activities, which include rectifying deficiencies, resolving disputes, billing and verifying payment, and, if necessary, contract termination.

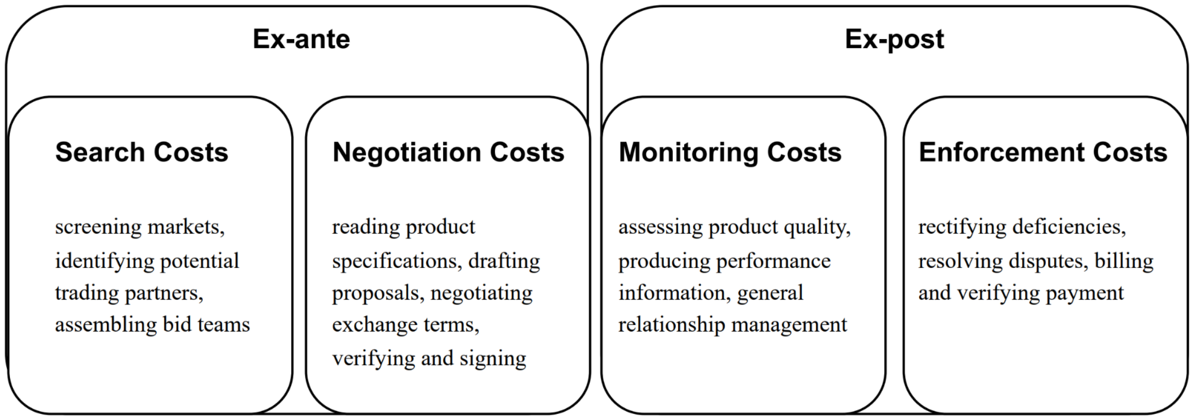

Figure 1. (ex-ante and ex-post transaction costs and associated activities)

Organisational theories explain why transaction costs are higher when selling to governments than to private firms, even for identical products (Bowen & Jones, 1986; Geyskens et al., 2006). Williamson (1999) identified fundamental differences between public institutions and private buyers. Public institutions have distinct incentive structures and management controls, which increase transaction costs and reduce pressure on the public sector to minimise them. Unlike private firms, which primarily focus on economic efficiency, governments must consider broader social values in their purchasing decisions, including transparency, open competition, and equal treatment (Tadelis, 2012). Purchase et al. (2009) demonstrate that to achieve these values, government purchasing regulations mandate additional contract management procedures and monitoring that are not typically required in private sector transactions. Johansson et al. (2016) found that public sector organisations implement control systems primarily in response to stakeholder pressure and legitimacy concerns, using a combination of results, behavioural, and social controls. Their research indicates that control systems in public-sector outsourcing relationships focus mainly on protecting against environmental risks and maintaining stakeholder support rather than facilitating internal efficiency.

The cumulative effect of these regulatory requirements significantly increases sellers' transaction cost expenditures when dealing with government entities. Tadelis (2012) argues that government contracting regulations create an additional layer of complexity and cost that only exists in public sector transactions, even when the product or service being sold is identical. This regulatory burden helps explain why transaction costs are typically higher in government procurement than in exchanges between private firms.

Research by Purchase et al. (2009) indicates that suppliers perceive greater value benefits from their business customers than their government customers, suggesting that government procurement departments may be disadvantaged when competing for supply. A study by Potoski et al. (2023) indicates that sellers face higher expenditures when dealing with governmental entities. Their study in Denmark compared the transaction costs when selling the same product to private or government entities. The study demonstrated that selling identical products to governments results in increased prices to the government. The authors provide quantitative evidence for this phenomenon, revealing that firms estimate transaction cost expenditures to be 10.36 per cent of the contract value when selling to governments, compared to 7.74 per cent when selling to other firms. This represents a 34 per cent difference in costs associated with government sales.

2.4 The Technology-Organisation-Environment Framework

To realise the potential implementation of AI technologies to reduce transaction costs, it is necessary to look at how different factors in organisations and their external environments enable this kind of innovation. This requires considering the bigger picture and how all these elements connect. First outlined by Tornatzky & Fleischer in 1990, the Technology-Organisation-Environment framework (TOE) aims to capture these variables and their interactions and has seen widespread academic use since its inception. These contexts involving variables inside and outside the firm will cover the scope of factors that would influence the adoption and implementation decisions a given organisation makes.

The first context to be considered is the technological one. This part of the framework examines the technologies available given the firm's technological infrastructure and further solutions available on the market. From such available solutions, the firm's technological evolution can go through three different types of change, as outlined by Tushman & Nadler (1986). The simplest of these change categories is incremental developments. These smaller innovations do not change the firm's operations, providing a straightforward, tangible improvement. Representing a step up from incremental improvements, synthetic changes do not need to use never-before-seen technology, instead utilising technology resources that are already there. However, it does repackage existing tools into a completely new solution. Finally, a radical change occurs when the firm lifts new technologies provided by the market (or occasionally developed in-house) into its day-to-day operations, creating a major change compared to earlier solutions, both in infrastructure and workflow.

The second context in the TOE framework is the Organisation. It aims to capture the factors that describe the organisation's properties related to structure, resources, firm size, or any other factors related to its nature. In many of these aspects, certain firms are more positively associated with adoption decisions than others. First, firms with organic and decentralised organisational structures, where smaller teams are emphasised, and employee responsibilities are less strictly defined, are more closely related to innovation (Daft, 1978). Secondly, top management communication processes that encourage innovation and informal communication networks among employees are well-established and benefit from such efforts (Tushman & Nadler, 1986; Daft, 1978). Finally, high organisational slack, meaning a high level of excess resources (in finances, skills, capacity or other measures) not used by everyday operations, has also been deemed beneficial for innovation (Baker, 2012). Although there is a list of variables that individually benefit innovation, it is when those factors are combined into an organisational structure that a firm becomes prone to it (Chansler et al., 2003).

Finally, the environmental context (also referred to as the external task environment) takes a broad view, containing everything that occurs outside the organisation itself that guides technology adoption and implementation decisions (Tornatzky & Fleischer, 1990). Important aspects include government regulations, the nature of competition, industry life cycles, and the type of labour the firm has to utilise in its operations (Marshall & Parra, 2019). In particular, external pressure to conform to regulations, innovations that give either the firm itself or its competitors an advantage, tools that enable the substitution of costly or scarce human work or being part of a rapidly growing and changing industry all work as motivators for an organisation's technological evolution decisions (Baker et al., 2012).

Novel artificial intelligence technologies represent a large departure from earlier solutions. They are more of a market-wide phenomenon that most organisations adopt without having previously worked with the same technologies (Crafts, 2021). Therefore, it can clearly be placed in the category of radical change in the technological context (Tushman & Nadler, 1986). Although the technology has been studied for decades, the sudden, explosive adoption of Large Language Models and Generative AI, in particular, represents a major shift impacting a very large number of workers. The advent of these is commonly dubbed the Fourth Industrial Revolution, on par with steam power, electricity, and information and communications technology (Crafts, 2021). Considering its already wide-spread usage and rapid pace of growth in a large part of major firms with good results for efficiency increases (McKinsey & Company, 2024), as well as its labour-replacing potential (Cazzaniga et al., 2024), it can be concluded that the pressures from the environmental context are in place to urge implementation decisions in many firms. As long as regulation does not hinder the mainstream adoption of recent artificial intelligence innovations, which governing bodies such as the EU have not explicitly done outside of possible clashes with data protection regulations (European Parliament, 2024), external pressures can be said to encourage the use of AI in general. The context with the most variation is, therefore, the organisational one. Firms that support regular technological innovation outside of AI due to their structure, current infrastructure and workforce competencies are more likely to become early adopters and reap the benefits of the first-mover advantage before their competitors catch up. Prominent examples of measures that indicate such organisational capabilities are digital maturity and high connectivity (Hradecky et al., 2022).

3. Methodology

This multiple case study utilises a qualitative, iterative research method to answer the questions defined in the given. This approach involves reviewing earlier literature and conducting in-depth interviews with bid managers, public sector procurement officers, and experts representing some external providers of AI solutions. The findings from the literature review showed the major trends and popular focus areas of transaction cost and public procurement research. Whereas interviews gave the perspectives of firms, public organisations, and experts to provide a deeper understanding and answer the research questions posed.

3.1 Research Design

Qualitative research aims to explore a subject, delving into data collected by researchers to find and map out new concepts and theoretical frameworks through the use of inductive reasoning (Hair et al., 2023). This research method aims to draw broader conclusions from patterns noticed in collected data. It is optimal when looking into a topic that has previously not seen many studies or comprehensive explanations in earlier literature (Miles & Huberman, 1994).

The choice of study type must align with the research project's objectives, whether descriptive, explanatory, evaluative, exploratory or a combination thereof (Saunders et al., 2019). Given the novel nature of AI technology implementation among public sector suppliers and the limited prior knowledge available, an exploratory approach was selected. Exploratory study is particularly valuable when investigating areas with scarce existing information and when the goal is to uncover new patterns and themes (Hair et al., 2023).

In exploratory research, investigators employ various methods to gather qualitative data, including focus groups, one-on-one interviews, visual materials, and behavioural observations (Hair et al., 2023). Recent findings indicate that interviews conducted through online channels, despite taking a longer time to elicit responses in semi-structured formats, lead to comparable results to in-person interviews in terms of self-disclosure, thematic content, and depth of the discussion (Hair et al., 2023). Given this study's exploratory nature, the researchers chose to have semi-structured, in-depth interviews as the primary data collection method. In addition, due to convenience and the suggested lack of obvious drawbacks online interviews were chosen.

The authors chose a multiple case study approach for this research as it enables an in-depth understanding of real-life phenomena and their context, particularly valuable when developing theory and practical recommendations in unexplored fields (Saunders et al., 2019). This methodology is especially appropriate for this study, which examines how AI implementation affects transaction costs for government suppliers and identifies the associated challenges and enablers from both public and private perspectives - an area that has yet to receive much attention.

This study employs a dual analytical approach to address its research questions. For RQ1, which examines how AI technologies reduce transaction costs, the authors adopt an abductive analysis approach following Dubois and Gadde’s (2002) systematic combining framework. This involves continuous movement between theoretical frameworks (particularly TCE) and empirical observations, allowing for theory refinement through iterative matching of framework, data, and analysis. For RQ2, which explores implementation challenges and enablers, the authors chose an exclusively inductive approach to allow new insights to emerge purely from the data. This is a grounded theory approach, where the conclusions emerge from the data collected rather than being based on pre-existing hypotheses. The data collected provides the basis for inductive reasoning and theory development, with the general goal of constructing theories to understand specific contexts and phenomena (Miles & Huberman, 1994). Following Timmermans & Tavory (2012), the abductive analysis relies on researchers' theoretical sensitivity while remaining open to surprising findings that may lead to theoretical innovation. The data collected from semi-structured interviews will be systematically analysed using thematic analysis to identify recurring patterns and concepts.

The authors employed methods like writing memos and comparing and contrasting incoming data with theory and previously received data. Additionally, the difference between methodologies utilised between the two research questions was kept throughout the research process, allowing the analysis to contribute insights relating to existing literature to answer the first question and develop new insights based on empirical observations for the second.

3.2 Literature Review

For the literature review, the authors applied inclusion and exclusion criteria to focus on peer-reviewed, English-language publications that addressed LLMs, AI implementation in public procurement processes, transaction costs or cost reduction for suppliers. This systematic approach allowed the authors to identify key themes and research gaps for further investigation in the intersection of AI, public procurement, and supplier transaction costs.

3.3 Semi-structured Interviews

The authors conducted semi-structured interviews with diverse procurement professionals from Swedish organisations, including public-sector procurement officers, private-sector bid managers, and AI solution providers. Interviews were selected as the primary data collection method because they effectively gather detailed information about complex or sensitive issues, mainly when open-ended questions are necessary (Hair et al., 2023). This approach aligns with the qualitative research principle that phenomena should be described before being theorised and understood before being explained, focusing on the everyday and situated aspects of human experiences (Brinkmann & Kvale, 2015).

Semi-structured interviews were selected as the optimal approach for this study, striking a balance between structured and unstructured formats. While structured interviews would have been too restrictive for exploratory purposes and unstructured interviews too broad to maintain focus on specific AI and bidding process aspects, semi-structured interviews provided the necessary flexibility while ensuring consistent coverage of critical topics, thereby enabling systematic data collection and the discovery of unanticipated findings (Brinkmann & Kvale, 2015; Hair, 2023).

The interview guide was structured to explore participants' experiences, processes, and perspectives on AI implementation in bidding processes while maintaining flexibility for emerging topics. Following initial agreements on data processing and anonymity, the questions were organised into five categories based on Brinkmann and Kvale's (2015) interview methodology: (1) introductory, (2) follow-up, (3) probing, (4) direct, and (5) interpreting questions. Introductory questions started with understanding participants' roles, organisational context, and the company’s bidding process. Follow-up questions were then asked to examine participants' experiences, challenges, and the perspectives of important stakeholders. Probing questions delved deeper into the most time-consuming parts of bid management. Direct questions focused on practical aspects such as opportunity identification, requirement interpretation and bid development. Interpreting questions encouraged participants to reflect on future possibilities, share their vision of AI in procurement, and verify researchers' understanding of their responses.

The approach followed the four-point qualitative sampling framework outlined by Robinson (2014). The framework consists of defining (1) Study population, (2) Sample Size, (3) Sampling Strategy, and (4) Sample Sourcing. The respondents were picked from what the authors considered professionals working in public procurement and related areas and divided into three groups: bid managers and those of similar roles on the supplier side, procurement officers from public authorities, and experts from companies providing AI solutions. Thus, the authors considered the perspectives of every major stakeholder group involved covered.

Given the study's exploratory nature and grounded theory approach, the authors aimed for 20 participants, allowing for theoretical saturation (Guest et al., 2006), which was determined by the repetition of themes across different interviewed organisations. Participants representing suppliers were chosen from the IT, construction, consulting, and transportation industries. They were found through public procurement portals such as TED, Tendsign, Kommersannons, and e-Avrop based on bid application and win data that is publicly available. The authors reached out to companies of interest through email or contacted them by phone.

The interviews were conducted via Microsoft Teams video conferencing platform. This platform was chosen for its reliability, accessibility, and built-in recording capabilities. After getting the respondents' consent, everything said in the interviews was recorded using the built-in speech-to-text function included in Microsoft Teams. This feature was used to generate initial transcriptions of the conversations. Afterwards, the authors manually reviewed the recorded text and made corrections upon discovering any errors or nuances not captured by the automatic system.

ID	Title	Industry	Workplace
1	Manager	Energy infrastructure	Supplier
2	Economy and bid manager	Engineering	Supplier
3	Project Manager	Energy infrastructure	Supplier
4	Chief operating officer	IT services	Supplier
5	Sales Manager	Data & IT services	Supplier
6	Chief executive officer	Communications	Supplier
7	Sales director	IT services	Supplier
8	Business unit manager	Construction	Supplier
9	Business development manager	Real estate	Supplier
10	Public buyer/Procurement department manager	Municipality	Public authority
11	Managing director/CEO	Consultancy firm	Consultancy with Public authorities
12	Market director	Energy infrastructure	Supplier
13	Sales manager	Machinery	Supplier
14	Product owner	IT services (AI)	AI Expert
15	Chief procurement officer	State Authority	Public authority
16	Specialist engineer	Safety services	Supplier
17	Chief technology officer	IT services (AI)	AI Expert
18	Chief of operations for business unit and product owner	Safety services	Supplier
19	Chief procurement officer	State Authority	Public authority

Table 1. (List of Interviewees)

3.4 Data Analysis

The analysis employs a dual approach to address the research questions. For RQ1, examining how AI technologies reduce transaction costs, the researchers adopt an abductive analysis approach following Dubois & Gadde's (2002) systematic combining framework. This involves continuous movement between theoretical frameworks (particularly Transaction Cost Economics) and empirical observations, allowing for theory refinement through iterative matching of framework, data, and analysis. Choosing this approach meant that the authors were looking for findings in the data within the TCE framework while allowing for novel insights to emerge. For RQ2, which explores implementation challenges and enablers, the authors employ a purely inductive approach following the Gioia methodology (Gioia et al., 2012). This methodology provides a systematic approach to qualitative data analysis through a three-stage analytical process: (1) first-order analysis using interviewee terms and codes, (2) second-order analysis developing researcher-centric themes, and (3) aggregating these themes into overarching theoretical dimensions.

3.5 Data Preparation

The initial phase of analysis began with the verification and cleaning of Microsoft Teams' auto-transcriptions. During interviews, one of the researchers reviewed live transcripts and made notes on any inaccuracies in the capturing. After each interview, each transcript was carefully reviewed and compared with notes taken during the meeting to capture nuances that might have been missed by the automated transcription software. The cleaned transcripts were then organised systematically. During this phase, the researchers conducted multiple readings of the transcripts to gain familiarity with the data and wrote preliminary memos capturing initial insights.

First-Order Analysis

Following data preparation, line-by-line coding was conducted using the participants' own terms and expressions. An initial codebook was developed and continuously refined as new concepts emerged. For RQ1, this coding was informed by existing theoretical frameworks, such as TCE, while remaining open to new patterns. For RQ2, the authors employed purely inductive coding to capture emerging themes.

Second-Order Analysis

The authors grouped first-order codes into theoretical categories through a method of constant comparison (Saunders et al., 2019). This process helped identify patterns across interviews and develop more focused codes that captured the underlying theoretical concepts. For RQ1, this process involved what Dubois and Gadde (2002) call "matching" - comparing empirical observations with theoretical frameworks and adjusting both as needed. For RQ2, categories were developed inductively from the data. Researchers created thematic hierarchies to organise these categories and their relationships, paying particular attention to how different aspects of AI implementation related to transaction costs and implementation challenges.

Aggregate Dimensions

In the final phase, second-order themes were combined into broader theoretical categories. For RQ1, these dimensions were developed with explicit consideration of the theoretical frameworks TCE and TOE, presented in the literature review section. For RQ2, dimensions emerged purely from the empirical data. Integrating it in this manner helped establish relationships between concepts and created a more comprehensive conceptual model.

3.6 Data Quality

To make sure the interview findings were valid and reliable, the authors put in place an expanded set of quality assurance measures throughout the research process. They tried to minimise individual bias and ensure consistency while actively seeking out, acknowledging and examining contradictory findings. The resulting divergent viewpoints were then integrated into the theoretical frameworks. Data collection continued until theoretical saturation was achieved, with consistent reviews of the material, verifying whether any significant themes would arise across different participant groups. Transcript quality was maintained through real-time monitoring of Microsoft Teams auto-transcription, with immediate post-interview review and correction, comparison with interviewer notes, and preservation of important non-verbal cues and context. Altogether, the quality assurance measures were utilised to ensure the robustness and credibility of the findings.

3.7 Ethical Concerns

Following the ethical research principles outlined by Saunders et al. (2016) in their book "Research Methods for Business Students," this study adhered to essential guidelines, including respect for others, harm avoidance, privacy protection, voluntary participation, informed consent, data confidentiality, and responsible analysis and reporting. The methodology was consistent with these principles in the interviewing phase, as participants were sent clear information about the nature of the research project and their contribution to it, both before agreeing to participate and right before each interview started. They were informed about how the data would be handled, including being asked for consent before the recording of live transcriptions. Responses were anonymised, and any sections containing identifying information pertaining to either the person's identity or organisation were edited or removed entirely.

4. Results

4.1 Interview Context

In the interviews conducted (see Table 1.) as part of the main study, all participants were asked contextual questions relating to their role and process in the organisation, followed by specific questions addressing RQ1 and RQ2. The implementation status of AI solutions varied significantly across participants, with some organisations already actively using AI tools while others still being in the planning or evaluation phases.

Several participants had already implemented or were actively testing AI solutions (I1, I3, I6, I7, I8, I9, I11):

- Interviewee 1 currently uses ChatGPT for bid writing and relationship management (email writing);
- Interviewee 3 reported using both ChatGPT Enterprise and custom in-house versions of LLMs for analysing tender documents and generating bid summaries;
- Interviewee 6 demonstrated extensive AI implementation, using it for bid strategy development, proposal writing, and CV extraction;
- Interviewee 7 reported AI being tested to analyse and respond to tender requirements;
- Interviewee 8 utilised Microsoft Co-pilot across multiple departments, alongside some ChatGPT usage;
- Interviewee 9 uses AI for meeting protocols and notetaking;
- Interviewee 11 noted that some employees personally utilised AI tools like ChatGPT to improve their performance, though this wasn't formally implemented at an organisational level.

Many participants (I2, I4, I5, I9, I16), particularly from smaller organisations, reported being in observational or planning phases regarding AI implementation, citing concerns about reliability, data security, and general lack of perceived necessity.

4.2 Impact on transaction costs

In this section, results related to TCE analysis are presented. The findings have been split into sections according to the corresponding TCE model - Search Costs, Negotiation Costs, Monitoring Costs, and Enforcement Costs.

4.2.1 Ex-ante Transaction Costs

Search Costs

Fragmented search landscape

The interviews revealed a fragmented procurement notification landscape in Sweden, with suppliers needing to monitor multiple platforms simultaneously, including TED, OPIC, Kommersannons, and e-Avrop, to identify relevant procurement opportunities (I2, I3, I8, I9, I15, I16). To manage this complexity, some organisations employ dedicated personnel who check these platforms regularly (I9, I18), and many subscribe to services that give notifications to streamline the process (I9, I12, I13). Interestingly, while this fragmentation creates additional work, several interviewees (I4, I5, I12) did not see AI implementation as particularly valuable for the initial procurement discovery phase.

AI in the Qualification Process

While procurement discovery was not considered problematic, the subsequent qualification process emerged as a significant pain point. Multiple interviewees highlighted the time-consuming nature of reading through and qualifying tender documents to determine their relevance and feasibility (I2, I3, I5, I12, I13, I18). As one interviewee emphasised, "To answer the questions, is this tender right for us, and are there any blockers? This is really important; we have to do it for every tender" (I5). This process typically involves multiple stakeholders and dedicated meetings to make bid/no-bid decisions (I6, I7, I8, I9, I12). Interviewees saw significant potential for AI in this phase, particularly in analysing procurement documents and highlighting key information for stakeholders (I2, I3, I6, I12, I14, I17). This could include “Picking out all the specifications and requirements from the documents” (I2) or looking at differences between similar procurements and interpreting the discrepancies (I18). Some interviewers highlighted the value of AI for monitoring long-term public sector plans and competitor performance (I1, I7, I9). However, the consensus among participants was that AI should support rather than replace human decision-making (I3, I6, I12, I14, I17), with one interviewee noting that AI "has not fundamentally changed the process but has sped it up" (I6).

Negotiation Costs

Internal Coordination Challenges

The bid preparation process was considered a complex task in coordination, requiring large amounts of internal collaboration across multiple stakeholders (I3, I5, I7, I8, I9, I12). This coordination must cover various aspects of the addressed business activities, including pricing, procurement size, and answer compilation. Interviewees particularly emphasised the time-consuming nature of compiling answers internally (I3, I5, I7), especially when specific competencies need to be verified (I3) or when requirements need to be matched with internal capabilities (I2). The process is further complicated by the need to gather and synthesise information from multiple sources within the organisation (I2, I3), creating a significant administrative burden in the bid preparation phase.

AI in Bid Writing

Interviewees identified multiple ways AI could streamline the bid writing process (I5, I6, I7, I13, I14, I17), including drafting proposals, creating fictive cases, utilising pre-made templates, and responding to requirement questionnaires. The impact of AI implementation can be substantial, with one organisation reporting their team could "handle twice as many bids per week compared to pre-AI" (I6). Beyond content generation, AI was seen as valuable for verification purposes, helping ensure compliance by identifying missing answers and information (I3, I5, I17). Additionally, several interviewees highlighted AI's potential in analysing employee CVs to quickly determine their fit with specific procurement requirements (I1, I6, I9, I17).

AI-Enabled Knowledge Management

A recurring theme across interviews was AI's potential role in organisational knowledge management (I2, I5, I6, I7, I14, I18). Interviewees envisioned AI as a tool for efficiently accessing and utilising knowledge about their firms, particularly in finding relevant information from many different sources and making question-answering processes more streamlined. This application was seen as especially valuable for organisations with geographically spread-out offices (I7) and for managing standardised administrative tasks (I6). Such tasks included leveraging historical bid data, reusing content from previous successful bids, and maintaining searchable databases of past solutions and projects. One organisation had already implemented an in-house AI knowledge database for this purpose (I18).

4.2.2 Ex-post Transaction Costs

Monitoring Costs

Relationship Management

In terms of relationship management and monitoring, organisations employed various feedback collection methods, including customer satisfaction questionnaires, support ticket tracking, employee surveys, and follow-up meetings (I6, I7, I8, I18). The intensity of these monitoring activities varied significantly across organisations, ranging from dedicated personnel conducting proactive monitoring (I18) to more reactive approaches that only addressed issues when they arose (I13). Many interviewees stressed the sheer importance of relationship management with their partners (I1, I8, I9, I12, I18), viewing this as essential for influencing decision-making, shaping future requirements in procurement specifications, and receiving notifications about opportunities ahead of time (I12, I8). In this context, AI was seen as a potentially valuable tool for summarising historical interactions and managing customer-specific knowledge (I1, I7, I18).

Proactive Market Engagement and Influence

The interviews emphasised the important role of proactive engagement with public procurement, with responses discussing its crucial role in building business relationships, as well as influencing future tender requirements and evaluation criteria (I4, I5, I7, I9, I12, I13, I19). Public sector representatives actively engage in dialogues with potential bidders and trade organisations before finalising procurement specifications (I19). At the same time, supplying firms work on trying to understand client needs, push for changes they consider important, educate customers and provide guidance to help with writing tenders. Request for

Information notices (RFI) were named as an important business tool, with several respondents (I5, I2, I8, I9, I18) emphasising their RFI participation as essential for the activity of shaping requirements in future procurements, collecting information about the market and its actors, and proactive selling.

However, some concerns were raised about the potential misuse of this influence, with some actors allegedly tailoring specifications to favour their solutions (I13, I17). In this context, AI was suggested as a potential tool for identifying overly restrictive requirements that might unfairly target specific suppliers (I13, I17).

Enforcement Costs

Dispute Resolution

Regarding dispute resolution and enforcement, the interviews revealed a strong preference for informal resolution methods over formal legal action across organisations (I6, I8, I9, I18, I19). As one procurement officer stated, "They usually solve any disputes with the supplier on the 'negotiation table'. It is extremely rare that appeals happen" (I19). This approach appears to be driven by the desire to maintain long-term relationships, with one interviewer mentioning 3-4 year cycles (I18), with formal legal action generally only considered for high-value contracts exceeding 55M SEK (I18). Several interviewees emphasised the importance of well-written contracts in preventing disputes (I6, I7, I10, I11), noting that the majority of conflicts arise from differences in requirement interpretations (I7) and that highly complicated evaluation criteria therefore increase the risk of complaints and legal appeals (I11). In this context, AI was seen as a possible tool for making difficult legal documents more easily accessible and understandable for recipients (I7, I10), helping to prevent misunderstandings before they could occur and escalate.

4.3.3 Second Order Factors

While the analysis primarily focuses on AI's direct impact on transaction costs, the interviews revealed several broader systemic changes that emerge as second-order effects of AI implementation in public procurement.

Standardisation vs Differentiation

An interesting theme emerging was AI's potential impact on bid standardisation and market differentiation. Multiple interviewees (I6, I10, I11, I15) anticipated that AI would lead to increased standardisation of bid documents, potentially making them "virtually indistinguishable" in quality and content. While this standardisation could democratise market access by lowering barriers to entry and improving bid completeness for smaller actors (I10, I17), several interviewees expressed contrasting views on its market impact. Some (I9, I13) were sceptical about AI truly levelling the playing field, arguing that smaller actors might still lack the operational capacity to deliver on contracts regardless of bid quality. Others (I8) suggested that AI might actually increase complexity, as public sector consultants could use AI to generate more detailed and specific requirements, potentially favouring larger, more established suppliers. Interviewees consistently predicted a shift toward more personal interaction in the evaluation process. Multiple participants (I10, I11, I15, I19) specifically emphasised that AI-driven standardisation would necessitate increased face-to-face meetings and interviews to properly evaluate suppliers' actual capabilities beyond their written submissions. This evolution was speculated to be accompanied by the increased importance of references and credentials (I6) and the development of product/service-specific evaluation approaches (I10). The public sector is expected to adapt through new analysis capabilities (I19) and policy changes (I1) while striving to maintain a balance between efficiency and proper evaluation (I10, I19).

Democratisation vs Higher Barriers of Entry

The potential democratising effects of AI in public procurement emerged as a complex theme in the interviews. Some interviewees suggested that AI could lower barriers to entry by making bid preparation more accessible and efficient (I10, I17), helping ensure bid completeness (I10), and enabling smaller actors to compete more effectively through improved bid quality (I17). Some interviewees predicted an increase in the number of bidders as AI would make it easier to handle the time-consuming bid process (I6, I10, I11, I17). However, several countervailing forces were identified as factors that could raise barriers to entry (I6, I8, I9, I11, I14, I17). Uneven AI adoption could create competitive advantages for early adopters (I6), while some predicted that AI usage might lead public sector buyers to create even more specific and detailed requirements (I8). One interviewee noted that while AI might facilitate bid writing, organisations still need underlying resources and competencies to deliver on contracts (I9). The need to invest in AI capabilities, maintain sophisticated systems, and combine technical AI expertise with domain knowledge were identified as potential challenges (I11, I14, I17).

4.3 TOE

The results of the TOE analysis are presented below. The findings have been split into sections according to the corresponding context (technological, organisational or environmental) and further into subsections according to the specific factors for each context.

Technological context

The interviews with bidding professionals concluded that AI had yet to overcome the obstacles it faces both in terms of current reliability limitations, professionals not being sufficiently knowledgeable about its potential use cases and correct usage methodology, as well as thinking it is not a necessity at the present moment (I2, I4, I5, I11, I15). As technology improves and people become more conscious about when and how it is used, it is predicted to disperse much more (I12, I15). However, many employees have already started using more easily mastered tools like Chat-GPT, mainly to skip over simple busywork in their daily tasks (I1, I3, I8, I9, I11, I14, I17). Similarly, multiple respondents noted the possibility of cutting time spent on administrative tasks as a driver of the decision to adopt AI. Automation in these areas can bring enormous efficiency improvements. (I6, I7, I8, 19)

Organisational context

In addition to the technology, organisations and people in it also affect whether and when AI will be adopted. There tends to be a cultural resistance against technological change in some organisations, further complicated by asymmetrical technical skill levels and undefined or mistaken expectations surrounding AI (I3, I14). As a result, there are often communication gaps between teams on the business and the technical sides of the company (I14, I18). On top of this, internal hierarchies can slow down adoption due to the need for approval from higher managers and the need for the entire company or department to learn to use the tool (I3). Finally, the role of culture and age has received contradictory answers, as two respondents thought these factors would need to be taken into account when adopting AI (7, 18, while others thought "fine-tuning reflexes" and accessible technology interface design could resolve such issues (I3, I14). To bridge these potential gaps, firms need to consciously work with internal education and change management, which could include having a "digital translator" between teams (I3, I7, I14, I18).

External Task Environment Context

A huge driver of early AI implementation by suppliers is the strategic belief that staying ahead of the curve and developing in-house solutions is beneficial (I1, I8, I14, I18). The reason for this is the faith that doing so would become a form of competitive advantage (I1, I6, I7, I11). This belief is driven not only by a fear of missing out on opportunities in the future but also by the possibility that AI usage itself can become its own product. (I1, I14)

Although AI still has a long way to go before it arrives at the extent of domination in public procurement that some have predicted, respondents widely agree that such a state is inevitable (I11, I12, I15). While procurement decision-makers still lack a lot of knowledge about the technology, it is being heavily promoted by people in the AI business, and it is a hot topic in procurement literature and conferences (I10, I11, I15). It is thought that the technology will gradually disperse and be useful in saving time in different stages of the bidding process (I12, I15, I19). Altogether, although AI is unlikely to be a decisive factor in bid creation in the very near future, it will most likely become very widely used over time. (I11, I12, I15, I19)

4.4 Implementation Challenges and Solutions

As part of this paper's second research question, the data was also analysed and organised into themes in a more explorative, unstructured manner. The topics in the following section are a collection of different challenges suppliers might face that could hinder them on the way to AI implementation in the bidding process. RQ2

The technology is not there yet.

Although experimental AI tools have already been made available for bid writing, it was universally agreed among participants who had tried them that the technology simply is not there yet (I2, I5, I9, I11, I17). These responses indicate that one of the most straightforward blockers to AI being implemented in the bidding process is its current state (I2, I3, I5, I9, I11). Despite generative models' ability to output documents that closely resemble well-written bids, it always turned out they had missed details and made up false information, at a rate one respondent put at around 20% of the content (I9), stating, "*It summarises many important points. But for me, it is not enough that it got eight out of ten correctly when I need a qualified bid with ten out of ten right.*" As bids must be extremely precise and perfectly conform to a long list of requirements, such errors can lead to the company being disqualified and directly losing out on a high-value business opportunity (I2, I5, I6). A public sector respondent also sees a risk for lower-quality bids if people entrust bid writing to AI (I19). One of the AI experts interviewed also expressed the opinion that customer expectations of AI systems' performance are too high and unrealistic (I14). As a result of all of these factors, bid managers are likely to be worried about entrusting the creation of important documents to artificial intelligence at this stage (I1, I3, I5, I9, I11).

Trust and reliability concerns

Even with the constantly evolving nature and improving performance of AI models, the authors have noted responses emphasising the numerous uncertainties and trust issues that arise with the technology, which are unlikely to go away soon, as they stem from how these systems operate (I1, I9, I14, I17). Partially, to address this aforementioned lack of reliability, professionals using the tool must implement checks to ensure the output's credibility and not become overly reliant on tools prone to inaccuracy (I1, I11, I12, I17, I18). In addition to this, having a proper system for checks and verification can help decrease the degree of mistrust that can occur, according to AI experts (I14, I17). To achieve this, the sampled interviewees thought the organisation should maintain human decision-making, ensure the relevance and quality of data, show source documentation, update the systems and data regularly, and find a balance between efficiency and control. (I7, I11, I12, I17).

Bridging the gap with education

There is an issue of people in organisations being resistant to change, which is amplified by a number of effects surrounding AI. There tends to be a cultural resistance against technological change in some organisations, further complicated by asymmetrical technical skill levels and undefined or mistaken expectations surrounding AI (I3, I14). As a result, there are often communication gaps between teams on the business and the technical sides of the company (I14, I18). On top of this, internal hierarchies can slow down adoption due to the need for approval from higher managers and the need for the entire company or department to learn to use the tool (I3). Finally, the role of culture and age has received contradictory answers, as two respondents thought these factors would need to be taken into account when adopting AI (7, 18, while others thought changing habits in minor ways and implementing accessible technology interface design could resolve such issues (I3, I14). One of them went on to say, "*It is not the culture you need to change, but the reflexes. You need to fine-tune those. And I have not seen any differences between the ages, to be honest. It is as hard with young people as with older people. But the broad majority have an interest [in the subject].*". To bridge any potential gaps, firms need to consciously work with internal education and change management, which could include novel approaches having a "digital translator" between teams (I3, I7, I14, I18).

Rapid Technological Evolution Outpacing Organizational Readiness

Multiple interviewees highlighted challenges related to the rapid development of AI technology. The fast-paced evolution makes it difficult to standardise processes and plan for long-term organisational impacts (I3, I6, I8, I19). This challenge is compounded by the presence of multiple competing AI solutions in the market without clear standards or known best-practice approaches (I3).

The margin of error often can be very slim in bid writing.

Multiple interviewees emphasised the extremely low tolerance for errors in public procurement submissions. As noted by interviewees, even minor mistakes or single-word errors can result in bid disqualification (I5, I6). To illustrate just how on-point every aspect of a submission needs to be, one interviewee brought up an example where they were disqualified from a tender: "*We missed a procurement last year, a huge one because, in our company description, there was supposed to be a maximum of 7000 words, and we left it with 7000 words exactly, which was stupid of course, but we did. And then they said, no,* [the company name] *in your logo is also two words.*"

AI introduction will be driven by the private sector

Multiple interviewees indicated that AI adoption in public procurement would be primarily driven by the private sector, with the public sector taking a more reactive stance (I11, I6, I18, I10). However, it was still emphasised by a public procurement official that the public sector as a whole will need to adapt to AI and regulate accordingly (I10).

Data Security and Privacy Concerns

Data security and privacy were noted to be substantial concerns among interviewees, particularly regarding the involuntary sharing of sensitive personal and company secrets through AI systems (I1, I5, I11, I14). Some of the professionals interviewed proposed solutions meant to address these worries through a variety of approaches, including putting data verification systems in place, developing AI-related solutions internally instead of using external ones, or establishing service-level agreements with AI providers focused on data security (I1, I14, I17). Regulatory issues surrounding the subject of data sharing were also a concern (I5), though the interviews indicated gaps in knowledge about such issues from the suppliers.

5. Analysis & Discussion

5.1 Conceptual Model

Based on the findings of the interviews, the authors propose an integrated conceptual model that combines elements from TCE and the TOE framework to explain more accurately how AI implementation affects supplier transaction costs in public procurement (Figure 1.) While TCE and TOE frameworks provide valuable insights individually, no single theoretical model adequately captures the observed phenomena. The integrated conceptual model uses these complementary perspectives to bridge a theoretical gap and provide a better understanding of how AI could affect supplier transaction costs in public procurement. This integration is particularly valuable given the finding that AI's impact extends beyond direct cost reduction to potentially cause broader systemic changes.

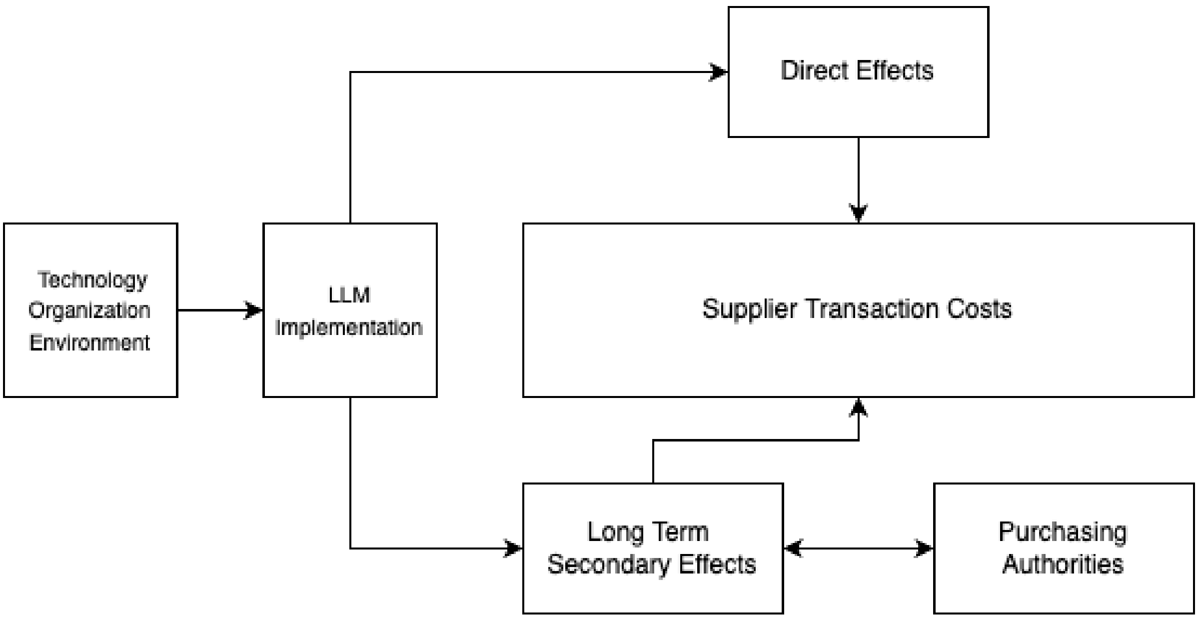

Figure 1. (Conceptual model for potential AI effects on supplier transaction costs)

The model illustrates how contextual factors, organised within the TOE framework, influence LLM implementation among suppliers. The technological, organisational, and environmental contexts each contain specific barriers that can hinder adoption (trust and reliability concerns, technology not being there yet, the margin of error being very slim in bid writing) as well as enablers that facilitate implementation (bridging the gap with education, having systems for checks and verification). These factors, identified through our analysis of RQ2, influence how suppliers implement LLM solutions in their bid management processes.

The model distinguishes two pathways on how these implementations impact transaction costs. The first pathway represents direct effects, where LLM tools can result in varying reductions of supplier transaction costs across the four TCE categories: search, negotiation, monitoring, and enforcement costs. These effects are primarily efficiency-driven (ex., time saved for making decisions) and relatively straightforward to observe in current practice. For example, streamlining the qualification process, bid writing automation and knowledge management, as well as summarising historical interactions.

The second pathway indicates longer-term secondary effects that could emerge from widespread AI adoption in the industry. These effects are more complex and systemic, involving interactions between suppliers and public sector buyers. The researchers maintain a neutral stance when predicting the direction of secondary effects, as the findings reveal their naturally complex and even contradictory nature. For instance, there have been explicit contradictions between *democratising and barrier-creating* effects, as well as between *homogenisation and differentiation*. These show that grouping these with simple negative or positive impacts would not capture the nuances necessary to understand the complexity and ambiguity of these phenomena. AI's influence in shaping public procurement may not be as simple as a straightforward improvement or deterioration but will be felt in the market as a more nuanced shift in dynamics that the various actors involved will have to consider carefully.

The model maintains a focused supplier perspective while acknowledging the role of public sector buyers in shaping these secondary effects. Given that the data only captures current and anticipated effects rather than longitudinal observations, feedback loops requiring stronger evidence for causal relationships were deliberately excluded. While the authors can reasonably speculate that interactions between different elements of the model will emerge over time, the current data cannot support definitive claims about their direction or magnitude.

5.2 Alignment with Theory

The findings regarding search costs in public procurement processes reveal consistency and contrasts with existing literature.

Search costs

Sweden's fragmented procurement notification landscape, requiring suppliers to monitor multiple platforms simultaneously, aligns with the broader challenges of search costs identified in TCE literature (Williamson, 1979). The complexity of this system increases the resources expended by suppliers to identify and evaluate potential opportunities, consistent with the concept of search costs as described by Barthélemy & Quélin (2006) and Potoski et al. (2023).

Interestingly, while the literature mentions search costs in overall transaction costs (Barthélemy & Quélin, 2006; Dyer, 1997; Potoski et al., 2023), the interviewees did not perceive AI implementation as particularly valuable for the initial procurement discovery phase. This lack of interest suggests that existing processes may have already optimised this stage, reducing the perceived need for AI intervention.

Our findings highlight a significant pain point in the qualification process. The ex-ante phase of transactions can be particularly resource-intensive, requiring significant investments in time and effort to ensure that potential partnerships are thoroughly evaluated (Barthélemy & Quélin, 2006; Dyer, 1997; Dyer & Chu, 2003; O. H. Petersen et al., 2019; Potoski et al., 2023). The time-consuming nature of reading through and qualifying tender documents resonates with the literature's emphasis on significant resources expended in identifying and evaluating potential partners (Barthélemy & Quélin, 2006; Dyer, 1997; Potoski et al., 2023). The potential for AI to analyse procurement documents and highlight key information for stakeholders addresses this aspect of search costs directly.

The emphasis on AI supporting rather than replacing human decision-making in the qualification process aligns with recent literature on the complementary role of AI in augmenting human capabilities (Brynjolfsson & McAfee, 2017; Loureiro et al., 2021). Implementing AI that aims to reduce transaction costs while maintaining adequate human control and decision-making would be ideal for suppliers selling to the public sector.

Negotiation Costs

Information gathered about the phase of negotiations in the bidding process showed a strong connection to what had already been described in the existing literature. As highlighted by the interviewees, the complex coordination challenges and extensive internal collaboration required in bid preparation align closely with the activities of ex-ante transaction costs in TCE (Dyer & Chu, 2003; Williamson, 1979). This complexity, spanning pricing decisions, procurement sizing, and answer compilation, reflects the resources expended in agreeing on exchange terms and transferring resources between parties, as described by Barthélemy & Quélin (2006) and Dyer (1997).

The time-consuming nature of compiling answers internally, especially when specific competencies need to be verified or requirements matched with internal capabilities, resonates with the literature's emphasis on the costs associated with drafting proposals and negotiating exchange terms (Lindholst et al., 2018; Potoski et al., 2023; Wuyts & Geyskens, 2005). This demonstrates the high administrative workload in the bid preparation phase, increasing the total transaction cost.

The presented results point to AI's potential to simplify and streamline many of the currently cumbersome aspects of the bid creation phase. This includes the creation of fictive cases, usage of pre-made templates, responses to requirement questionnaires, and the drafting of proposals. The findings here align with recent research showing that AI excels at generating texts with rigid, formulaic structures and can simplify administrative tasks (Dang et al., 2022; Wirtz et al., 2019; Casal & Kessler, 2023; Batubara et al., 2024; Brühl, 2024). The one reported result of AI-enabled teams handling twice as many bids per week compared to pre-AI implementation suggests potentially a significant efficiency gain.

The findings on AI's role in organisational knowledge management, particularly in efficiently accessing and utilising internal knowledge, extend beyond traditional conceptions of negotiation costs in TCE. This use of AI to leverage historical bid data and maintain searchable databases of past solutions aligns with literature showing how AI-enabled systems can "effectively operate" and "analyse large amounts of data" in organisational contexts (Reis et al., 2019) while performing "formal logical tasks" that enhance workflow processing and data management (Wirtz et al., 2019). The ability to interpret unstructured data and streamline document processing (Singh, 2023) extends traditional conceptions of how organisations can manage and utilise their historical knowledge.

While some literature emphasises the potential for AI to replace human decision-making (Gruetzemacher et al., 2020), The findings suggest a more nuanced approach where AI augments rather than replaces human capabilities in the negotiation process. This aligns with research indicating that successful AI implementation depends on integrating these technologies while maintaining appropriate human oversight (Brynjolfsson & McAfee, 2017), particularly in cases where AI enhances rather than substitutes professional judgment (Loureiro et al., 2021). This is especially relevant in public organisations, where AI-based systems can support complex human processes while maintaining quality (Wirtz et al., 2019).

Monitoring Costs

The variety of feedback collection methods organisations employ, including customer satisfaction questionnaires, support ticket tracking, employee surveys, and follow-up meetings, aligns with the TCE framework's emphasis on monitoring costs as a component of ex-post transaction costs (Dyer, 1997; Williamson, 1979). These activities reflect the resources expended to verify whether the product or service meets the terms of the agreement (Anguelov, 2020; Dyer, 1997; Romzek & Johnston, 2002).

The critical importance of relationship management emphasised by many interviewees extends beyond traditional TCE conceptions of monitoring costs, which typically focus on verifying contract compliance and obligations (Anguelov, 2020; Romzek & Johnston, 2002). Concentrating on trying to influence decisions, pushing for changes in requirements, and being notified about upcoming procurements demonstrates their preference for a more strategic approach to monitoring activities, including relationship management (Potoski et al., 2023). This usage is well-aligned with Brown et al. (2016), which emphasised the importance of relational governance in complex contracting situations, where relationship-building through recurring interactions and mutual understanding between parties helps achieve a high degree of cooperative behaviour.

A novel implementation of technology to decrease monitoring costs was the potential application of AI to summarise historical data, like previous interactions and knowledge about individual clients. This parallels the literature on monitoring activities, including "assessing product quality, producing and supplying performance information, and general relationship management" (Potoski et al., 2023). AI's capability in "interpreting unstructured data" (Singh, 2023) could enhance the efficiency of these monitoring processes while potentially accelerating the "learning effect from repeated contracting experiences" that Brown et al. (2016) identify as crucial for reducing transaction costs."

Enforcement costs

Our findings regarding enforcement costs in public procurement processes reveal interesting nuances when compared to the existing literature on TCE. In TCE, enforcement costs are typically associated with the resources expended to rectify deficiencies in the contract relationship and address issues arising after the agreement (Williamson, 1996; Melese et al., 2007; Wynstra et al., 2018).

First, the respondents expressed having a strong preference for methods of conflict resolution that do not require explicit formal legal action. This is consistent with previously published literature concerning enforcement costs and emphasises the importance of addressing faulty performance and resolving disputes through informal means and relationship management wherever possible (Potoski et al., 2023). This desire to solve issues at the “negotiation table” demonstrates organisations’ efforts to build relational capital (Villena et al., 2011) and gain the benefits of recurring interactions (Brown et al., 2016), thus decreasing the high amount of transaction cost connected to difficult legal processes (Potoski et al., 2023).

The findings highlight the importance of well-written contracts in preventing disputes, which aligns with literature emphasising the relationship between contracts and transaction costs (Dyer, 1997; Potoski et al., 2023). The observation that most conflicts arise from requirement interpretations underscores the challenges of contract completeness discussed by Hart and Moore (1999). This is further evidenced by the significant resources required for negotiating terms, identifying contingencies, and drafting precise specifications (Barthélemy & Quélin, 2006; Dyer, 1997). When contracts are unclear, organisations face increased enforcement costs related to dispute resolution and ex-post bargaining (Dyer, 1997), as well as higher monitoring costs to ensure compliance with agreed terms (Anguelov, 2020; Romzek & Johnston, 2002)

The results suggest a potential role for AI in reducing transaction costs through improved text processing and contract management. This application matches the literature showing that LLMs are useful, particularly in handling "generating simple texts, summarising long chunks of text, and quickly pulling information from external sources" (Brühl, 2024; Batubara et al., 2024). However, the limited discussion of AI's role in enforcement costs in the interviews suggests that while these technologies can help with ex-ante costs, their impact on ex-post enforcement costs may still be in the early stages.

Standardisation vs Differentiation

Our findings reveal complex secondary effects of AI implementation in public procurement, particularly regarding the tension between bid standardisation and market differentiation. While AI tools could standardise bid documents and potentially lower transaction costs, this standardisation presents new challenges. As Tadelis (2012) notes, public procurement must balance efficiency with broader social values, including transparency and fair competition. The standardisation of bids through AI could make it harder for high-quality suppliers to signal their true value, echoing Akerlof's (1970) concerns about information asymmetry in markets. As the literature discusses, buyers are interested in getting optimal value for purchase (Petersen et al., 2021; Williamson, 1996). This could force procuring agencies to change evaluation criteria by, for example, moving to more in-person interactions, potentially offsetting some efficiency gains in the reduction of negotiation costs (Johansson et al., 2016). As Romzek & Johnston (2002) argue, organisations often need to implement additional verification mechanisms when verifying quality through documentation alone becomes harder. While AI may reduce certain transaction costs in bid preparation, its impact on overall transaction costs remains uncertain due to potential increases in verification and monitoring requirements, which may increase the intensity of exchange activities (Lindholst et al., 2018).

Democratisation vs Higher Barrier of Entry

The findings reveal complex secondary effects of AI implementation in public procurement, particularly regarding the tension between democratisation and increasing barriers to entry.

This contradiction can be better understood through the lens of the Technology-Organization-Environment (TOE) framework (Tornatzky & Fleischer, 1990). While AI represents a radical technological change offering significant efficiency gains in bid preparation, the organisational context becomes crucial in determining adoption success.

The success of AI implementation appears heavily dependent on organisations' existing technological readiness and resource availability (Baker, 2012; Hradeczky et al., 2022; Bornstein & Radovanovic, 2023), suggesting that early adopters with stronger digital infrastructure may gain significant advantages in public procurement processes. This aligns with Haleem et al.'s (2022) findings regarding competency gaps in AI adoption, where larger organisations' superior resources for AI implementation could create new forms of competitive advantage. Contrary to initial expectations of democratisation, AI-driven standardisation might increase barriers to entry through these organisational disparities instead.

The context of the external task environment adds yet another layer of complication due to the increased competition in the public market (Marshall & Parra, 2019), possibly pressuring supplier firms to implement AI technologies in spite of their resource constraints. Thereby, tension arises between the goal of public procurement policy to ensure fair competition (European Commission, 2024) and the practical barriers created by technological developments.

The findings suggest that while AI may reduce direct transaction costs, it could simultaneously introduce new forms of organisational complexity that could concentrate market power among better-resourced suppliers.

Enablers and Challenges

While the analysis of the results in relation to the first research question reveals the effect of AI adoption on transaction costs, understanding the practical challenges and enablers of AI implementation is just as important for realising these benefits. The following section examines these implementation factors through the TOE framework (Tornatzky & Fleischer, 1990), providing a complementary perspective on how organisations can effectively achieve the transaction cost reductions identified above.

Firstly, the theme of current technology not being mature enough for important areas of the bidding process is a typical challenge of implementation decisions, fitting neatly into the technological context (Tornatzky & Fleischer, 1990). Strong consequences and risks are associated with letting artificial intelligence write legally complex, precise documents, where a mistake or wrong piece of information can make or break a bid. Since these AI models are still maturing in development and make mistakes (Hong et al., 2023), these cases can often occur in AI-written bids, making bid managers' current choice of not entrusting the writing process to text-generation models more than warranted. However, if AI models keep improving at the fast rate seen in past years, this complication will likely be less of a challenge as time goes on, with consistently reliable options present on the market having the potential to develop into a driver instead of a blocker when it comes to AI adoption decisions (Hong et al., 2023). This can already be seen with other applications of AI in bid managers' work, such as its potential to greatly speed up individual employees' daily busywork (be that writing e-mails or making quick fixes to small drawing mistakes in engineering documents), as well as general administrative tasks, which have already garnered a lot of attention from many and literature (Wirtz et al., 2019).

Similarly, the application of AI as a pre-qualifying and knowledge management tool could be especially appealing due to the need to access organisational information for use in processes related to public procurement and get to the bid writing process as fast as possible. The issue of cultural and skill gaps preventing the adoption of AI in supplier firms, on the other hand, fits squarely under the umbrella of the organisational context (Tornatzky & Fleischer, 1990). In the case of AI adoption, our respondents have identified a disconnect between people of different competencies in organisations, mainly between technical and business-oriented staff (Haleem et al., 2022). This has also been named as a source of mistrust in the technology. Finally, the topic of whether age plays an important role in the motivation to adopt generative AI in bid writing processes has received contradictory opinions from the interviewees of this study. Although papers using the TOE framework argue that structure and culture impact the motivation and ease of technological transition, such as developmental culture being promoted by (Cheng & Liu, 2008), the findings of this paper have shown that fine-tuning reflexes and minor habits may already be enough to tackle this obstacle. Naturally, internal education on the nature and correct usage of the technology itself should also be an area of focus within the organisation, as having the right competencies is also crucial when adopting a brand-new set of tools.

The theme suggests a need for high levels of transparency in technology, which is a factor that reaches into both the technological and the organisational contexts and is closely aligned with the issues raised by Arrieta et al. (2020). It argues for implementing policies and processes that ensure the optimal functioning of the technology by way of constant checks and verifications of AI inputs and outputs, thereby ensuring that the model is used correctly and operates without issue. At the same time, creating a well-organised, transparent system of verification also gives employees the impression that the AI is easily understood and kept in check, thereby reducing the level of mistrust among workers, tackling a major organisational challenge of resistance to improvement innovations, a phenomenon which has previously garnered attention in management research (Bao, 2009).

In the environmental context, the major trends seem to support AI adoption decisions. The primary factor here is the notion of the first-mover advantage with a radical technology change (Tushman & Nadler, 1986), where effectively utilising one's AI competencies moves them ahead of the competition, be that through reaping the benefits early or turning one's skills into a product to sell (Marshall & Parra, 2019). Adding to this is a certain fear of missing out (referred to as FOMO by one of the AI experts interviewed), wherein some actors believe they will not be able to reap the rewards of efficient AI usage if they wait too long before they follow their peers. All of this is further supported by the hype from external sources, such as AI companies, industry conferences and researchers, even with the low level of certainty these actors currently promote implementation.

6. Contributions and future research

6.1 Practical Implications

The contributions of this paper will primarily be useful for bidding practitioners but also provide insights for public procurement decision-makers and private actors providing services related to bidding, such as consultants and software manufacturers. The study has identified the current potential of such tools, as well as some challenges associated with AI implementation and enablers that encourage early adoption.

Based on the findings presented, the current state of the technology is a great fit for the qualification phase of the bidding process. As one of generative AI's greatest strengths is condensing long texts into concise formats, companies could rely on such technologies to speed up the first evaluation process rather than reading through a long list of documents for every announcement that comes out. Thereby, they could cut down much of the time required to select the bids to take further into the process, significantly lowering the resources that need to be dedicated to this kind of busy work. In the bid creation phase, the technology can similarly be implemented as a knowledge management tool by letting it process large amounts of organisational data, including the firm's resources, competencies, previous bids and other historical data, and much more, and letting the user easily access this information at will. This application would increase efficiency, specifically when it comes to the large-scale coordination bid managers are required to undertake to gather information from different sections of the company, all of whom generally handle different tasks. When handing over the actual writing of the bid to an AI, though, it is risky with the level of precision required to conform to the strict legal specifications needed for tenders. As such, the results of this paper indicate that meaningful future developments would have to occur in the technology before it can be trusted with tasks of this nature.

When it comes to implementing AI solutions (especially where solutions are created in-house rather than purchased as ready-made packages), there are some sizable challenges, technological and human alike. Primarily, one needs to ensure that AI systems get the right input and produce reliable results. To achieve this, strict processes must be implemented, and datasets and models must be updated. Secondly, there is a need to close the knowledge and cultural gap between different kinds of employees and help everyone understand the technology and how to best utilise it. The stern processes and subsequent knowledge that the tool is used cautiously help increase trust, but internal education may also be necessary.

There are many reasons to adopt novel AI technologies into one's bidding processes, but getting ahead of competition on the public market is among the most decisive motivators. A company with the resources and capabilities necessary to adopt AI ahead of the curve will likely experience high cost and time savings other firms cannot match, giving them an advantage in the rate at which they can put out bid applications and manage their knowledge base. Additionally, in-house solutions can become their products, encouraging firms with the right prerequisites to switch.

6.2 Theoretical Implications

This study makes several contributions to existing theory while acknowledging the limitations inherent in the research approach and context.

The findings suggest that examining AI implementation through TCE and TOE frameworks provides complementary insights into how suppliers approach AI adoption in public procurement. While TCE helps identify potential areas for transaction cost reduction, the TOE framework reveals crucial implementation factors that moderate these benefits. For instance, the data shows that even when AI tools demonstrate clear potential to reduce certain transaction costs (such as in bid writing or document analysis), organisational factors like trust issues and verification needs can create new forms of costs that can partially offset these gains. This interaction between frameworks extends existing theory by demonstrating how technological adoption factors can modify traditional transaction cost dynamics in public procurement. However, it needs to be acknowledged that these relationships are based on early-stage AI implementation and may evolve as the technology matures.

The interviews revealed potential secondary effects of AI implementation that extend beyond direct transaction cost impacts. Specifically, some participants identified tensions between bid standardisation and differentiation, as well as simultaneous democratising and barrier-creating effects. While these effects emerged consistently in the interviews, the authors acknowledge that they represent perceived or anticipated outcomes rather than demonstrated results. Their long-term impact on market dynamics requires further research.

The findings presented also focus on the factors related to the organisational environment of the TOE framework. A prevalent theme was the need for a proper verification system and building employee trust towards the technology. However, there was some variation in what representatives from each organisation thought was important to consider in one's approach. The authors concluded that the organisation's ability to establish these processes is critical to whether the implementation of generative AI will be successful.

The findings highlight how specific characteristics of public procurement, particularly the low tolerance for errors in bid submissions and strict compliance requirements, affect AI implementation decisions. The level of quality required in different procurement steps appears to influence adoption patterns. The findings indicate institutional constraints in public procurement can create unique barriers to technology adoption, even when that technology could potentially reduce transaction costs. This creates a conflict between requirements imposed by the public sector and potential increases in efficiency, which indicates that prominent existing frameworks related to technology implementation should be adjusted when dealing with the strictly regulated public market.

6.3 Limitations

Although this study aimed to capture detailed qualitative information from various relevant actors related to public procurement, there are still several gaps its scope could not cover. Therefore, this paper has several limitations that should be addressed.

Firstly, the study's methodology has some inherent weaknesses that may impact how well its results reflect the reality of the subjects discussed. An interview-based approach is, by its nature, impacted by people's innate subjectivity and perception, and responses may not correspond to their real behaviours. To get an even clearer picture of bid managers' day-to-day work, conducting an observational study and shadowing professionals as they go about the bidding process could also be beneficial. Additionally, the study worked from a sample of convenience due to the limited time and reach the authors had to work with. Due to this, it is possible that certain views held by professionals who did not have time or a desire to be interviewed were not adequately represented. Still, the authors think that the size and diversity of the sampled actors were large enough to get a general picture of the current state of bid management. Lastly, the research focused exclusively on players in the Swedish public procurement market, not just for convenience but also due to said market's well-developed nature.

The second major limitation was the nature of the technologies described. As artificial intelligence continues its speedy evolution while getting more and more dispersed, it is difficult to foresee where the field will be in as little as a few years. Because of this tendency, the insights provided by this paper might become somewhat outdated over time. Therefore, the authors also aimed to study general attitudes among practitioners and possible application areas rather than what AI systems could or could not achieve now. Even so, the inherent uncertainty of such rapid change in the technology is bound to affect the relevancy of the findings, especially regarding the even less predictable secondary effects.

6.4 Future Research

This article's findings and limitations open up opportunities for further exploration of the phenomenon of novel artificial intelligence technologies in bid management. First and foremost, implementing AI technologies carries a non-insignificant level of expenses, which could be considered a major transaction cost when viewed in the bidding process. Although some actors are likely to gain more than what they put in, especially early on, it could happen with AI's dispersal that late adopters will eventually have no choice but to start using AI as entry barriers become higher, never benefitting from the competitive advantages their rivals might have. Studies should explore the extent of the cost associated with making the switch and compare it to the costs it removes in the short and long term.

Due to the uncertainty of AI's evolution, longitudinal research should be conducted to monitor how AI technologies evolve and compare with the secondary effect predictions in this paper. Moreover, some respondents brought up the topic of AI usage deteriorating human skills and knowledge about bid writing in the long term. Although this was not a big enough point of discussion among participants to be included as a major theme, whether this comes to pass should be examined, perhaps among early adopter organisations. Finally, the geographical constraint of this thesis' scope means the authors inspected a very developed public market with strong economic power. Future research should survey markets that operate differently due to factors such as limited public funding or high rates of corruption.

7. Conclusion

This thesis sought to answer a two research questions:

RQ1: How does the implementation of large language models reduce transaction costs for suppliers in public procurement processes?

RQ2: What enablers and challenges are associated with large language model implementation from a private and public view?

Regarding RQ1, the findings reveal that LLM implementation can reduce supplier transaction costs across multiple dimensions, with the strongest impact on negotiation costs through automated bid writing and knowledge management capabilities. While search costs saw a limited direct reduction, AI showed promise in streamlining qualification processes. Monitoring costs benefited from improved relationship management capabilities, while enforcement costs saw minimal direct impact. However, this study also identified important secondary effects, including potential homogenisation of bids and market structure changes, which could offset some initial direct cost reductions.

For RQ2, the authors identified several key enablers and challenges affecting LLM implementation. Primary enablers include potential competitive advantages from early adoption, efficiency gains in administrative tasks, and improved knowledge management capabilities. Major challenges include current technological limitations and reliability concerns, particularly regarding bid writing accuracy requirements, data security concerns, and organisational resistance to change. Implementation can be considered successful if human oversight is maintained, robust verification and transparency systems are put in place, and change management and retraining go through in a fruitful manner.

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Appendix

Questions to Suppliers

INTRODUCTORY QUESTIONS:

- What is your role?
- What digital tools or platforms do you currently use in your bid preparation process?
- Who are the key stakeholders you work with?

FOLLOW-UP QUESTIONS:

- Have you implemented any AI or machine learning tools?
- How do different stakeholders view it?
- Has AI impacted how you collaborate?
- Have you worked on best practices and taught them across the company?
- What skills or training is needed to use it?

PROBING QUESTIONS:

- Can you elaborate on how this tool has impacted your workflow?
- What are the most time-consuming aspects?
- What about culture and blockers?
- How do you measure success or failure?
- What challenges do you face in rectifying deficiencies/resolving disputes?
- How do you stay informed about new technologies or digital solutions?

DIRECT QUESTIONS:

- How do you typically search for opportunities?
- How do you manage reading/interpreting product specifications?
- What tools/methods do you use to draft proposals?
- How do you monitor product quality and performance?
- How do you manage relationships with public sector clients?
- Are there regulatory/compliance issues that might hinder AI adoption?
- What are the challenges/problems/limitations you see with AI?

INTERPRETING QUESTIONS:

- Can you walk me through your typical bid preparation process?
- How do you envision AI transforming public procurement in the next 5-10 years?
- How could AI improve bid management in the future?
- What are your goals/what would you want to achieve?
- How do you see proactive search and preparation?
- Is there something we did not ask that you think is worth asking?

Questions to the Public Sector Officials

INTRODUCTORY QUESTIONS:

- What is your role and experience in public procurement?

DIRECT QUESTIONS:

- Have you noticed suppliers using AI or advanced digital tools in their bid submissions?
- Are there any regulatory considerations or guidelines being discussed regarding suppliers' use of AI in public procurement?
- Do you have to deal with a lot of conflict resolution in your work with suppliers?

FOLLOW-UP QUESTIONS:

- What kinds of tools have you observed?
- How has this impacted the quality or nature of the submissions?
- Has this created any challenges in your evaluation process?
- If so, is there anything that could be done to simplify that process or to make it occur less often?

PROBING QUESTIONS:

- From your perspective, how has digitalisation changed the way suppliers interact with your procurement processes in recent years?
- What is your view on suppliers using AI tools to:

    - Search for procurement opportunities?
    - Generate bid content?
    - Analyse requirements?
    - Handle documentation?
- Have you noticed any changes in:
    - The number of bids received?
    - The quality of bids?
    - The diversity of suppliers? That might be attributed to increased digitalisation or AI usage.

INTERPRETING QUESTIONS:

- Do you have any concerns about suppliers using AI in their bid preparations?
- How do you think the increasing use of AI by suppliers might affect:
    - The procurement process as a whole?
    - The quality of submissions?
    - The number of bidders?
    - The evaluation process?
- Do you think public procurement processes need to adapt to accommodate or regulate suppliers' use of AI? If so, how?
- Looking ahead to 5-10 years, how do you think AI will change the relationship between public procurement and suppliers?
- Is there any way procurement officials could harness digitalisation or AI to make their requirement lists for procurements more relevant?
- What are your thoughts on the way public organisations in different places work very differently with their suppliers?

Questions to AI solution providers

Introductory Questions:

- What is your role?
- How has the market demand for AI procurement solutions evolved?
- What kind of collaboration exists between different stakeholders in the procurement process?

Follow-up Questions:

- What kind of feedback do you receive about time and resource savings?
- What new features or capabilities are your customers requesting?
- How do your customers measure the success/ROI of implementing your AI solutions?
- How long does it typically take for customers to fully adopt and integrate your solution?

Probing Questions:

- What specific transaction costs or inefficiencies do your customers typically try to address with your software?
- What kind of resistance or concerns do you encounter from potential customers?
- What trends do you see in how suppliers approach public procurement?
- What aspects of public procurement do you think are still underserved by current AI solutions?
- What would you say are the biggest misconceptions about AI in procurement?

Direct Questions:

- Which features of your software do customers find most valuable in reducing their workload?
- How does your solution integrate with existing procurement platforms?
- How does your solution help with bid/tender discovery?
- What features help with requirement analysis and interpretation?
- How do you assist with proposal generation and submission?
- What support do you provide for post-award contract management?
- How do you help customers overcome initial scepticism about AI?

Interpreting Questions:

- What are the main challenges your customers face when implementing your AI solutions?
- How do you envision AI procurement tools evolving in the next 5 years?

- Is there anything else you think is important to understand about AI's role in public procurement?

AI Usage Disclosure

This section describes how the authors used such tools in their thesis writing process and what measures were taken to minimise risk.

ChatGPT was used for the literature review:

1. Employed for initial screening and summarising of research papers;
2. Helped identify relevant papers for further manual review;

Grammarly was used for writing enhancement:

1. Applied for grammar checking;
2. Used to improve writing style and clarity;
3. Helped maintain consistent language throughout the thesis.

The usage of the tools improves the quality of the thesis in the following way:

1. Significantly reduced time spent on initial literature review;
2. Enabled processing of a larger volume of research papers;
3. Grammarly improved the overall writing quality and readability of the thesis.

The authors acknowledge the risk of misinterpretation of research papers by AI, and the following measures were taken to minimise this risk:

1. Used AI only for initial screening;
2. Conducted a thorough manual review of all key papers;
3. Verified all AI-suggested summaries against original sources.

The authors gained the following insights on AI usage in thesis writing:

1. AI tools can significantly improve research efficiency when used with caution;
2. It is still important to maintain human oversight and verification of AI-generated content;
3. AI assistance can be combined with traditional research methods.