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The Quest for the Contract

How Swedish SMEs Adopt AI as a Strategy to Navigate Challenges in Public Sector Sales

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Abstract. Swedish small and medium-sized enterprises (SMEs) face challenges in public sector sales, including complex procurement procedures, limited resources, and restricted access to strategic insights. While research highlight external interventions, emerging literature emphasizes the need for internal, self-driven strategies to improve SME performance in the public market. Simultaneously, artificial intelligence (AI) has shown promise in optimizing private sector sales; however, little is known about how SMEs adopt AI as public sector suppliers.

This study investigates how Swedish SMEs adopt AI as a sociotechnical process in public sector sales and examines the resulting organizational outcomes. Guided by sociotechnical systems (STS) theory, the study utilizes 19 semi-structured interviews with public sector sales leaders from 19 Swedish SMEs.

Findings reveal that adoption initiates informally, driven by individuals addressing operational inefficiencies. Adoption is supported by superusers, information-sharing, demonstrations, and experiential learning, facilitated by AI access, and encouraging AI exploration, questions, and learning. Integration is challenged by cognitive, emotional, and organizational barriers shaped by societal narratives and internal constraints. Many firms remain in early adoption stages, and formal role redesign is rare, yet successful integration improves bid-writing efficiency, opportunity qualification, and market participation. Over time, these gains enhance bid quality, strategic focus, and employee well-being. However, risks such as AI overreliance and diminished human input are noted. By connecting outcomes to public sector sales challenges, the study shows how decentralized, human-centered AI adoption can help SMEs navigate barriers to the public market, including information access, opportunity detection, decision-making, administrative burdens, resource requirements, compliance, and psychological barriers.

Keywords: Public Procurement, Public Sector Sales, AI Adoption, SMEs, Sociotechnical Systems Theory

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Arvid & Hugo

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Definitions

Term	Definition
Public Procurement	The set of activities of public sector organizations as buyers, including need specification and procurement management (Edler et al., 2015; Malacina et al., 2022)
The Public Market	The broader economic space where public buyers meet private sellers (Fountoukidis et al., 2023)
Public Sector Sales	The supplier's full-cycle sales process, including opportunity identification, bid preparation, and post-bid follow-up (Morcov & Puiu, 2023)
Bid	Formal supplier offer responding to a procurement notice (Tendium, n.d.)
Procurement Document	Formal materials issued during procurement, including specifications, terms, and criteria suppliers must address in their bids (Upphandlingsmyndigheten, 2019)
Artificial Intelligence (AI)	Systems or machines that mimic human intelligence to perform tasks and improve over time using collected information (Andersson et al., 2025; Makarius et al., 2020)
Self-Help Strategy	Independent SME actions to overcome public procurement barriers by building capabilities, innovating, and engaging strategically to boost competitiveness (Akenroye et al., 2020)
Small and Medium Enterprises (SME)	Companies with under 250 employees and annual turnover below €50mn or balance sheet total under €4mn (Publications Office of the European Union, n.d.)
AI Adoption	Process of integrating AI into operations through organizational, technological, and human adjustments to realize its benefits (Enholm et al., 2021; Makarius et al., 2020)
Sociotechnical System	Constitutes a joint system that integrates people, culture, roles, organizational structure, along with technologies, processes, and tools (Xu and Gao, 2025)

1. Introduction

1.1 AI Adoption as a Self-Help Strategy for SMEs in Public Sector Sales

Traditionally, small and medium-sized enterprises (SMEs) have encountered significant challenges when competing for public contracts, often hindered by complex procurement processes, resource constraints, and limited access to strategic insights (McKevitt & Davis, 2013; 2015). To counter the challenges, SMEs must develop self-help strategies to enhance their performance in public markets (Akenroye et al., 2020). In other sales contexts, artificial intelligence (AI) has already been found to transform and optimize sales processes (Rane et al., 2024). Following these technological developments, many companies have begun integrating AI solutions to enhance their effectiveness in selling to the public sector (Mårtensson, 2020). However, while the promise of AI is compelling, the process of integrating these technologies into public sector sales environments is not without complexity. True AI adoption extends beyond deployment, requiring continuous employee engagement and adaptation to ensure AI enhances rather than disrupts organizational processes, ultimately fostering the development of sociotechnical capital and thus performance gains (Makarius et al., 2020).

While the significance of AI in public markets from a buyer perspective is recognized by an increasing number of researchers (e.g., Andersson et al., 2025; Sanchez-Graells, 2024; Siciliani, 2023), there is still a scarcity of research on how suppliers, and specifically, SMEs selling to public entities, can improve their performance in the public sector (Akenroye et al., 2020; Calderón et al., 2018; Rejeb et al., 2023). Consequently, how AI can be adopted and facilitate SME success is left unexplored.

1.2 The Underrepresentation of SMEs in Public Sector Sales

SMEs comprise 99.9 percent of all Swedish companies (Tillväxtverket, n.d.), yet their participation in public sector sales does not reflect their significant role in the broader business landscape. While SMEs are awarded approximately 75 percent of public contracts (Upphandlingsmyndigheten, 2025), these tend to be of significantly lower value. Exemplifying structural imbalances in public sector sales, Företagarna (2021) reports that the average annual municipal revenue per SME supplier is SEK 1.4 million, compared to SEK 21 million for large enterprises. Moreover, despite SMEs comprising over 96% of suppliers, only 59% of municipalities' total purchasing volume goes to them, indicating an unequal distribution of contract sizes and market opportunities. Furthermore, in most sectors, the top 10% of SME suppliers account for 85-90% of total municipal procurement spending, a concentration that indicates unequal opportunities among SMEs, which may hinder market access, competition, and innovation in public sector sales (Företagarna, 2021).

The imbalance is puzzling as SMEs contribute significantly to society in terms of economic development, job creation, innovation, and national income (Akenroye et al., 2020). This discrepancy reflects significant challenges for SMEs in public sector sales, such as administrative complexity, resource constraints, and limited process understanding, hindering fair competition, and leaving SMEs at a disadvantage (McKevitt & Davis, 2013; 2015). To be competitive in the market, SMEs must overcome the obstacles that hinder their efficiency and limit their ability to secure contracts (Rejeb et al., 2023).

1.3 A Short Introduction to the Swedish Public Market

Public procurement represents a significant part of Sweden's economy, with procurement obligations totaling 921 billion SEK in 2024, equivalent to 17.7% of GDP (Upphandlingsmyndigheten, 2025). The Swedish public market is decentralized, with national, regional, and local government agencies acting as buyers procuring goods and services from private-sector suppliers.

The public market is shaped by interactions between public buyers and private suppliers, with suppliers playing a vital role not only as vendors but as active participants whose willingness and ability to submit competitive bids directly affect procurement outcomes. A diverse supplier base, including firms of various sizes, is essential for fostering effective competition, considered crucial for the efficient allocation and use of public funds (Upphandlingsmyndigheten, 2025).

Municipalities and regions conduct most public procurements, given their responsibility for key public services like healthcare, education, and infrastructure (Upphandlingsmyndigheten, 2025). These processes are regulated by the Public Procurement Act (LOU), based on EU directives, to ensure transparency, competition, and equal treatment of suppliers (Lag om offentlig upphandling [LOU], 2016).

1.4 Consistency in Research Terminology

Terminology in the public market and associated research is often inconsistent (Lloyd & McCue, 2004). To ensure coherency, this thesis defines public procurement as the activities of public sector organizations as buyers, including need specification and procurement management (Edler et al., 2015; Malacina et al., 2022). The public market refers to the broader economic space where public buyers interact with private sellers, shaped by unique market dynamics (Fountoukidis et al., 2023).

Public sector sales describe the full-cycle process from the supplier's perspective, including opportunity identification, bid preparation, and post-bid follow-up (Morcov & Puiu, 2023). Defining it as a distinct perspective within the public market highlights the importance of understanding supplier-side processes and behaviors.

1.5 Research Gap

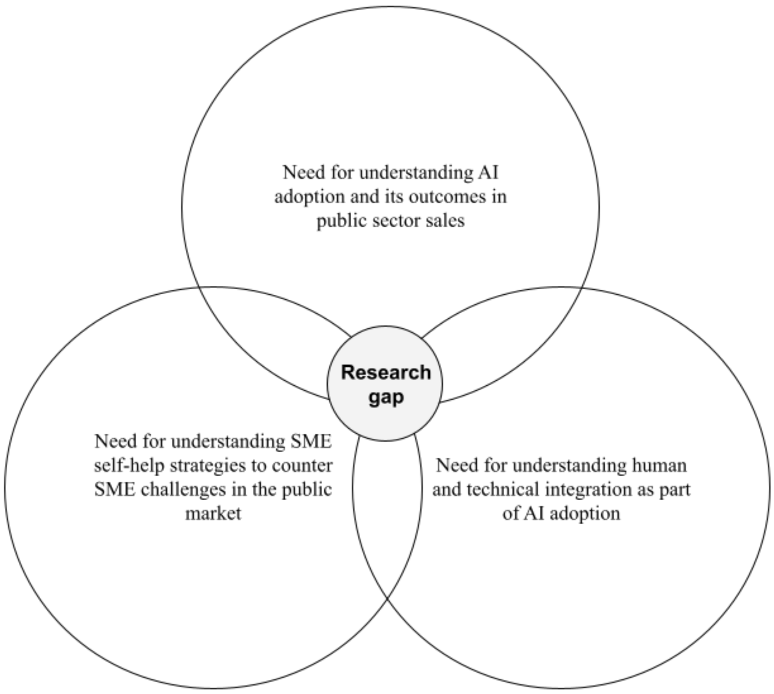
Supplier-focused studies in the public market are limited (Calderón et al., 2018; Karttunen et al., 2022; McKevitt & Davis, 2013), prompting scholars to call for greater attention to the supplier perspective to strengthen theoretical understanding of the public market (Uyarra et al., 2014). While supplier literature highlights barriers SMEs face in public sector sales (e.g., Loader, 2013; Uyarra et al., 2014), most research on overcoming these barriers focuses on buyer and policy solutions, with limited attention to how SMEs can develop self-help strategies to enhance success (Akenroye et al., 2020). Therefore, research is needed on how SMEs can strengthen their participation in public sector sales, specifically via enhanced sales capabilities (Rejeb et al., 2023).

AI could help SMEs improve their success, highlighting the need for research on how AI adoption can overcome efficiency barriers and enhance competitive procurement (Rejeb et al., 2023). AI's potential to enhance the public market has been studied from the buyer's perspective (Andersson et al., 2025). Similarly, from a supplier's perspective in the context of sales, AI has been shown to optimize the sales process (Rane et al., 2024). However, the adoption and outcomes of AI in SMEs selling to public entities remain underexplored, presenting a valuable research opportunity.

Research on AI adoption generally focuses on technological understanding rather than on the organizational factors of its implementation (Enholm et al., 2021, Makarius et al., 2020). Consequently, a deeper understanding of how human factors are managed internally when adopting AI is requested (e.g. Chowdhury et al., 2022; Chowdhury et al., 2023; Enholm et al., 2021; Holton & Boyd, 2019; Makarius et al., 2020; Mikalef and Gupta, 2021; Phan, 2017; Vlačić et al., 2021). In sales, AI adoption depends on effective human-AI integration (Chen & Zhou, 2022) and unlike older technologies, AI can collaborate, learn, and adapt through employee interactions, requiring attention to social dynamics in adoption. However, implementation efforts often neglect employees, and without their understanding of AI's purpose, functionality, and active engagement, AI is unlikely to deliver meaningful value for the organization (Makarius et al., 2020).

There is thus a need for supplier-focused research in the public market, particularly on how SMEs can improve their performance in selling to the public sector. While AI may enhance sales processes, its adoption by SMEs to improve their sales in public markets has not been sufficiently explored. Additionally, existing research overlooks the human dynamics in the adoption process, creating an opportunity to study AI adoption from a sociotechnical systems (STS) perspective in this unique context. The research gaps are summarized in Figure 1.

Figure 1. *Research Gaps*



1.6 Research Purpose and Question

The purpose of this study is to explore how Swedish SMEs adopt AI as a sociotechnical process in the context of public sector sales, integrating an organizational and employee perspective. Accordingly, this study focuses on how SMEs integrate AI into their sales processes, with particular attention to how human factors are managed throughout adoption. Additionally, it aims to explore the organizational outcomes of SMEs' AI adoption to understand how it contributes to their performance in public sector sales. The authors do this by interviewing 19 different individuals at 19 different Swedish SMEs who all had experience in adopting AI into their organization's public sales process.

By incorporating current research on SME challenges in public sector sales, AI, and STS theory as a theoretical lens, this study aims to answer the following research question:

"How do Swedish SMEs selling to the public sector adopt AI as a sociotechnical process, and what are the organizational outcomes of this adoption?"

1.7 Delimitations

This study focuses on the adoption of AI by Swedish SMEs in the context of public sector sales, specifically from the supplier's perspective. It does not examine procurement of AI by public buyers but investigates how SMEs adopt AI to navigate the sales process. The research explores enablers, inhibitors, and outcomes of AI adoption for SMEs, addressing a gap in existing literature that has largely emphasized public procurement practices while underrepresenting supplier experiences and AI integration.

Large enterprises are excluded due to the unique challenges SMEs face in public sector sales, such as limited resources, administrative burdens, and a need for efficiency-enhancing technologies.

2. Literature Review and Theoretical Underpinnings

2.1 SME Challenges in the Public Market

Academic interest in the public market has increased in recent decades, focusing on comparisons between public and private sector procurement, the strategic role of procurement, organizational scope, public procurement policies, and effectiveness (Calderón et al., 2018). While some research has explored the role of suppliers in the public market, much of the discourse has focused on buyer-centered barriers like procurement specifications, skills, user-supplier interactions, and risk management practices (Uyarra et al., 2014).

On the supplier side, SMEs have been a core focus in public market research (Rejeb et al., 2023). SMEs are underrepresented in public markets (Rejeb et al., 2023) and are disproportionately affected by barriers and challenges that hinder their effective participation (Uyarra et al., 2014). Consequently, numerous studies have explored these challenges (e.g. Karjalainen and Kemppainen (2008), Loader (2013, 2015), McKevitt and Davis (2013, 2015), and Uyarra et al. (2014).

Loader (2013) identifies 23 types of SME barriers, categorizing them into three groups: public sector environment, public procurement process, and the small business sector (Appendix A). Building on these categories, Akenroye et al. (2020) present external factors such as barriers associated with the public sector environment and the public procurement process, and internal factors about barriers within the SME organization. Loader identifies external factors such as public policy, risk-averse and pro-large business cultures, and decentralized organizational structures. Loader also highlights resource demands placed on firms in the public sector sales process and the disadvantages that large-volume contracts pose for small suppliers. Additionally, SMEs often face difficulties identifying contract opportunities in public markets (Akenroye et al., 2020), and overly prescriptive or vague public procurement specifications are further external challenges (Loader, 2015).

Regarding internal factors for SMEs, Loader (2013) highlights a lack of resources and capabilities in management, marketing, language, and technology, along with insufficient bid-completion skills and perceptions of unfairness. Akenroye et al. (2020) state that SMEs view public sector sales as costly and time-consuming, which, in combination with limited knowledge, leads to less commitment of resources to develop competitive bids. Similar issues are found by Calderón et al. (2018), with additional challenges of long processes, excessive administration, and insufficient information or electronic resources. SMEs also face inadequate IT systems and skills, hindering their ability to leverage technology for more efficient bidding processes (Akenroye et al., 2020).

Given the barriers of SMEs, an increasing stream of research investigates their resolution (e.g. Akenroye et al., 2020; Calderón et al., 2018; Fayos et al., 2022; Loader, 2013, 2015; Loader & Norton, 2015; McKevitt and Davis, 2013, 2015). Most literature focuses on public buyers and how they can reduce barriers and increase SME participation (Akenroye et al., 2020). For example, McKevitt and Davis (2015) identify three mentor roles buyers can adopt to support SMEs, while Loader and Norton (2015) emphasize policy actions that can assist SMEs.

Loader (2013) suggests three approaches to improve SME success: governments providing preferential treatment, creating a level playing field, and SMEs adopting self-help strategies to enhance their success. This highlights the need to explore how SMEs can overcome challenges and improve their participation in the public market (Rejeb et al., 2023). While literature on SME self-help is limited, Akenroye et al. (2020) and Calderón et al. (2018) discuss how dynamic capabilities help SMEs overcome barriers, and Fayos et al. (2022) emphasize the role of networking capabilities.

2.2 AI in Business-to-Business (B2B) Sales

Given the limited research on AI in public sector sales, insights from the broader B2B sales field are valuable. AI is transforming B2B sales by streamlining operations, enhancing decision-making, and unlocking new insights and capabilities for businesses (Rane et al., 2024). In sales, AI's applications and benefits are endless and continuously improving (Rodriguez & Peterson, 2024). This is unsurprising, as AI is recognized as having the greatest potential in sales and marketing (Davenport et al., 2020), with applications spanning every stage of the sales process (Paschen et al., 2020b).

Rodriguez and Peterson (2024) highlight three primary ways AI impacts the sales process. First, AI enhances efficiency and effectiveness of sales operations by automating tasks, saving time, improving accuracy, and providing insights for lead generation. This is supported by Rane et al. (2024) and Fischer et al. (2022), though the latter note that complex, non-routine tasks remain harder to automate. Second, AI boosts administrative efficiency by automating data collection, entry, forecasting, and analytics, allowing sales professionals to focus on decision-making and selling. Third, AI helps businesses better understand customer needs (Rodriguez &

Peterson, 2024) and supports personalized solutions (Campbell et al., 2020), leading to stronger customer relationships and improved experiences (Rodriguez & Peterson, 2024). Han et al. (2021) further support this, noting AI's role in gathering information, enhancing customer satisfaction, and retaining clients.

Rane et al. (2024) find that AI adoption enables delivery of relevant content to customers, automates sales tasks, enhances competitor analysis, supports decision-making, improves customer insights, and boosts operational efficiency. Similarly, Paschen et al. (2020b) emphasize that AI enhances customer prospecting, enables personalized targeting, facilitates rapid responses to concerns, and streamlines workflows.

While AI offers benefits, its adoption in sales poses challenges for individuals and organizations (Alavi & Habel, 2021). Rane et al. (2024) refer to Alshurideh et al. (2023), Prior and Keränen, (2020), Singh et al. (2019), and Vladimirovich (2020), highlighting adoption issues including data privacy, investment in technology and talent, and integration difficulties. Additionally, lengthy sales processes and market dynamics further complicate adoption (Rodriguez & Peterson, 2024).

Alavi and Habel (2021), citing Morgan (2019), report that 70% of digital transformations fail due to employee resistance. Chen and Zhou (2022) argue that effective human-AI integration is key to successful AI adoption in sales, and misalignment of salespeople and AI may frighten salespeople during adoption (Fischer et al., 2022). In this context, Paschen et al. (2020a) emphasize that the value and integration of humans and AI depend on human actions and resources. Therefore, training salespeople to interpret data inputs and AI outputs is essential for adoption. Chen and Zhou find that perceived ease of use is most critical for adoption, underscoring the role of education. Similarly, Rodriguez and Peterson (2024) note that AI features shape perceptions of usefulness and ease of use, which may differ from prior technologies due to the advanced skills AI demands, such as prompt engineering.

During adoption, salespeople may resist AI due to fears of job loss or role changes. To ease concerns, managers should communicate the continued value of human contributions and emotional skills in the sales process (Paschen et al., 2020b). Resistance to adoption also stems from a lack of supporting infrastructure, making it vital for managers to foster digital readiness, invest in technology infrastructure, and foster a supportive, AI-friendly culture that actively embraces AI (Chen & Zhou, 2022). Moreover, organizational processes and structures may need adjustment to integrate AI effectively (Paschen et al., 2020b).

Managers must also build trust through education and change management, as distrust can hinder AI adoption and limit its potential value (Paschen et al., 2020a). Trust in AI's transparency, capabilities, and reliability is crucial, and concerns about accountability, bias, and data privacy pose barriers to adoption (Rodriguez & Peterson, 2024). To reduce concerns and uncertainty, training and information provision that build AI understanding and engagement are important (Chen & Zhou, 2022). However, adoption behavior may vary; some salespeople accept AI output unquestioningly, while others remain skeptical (Rodriguez & Peterson, 2024).

Finally, Rodriguez and Peterson (2024) state that salespeople's perceived control, such as understanding or overriding AI recommendations, influences adoption. Chen and Zhou (2022) add that internal locus of control and self-efficacy are critical traits for adoption, and where absent, training is necessary to help employees adopt AI. Rodriguez and Peterson also note that strong intentions to use AI and beliefs that it will enhance efficiency and effectiveness increase the likelihood of adoption. Moreover, they state that experiences with AI's responsiveness, adaptability, and accuracy shape usage and engagement.

2.3 AI in Public Procurement

Most AI literature in the public market centers on the buyer's perspective. Still, this literature could offer insights and enable the juxtaposition of findings on the supplier side. In one review, Sava (2023) found that the field is interdisciplinary, spanning technology, law, policy, and management.

The digitization of public procurement has generated vast data, paving the way for AI in the process (Nowicki, 2020). Andersson et al. (2025) highlight AI's perceived benefits in public procurement, including enhanced operations, efficiency, and monitoring. Similarly, García-Rodríguez et al. (2019) find efficiency improvements in project management, decision-making, and error minimization. Further, García-Rodríguez et al. (2021) add that AI can enhance transparency and quality, with a 1% efficiency gain potentially saving €20 billion annually in the EU. Nowicki (2020) finds potential across the procurement process, such as improved supplier market intelligence, streamlined processes, and enhanced monitoring. Finally, AI also shows promise in fraud detection (Nai et al., 2022).

Despite its potential, AI must be adopted thoughtfully and with preparation to deliver results (Nowicki, 2020). Andersson et al. (2025) report low AI maturity in previous research and among governmental agencies and highlight organizational, process, technological, and data management issues. Nowicki (2020) emphasizes high implementation costs, but also security concerns, as AI depends on data-quality and amount. Additional hurdles include regulatory compliance, strict IT security demands, and limited AI expertise in procurement teams (Andersson et al., 2025).

2.4 Theoretical Framework

2.4.1 AI Adoption from a Human Perspective

The growing adoption of AI to drive business value has spurred research on how to utilize AI to achieve organizational goals (Enholm et al., 2021). However, despite recognizing AI's potential, many organizations fail to realize its value, often due to challenges of integrating AI with employees, processes, and business strategy (Chowdhury et al., 2022, 2023). Additionally, many organizations have not managed to successfully augment or replace humans with AI (Barro & Davenport, 2019). Thus, understanding how to manage human factors internally when adopting AI (Enholm et al., 2021) and how to foster effective AI-human integration to enable organizational AI adoption and value is important (Makarius et al., 2020). AI does not inherently generate benefits or harm, highlighting the need to consider the complex sociotechnical interactions shaping these outcomes (Van-Noordt & Tangi, 2023). Accordingly, Sociotechnical Systems (STS) theory and the AI adoption framework by Makarius et al. (2020) are applied to better understand AI adoption as a process of integrating humans and technology.

Originating from Trist (1981), STS theory emphasizes the interdependence between social and technological elements in organizations. STS theory aims to explain organizational behavior and provides insights into the connections between humans, technology, and outcomes. Hence, it provides a framework for analyzing human-technology interactions and their influence on outcomes within specific contexts (Makarius et al., 2020). While initially applied to industrial settings, STS theory has since evolved to address contemporary challenges, including digital transformation and AI adoption (Bockshecker et al., 2018; Sartori & Bocca, 2023).

A sociotechnical system comprises two subsystems: the social system (people, culture, roles, and organizational structures) and the technical system (technologies, processes, and tools) (Xu & Gao, 2025). Referring to the works of Trist & Bamforth (1951), Emery & Trist (1960), Mumford (2006), and Baxter & Sommerville (2011), Xu and Gao (2025) state that the performance of an STS relies on joint optimization of both subsystems. Neglecting one while focusing on the other reduces performance, while joint optimization accelerates technology adoption and enhances organizational performance.

Traditional STS perspectives emphasize human agency in shaping technology, however, AI challenges this due to its capacity for autonomous decision-making and continuous adaptation (Van de Poel, 2020). Scholars are exploring AI's integration into sociotechnical systems, focusing on its impact on decision-making, accountability, and governance (Van de Poel, 2020). Kudina and van de Poel (2024) argue that a sociotechnical view is necessary for AI's explainability, as technical solutions alone cannot address trust and accountability issues in AI decision-making. Moreover, simply plugging AI into organizations is insufficient to leverage complementarities of humans and AI. Instead, fostering organizational learning and enhancing human collaboration is essential (Herrmann & Pfeiffer, 2023).

2.4.2 A Sociotechnical Framework for Understanding AI Adoption

Since STS theory offers a lens to analyze and explain behaviors of organizations, their members, and the interactions between people, technology, and outcomes, it also facilitates the understanding of how human-AI integration can drive competitive advantage (Makarius et al., 2020). STS theory thus underlies the concept of sociotechnical capital, defined as "the combination of AI technology and people in organizations that leads to a source of competitive advantage" (Makarius et al., 2020, p. 265). Effective human-AI integration, where both operate as a unified system, is key to building such capital. Accordingly, Makarius et al. (2020) proposes a sociotechnical process framework for AI adoption where successful integration leads to sociotechnical capital and thus organizational advantage. AI-human integration remains under-researched in the literature, except Makarius et al.'s established framework (Chowdhury et al., 2022; 2023) prompting its application.

Makarius et al. (2020) conceptualize AI integration in the workplace through two dimensions: *novelty* and *scope*, which together shape AI's transformation of work and organizational structures (Table 1). Novelty refers to how much AI changes tasks, from automating routine work to independently handling complex tasks. Scope reflects how AI changes the content and context of work. Content-changing AI impacts specific tasks while context-changing AI reshapes workflows and organizational processes. As AI evolves toward greater novelty and broader scope, its impact shifts from efficiency to strategic transformation. However, advanced AI requires careful implementation to avoid underuse, resistance, or misalignment with human expertise (Shrestha et al., 2019). To maximize AI's potential, organizations must align technological changes with workforce adaptation and capability development (Makarius et al., 2020).

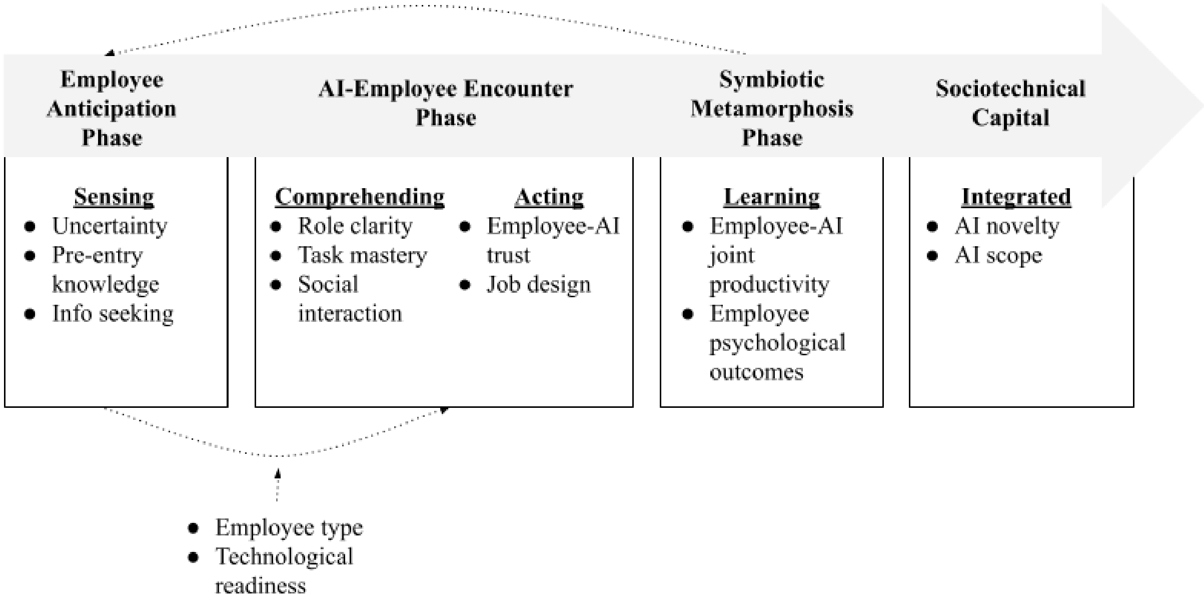
Table 1. *AI integration model. Adapted from Makarius et al. (2020).*

Scope of AI

AI Novelty	**Content-Changing AI**	**Context-Changing AI**
High	**Autonomous:** (Self-driven vehicles) **Employee-AI Relationship:** Independence **Human Role:** Keep in check	**Authentic:** (Superintelligence) **Employee-AI Relationship:** Singularity **Human Role:** Comprehend
Medium	**Augmentation:** (Robots in surgery) **Employee-AI Relationship:** Complementary **Human Role:** Collaborator	**Alteration:** (Deep learning) **Employee-AI Relationship:** Symbiotic **Human Role:** Co-creator
Low	**Automation:** (Assembly line robots, automated assistants) **Employee-AI Relationship:** Substitution **Human Role:** Controller	**Amplification:** (Predictive AI) **Employee-AI Relationship:** Supplementary **Human Role:** Conductor

Makarius et al. (2020) also introduces the AI Socialization Framework, which outlines how organizations can guide employees through AI adoption by fostering understanding, trust, and engagement (Figure 2). The framework conceptualizes AI adoption as a three-phase process: anticipatory socialization, encounter, and metamorphosis.

Figure 2. *Systematic framework for AI socialization. Adapted from Makarius et al. (2020)*



Before implementation, anticipatory socialization prepares employees by helping them make sense of AI. Organizations must manage *uncertainty* by transparent communication about AI's role, mitigate concerns regarding job displacement, and clarify AI's benefits. Further, employees' *pre-existing knowledge* of AI influences their openness to adoption, necessitating targeted training and education initiatives. Employees might also *seek information* about AI's impact on their roles, requiring structured onboarding programs, training sessions, and Q&A opportunities to foster understanding. Overall, this stage should reduce resistance and foster openness to change (Makarius et al., 2020).

Furthermore, AI adoption is influenced by two key contextual factors: *employee type* and *technological readiness*. Frontline employees (FLEs), especially in customer-facing roles, may exhibit greater resistance to AI due to concerns over diminished human interaction in service encounters. Moreover, advanced digital infrastructure and AI expertise facilitate AI adoption. Employees in tech-oriented firms generally adapt more easily to AI than those in traditional sectors, where digital transformation demands greater training efforts (Makarius et al., 2020).

In the encounter phase, once AI is introduced, comprehension and action strategies facilitate employees' learning and adoption. Comprehension strategies clarify how AI affects individual roles and tasks. *Role clarity* ensures employees understand their responsibilities concerning AI, while *task mastery* involves developing the skills required for effective collaboration with AI. *Social interactions* between employees and AI systems further influence how AI is perceived within the workplace (Makarius et al., 2020). Furthermore, action strategies address employee engagement with AI. *Trust* development is crucial, as employees must perceive AI as a reliable and explainable tool. Therefore, establishing transparent decision-making mechanisms that foster confidence in AI outputs is important. Simultaneously, *job design* must evolve to accommodate AI, ensuring that employees shift towards tasks requiring human expertise, such as critical thinking, creativity, and ethical judgment (Makarius et al., 2020).

Finally, in the metamorphosis phase, AI becomes embedded into workflows, with long-term adoption requiring continuous learning, cross-functional collaboration, and iterative improvements aligned with organizational goals. AI automates routine tasks, increasing productivity and enabling employees to focus on strategic functions. Additionally, successful AI integration fosters positive psychological outcomes, such as enhanced job satisfaction and reduced resistance to change. Effective AI socialization culminates in the development of sociotechnical capital, a competitive advantage derived from successful AI-human integration (Makarius et al., 2020).

AI adoption thus extends beyond deployment, requiring ongoing employee engagement and adaptation to ensure AI enhances rather than disrupts organizational processes, underlying creation of sociotechnical capital (Makarius et al., 2020).

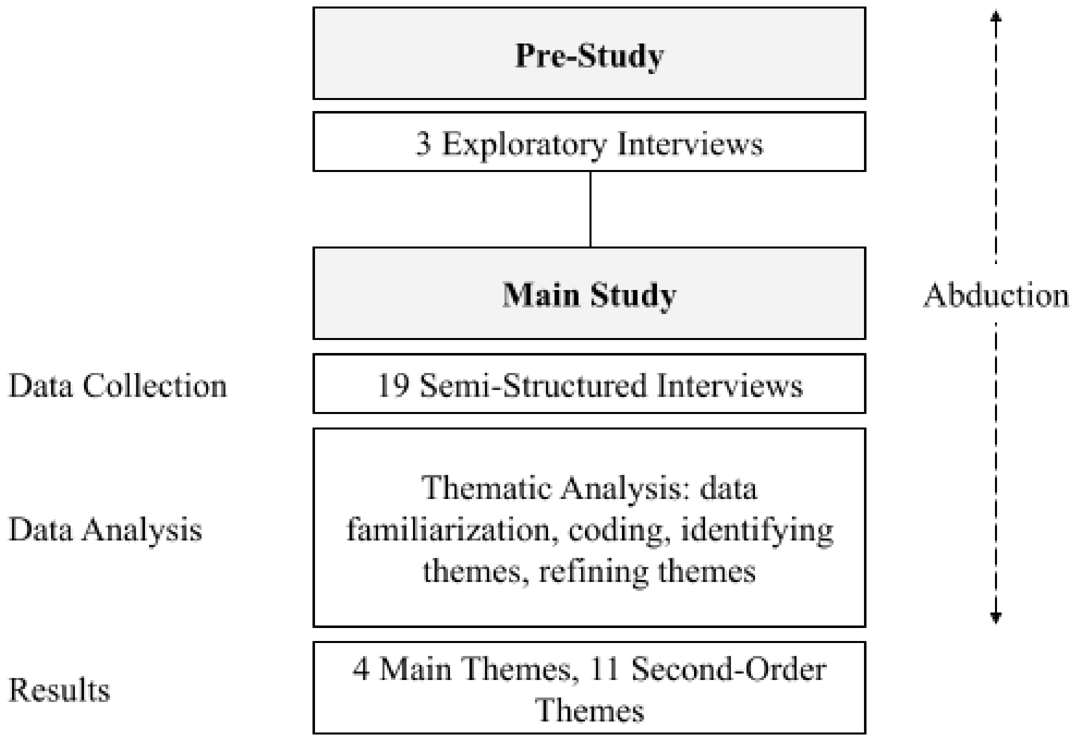
2.4.3 Outcomes of AI Adoption

Enholm et al. (2021) explore the impact of AI on competitive performance, distinguishing between *first-order effects* at the process level and *second-order effects* at the organizational level. First-order effects focus on AI-driven improvements in processes, such as efficiency, automation, and decision support, discussed in prior work on process efficiency (e.g. Coombs et al., 2020; Kirchmer & Franz, 2019), insight generation (Mikalef & Gupta, 2021), and business process transformation (Wamba-Taguimdje et al., 2020). Second-order effects encompass AI’s influence on firm-wide outcomes, including financial performance, market positioning, innovation capacity, and potential negative impacts. These effects build on research linking AI to financial gains (Alsheibani et al., 2018; Davenport & Ronanki, 2018), market-based agility (Wang et al., 2019), and strategic organizational change (Eriksson et al., 2020).

3. Methodology

To provide an overview of the research, Figure 3 summarizes the research process.

Figure 3. *Research Process*



3.1 Pre-Study

A pre-study was conducted to validate the relevance of focusing the research on SME challenges in public sector sales, examine AI's potential support for SMEs, deepen the understanding of procurement processes to refine the interview guide, and evaluate the applicability of STS theory as the theoretical framework.

The pre-study, based on interviews with three experts (Appendix B), confirmed that the public market is a complex, regulated system posing significant challenges for SMEs. Key obstacles identified included interpreting technical requirements, structuring compliant bids, and managing administrative burdens, with rigid procurement procedures disadvantaging smaller firms. Despite policy initiatives to support SMEs, their effectiveness was deemed limited. The findings also highlighted that internal factors, such as resource allocation and viewing procurement as bureaucratic rather than strategic, hinder SME participation. A shift towards proactivity was suggested, emphasizing the need for technical competence and organizational change in how SMEs approach public sector sales.

The role of AI in addressing these challenges emerged as a potential but debated opportunity. While AI was seen as capable of reducing SMEs' administrative burdens, improving requirement interpretation, and minimizing disqualification risk, opinions differed on its ability to foster strategic engagement in the public market. Some viewed AI as an efficiency tool, while others saw it as enabling broader organizational change. Thus, the pre-study suggested that AI should not be seen as a standalone technical intervention, but as a component embedded within organizational processes interacting with the wider public market.

The pre-study influenced the main study design. First, it confirmed the relevance of focusing on SMEs as a distinct group facing unique challenges in the procurement context. Second, it highlighted the need for an interview guide capturing both technological and social aspects of AI adoption, along with participants' broader experiences in public markets. Third, the findings emphasized the research setting's complexity and the need for a dynamic, process-oriented approach, thus it provided the initial validation for applying STS theory.

3.2 Partnership with Tendium

This thesis was made through an unpaid partnership with Tendium, a Software as a Service provider, developing AI-driven tools to support companies in public sector sales. Importantly, one author has worked at Tendium since 2020. This partnership granted direct access to a network of companies using AI in their public sector sales processes, a complex and internal area that is difficult to study externally. Hence, without this collaboration, gaining access to relevant participants with firsthand AI adoption experience in public sector sales would have been challenging. However, while Tendium facilitated participant contact, the firm was not involved in the design, analysis, or conclusions of this research.

3.3 Organizational vs Individual Focus

During the research, it became evident that the boundary between organizational dynamics and individual experiences is naturally blurred, particularly in SMEs where small teams link individual actions to organizational outcomes. Rather than viewing this as a limitation, the authors embraced it as a necessary complexity for understanding AI adoption. Individual initiatives, resistance, and learning are closely tied to cultural, leadership, and structural factors (Makarius et al., 2020). This holistic approach reflects the sociotechnical nature of AI integration, offering a richer understanding of how human and technological elements evolve together.

3.4 Research Philosophy and Approach

3.4.1 Interpretivist Philosophy and Qualitative Research

This study adopts an interpretivist philosophical stance within the phenomenological strand, focusing on participants' recollections and interpretations of their experiences (Saunders et al., 2019). Reality is shaped by human actions and meanings, aligning with a social constructionist ontology. Epistemologically, the study centers on participants' perceptions to provide new understanding of the research topic, and consistent with interpretivism, the authors acknowledge their role in the research by interpreting the collected data.

A qualitative research methodology was chosen to explore how Swedish SMEs adopt AI in public sector sales and its implications, given the topic's exploratory nature and limited existing research. Qualitative methods are ideal for studying complex, socially constructed phenomena, aiming to understand meanings, experiences, and interpretations rather than quantify relationships (Frostling-Henningsson, 2017; Fossey et al., 2002). This approach was well-suited to understanding how individuals in SMEs interpret and respond to AI adoption challenges and opportunities through in-depth engagement with their lived experiences.

The choice of a qualitative design aligned with the study's interpretivist philosophy, which views reality as constructed through human interaction and meaning-making (Saunders et al., 2019). A quantitative approach was unsuitable, as the study aimed to uncover emerging themes and patterns rather than test hypotheses or measure variables (Bell et al., 2022). Given the novelty and uncertainty of AI adoption in public sector sales, a flexible and open-ended approach was necessary. An exploratory qualitative design enabled this adaptability, vital when investigating understudied or evolving phenomena (Saunders et al., 2019).

Finally, a cross-sectional design was employed to capture diverse experiences within a limited timeframe. Although it did not track changes over time, it allowed the identification of common patterns and variations among SMEs by collecting data at a specific point in time (Bell et al., 2022; Saunders et al., 2019). Overall, the qualitative, interpretivist, and exploratory approach was well-suited to generating a rich, nuanced understanding of AI adoption as a sociotechnical process within Swedish SMEs.

3.4.2 Abductive Theory Development

To develop theory and challenge preconceptions, this study adopts an abductive approach, in which the authors iteratively moved between the literature and empirical data (Bell et al., 2022). This approach facilitated a continuous interplay between theory and empirical findings, enabling ongoing refinement and reinterpretation (Alvesson & Sköldberg, 2017). Given the study's exploratory nature, this adaptability was essential for remaining open to new insights. Furthermore, an abductive approach is particularly useful for modifying and expanding existing theory in areas with limited prior research (Dubois & Gadde, 2002). Considering the broader literature on AI adoption and the scarcity of research on AI adoption among SMEs in public sector sales, this approach was deemed suitable.

The abductive process was evident from the outset. Initially, the authors focused on literature addressing enablers and inhibitors of AI adoption, along with related AI capabilities. However, expert interviews revealed that SMEs might face challenges related to human-machine interactions, such as resistance and skepticism. When similar concerns emerged in participant interviews, the authors decided to incorporate STS literature to enhance the analysis and deepen the understanding of AI adoption in the public sector sales context.

3.5 Research Method

3.5.1 Sampling

Participants were strategically sampled with guidance of the research question and objectives, following a purposive sampling approach (Bell et al., 2022). The study prioritized individuals with direct experience in adopting AI in their work. Given the focus on SMEs in public sector sales, participants were required to be part of an SME and involved in the bidding process for public contracts. Accordingly, individuals responsible for bidding within their organizations were targeted. Initial sampling criteria were defined to guide and delimit the participant recruitment process (Table 2).

Table 2. *Sampling Criteria*

Sampling criteria
Responsibility for bidding process
Employed by SME selling to public organizations
AI adoption experience
Swedish or English-speaking

The criteria ensured some homogeneity, as all participants had experience with AI adoption and worked in SMEs involved in public sector sales. However, role and occupational diversity emerged, with both senior management and bid management represented. Participants also varied in demographic, geographic, and psychological dimensions. Together with their unique organizational contexts, this diversity allowed the study to capture a wide range of perspectives and experiences, aligning with the research question and interpretivist philosophy.

To reach participants, the authors collaborated with Tendium to gain access to its customer network. In compliance with privacy regulations, an initial email was sent to customers from the company's official email address informing recipients about the study's purpose and requesting permission to share their contact information with the thesis authors (Appendix C). Upon approval, follow-up invitations were sent, outlining the research topic, the voluntary and anonymous nature of participation, estimated interview duration, and the required familiarity with the public market (Appendix D). Additional participants were purposively sampled via LinkedIn, applying the same sample criteria across all channels. Follow-up messages to non-respondents were sent after four weeks to avoid spamming and undue pressure. All participants signed and returned a consent form detailing confidentiality, data management, and their rights, securing voluntary participation and informed consent (Bell et al., 2022; Saunders et al., 2019).

In total, approximately 300 professionals were contacted, resulting in 19 interviews, at which theoretical saturation was achieved (Appendix E). The response rate reflects the challenge of researching a highly internal and business-critical topic. Access to individuals with relevant AI adoption experience in public sector sales is limited, and participation is often hindered by time constraints, confidentiality concerns, and the strategic nature of the subject.

3.5.2 Data Collection and Interview Process

Data collection followed a mono-method approach, employing semi-structured interviews as the sole data collection technique. The study's exploratory nature and interpretivist philosophy required an understanding of participants' reasoning, attitudes, and perceptions. Semi-structured interviews were appropriate, as they allow for probing and in-depth exploration of topics (Leavy, 2017; Saunders et al., 2019). Such interviews also allow unanticipated topics to emerge, offering deeper insights into the research subject (Saunders et al., 2019). Hence, this approach allowed for the collection of rich, meaningful data to address the research question.

In preparation for interviews, an interview guide with broad, open-ended questions was developed based on the research question and aims. Further, the authors' understanding of the topic, informed by literature and relevant theory, inspired the interview themes. The guide was not rigidly applied, allowing the authors to probe responses and explore emerging topics. Throughout the interview process, the guide was refined as new insights arose. The final version is included in Appendix F.

Interviews began with simple questions to facilitate cognitive access (Saunders et al., 2019), and ethical information covering participation, confidentiality, and recording was reiterated at the start. As all interviews were conducted via Microsoft Teams, recording consent was essential. The online format accommodated geographical diversity and allowed both parties to engage in safe, non-intrusive settings (Hanna, 2012). To ensure that participants had shared the perceptions and experiences that they valued, they were at the end of each interview asked to add or deepen any perceptions. Finally, in line with participant validation (Saunders et al., 2019), transcripts were shared with participants for review, enabling them to correct, comment, and confirm accuracy.

3.5.3 Data Analysis

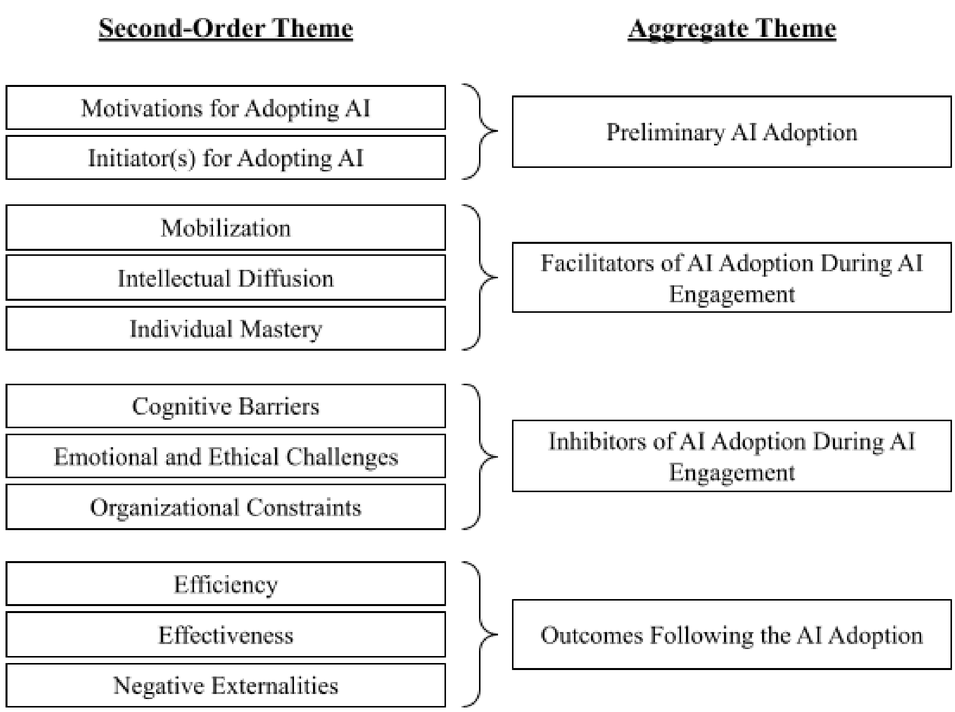
All interviews were transcribed using Klang AI and then reviewed by the authors for accuracy against the recordings. To analyze the data, thematic analysis was applied to identify emerging themes and patterns across the datasets (Braun & Clarke, 2006). This approach enables structured analysis of qualitative data, facilitating the development of rich descriptions, theorizing, and explanations (Saunders et al., 2019). Thematic analysis is a flexible analytical strategy (Bell et al., 2022) not tied to a specific theoretical methodology (Saunders et al., 2019), making it suitable for identifying themes to address the research question. The analysis followed

Braun and Clarke's (2006) procedure: familiarization with the data, coding, theme identification and review, theme definition and naming, and report production. The procedure was not linear; instead, data were analyzed recursively throughout the research process.

The authors began familiarizing themselves with the data during collection, particularly after each interview, when the authors discussed reflections and key takeaways. Further familiarization occurred during transcription as each interview was transcribed and coded throughout the research. The research question guided the coding process, but the abductive approach allowed for the organic emergence of new codes from the data while remaining mindful of relevant literature. As the dataset grew, new codes were continuously added, and previous transcripts were re-coded. This recursive, constant comparison approach ensured attention to alternative interpretations of patterns and theories, minimizing bias, and aligning with a reflexive research approach (Saunders et al., 2019). An example of the coding is provided in Appendix G.

During coding, similar codes were merged (Appendix H), and potential themes were noted. However, the systematic search for themes began after all transcripts had been fully coded. At this stage, codes were grouped to form initial themes, which were then refined, consolidated, and defined into aggregate and secondary-level themes (Figure 4).

Figure 4. *Empirical Results*



3.6 Ethics

3.6.1 Ethical Philosophy

The authors' ethical stance was rooted in a deontological perspective, emphasizing adherence to established rules for research conduct (Saunders et al., 2019). Accordingly, the authors complied with national regulations, the SSE MSc student handbook, SSE policies on personal data processing, and SSE guidelines on generative AI.

3.6.2 Participation and Consent

The first email to prospects from Tendium's official legal address, requesting permission to share their contact details, ensured compliance with Tendium's privacy policy and GDPR. The second email, sent to those who consented and LinkedIn recruits, provided additional information about the research topic, the voluntary and anonymous participation, estimated interview duration, and required prior knowledge, allowing participants to prepare adequately.

Internet-based communications followed netiquette principles, with follow-up emails sent after four weeks to avoid spamming and undue pressure. Participants signed and returned a consent form detailing confidentiality, data management, and their rights. By providing clear information, avoiding coercion, and obtaining signed consent, the authors ensured participants made an informed and voluntary decision to participate, in line with informed consent principles (Bell et al., 2022; Saunders et al., 2019).

3.6.3 Data Collection and Protection

Ethical information covering confidentiality, recording consent, participation rights, and the option to decline any question without explanation was provided at the start of each interview. Strict data confidentiality was maintained throughout the project, given the sensitivity of AI adoption and its implications for competitive advantage. To protect privacy, no information about other participants, employers, or perspectives was shared. Transcripts were anonymized, document names were coded, and all data and recordings were securely stored on the Stockholm School of Economics' OneDrive servers and deleted after project completion.

3.6.4 AI Usage

The authors utilized AI tools, including ChatGPT, Grammarly, and Klang AI, to support the research project. A detailed disclosure of AI usage can be found in Appendix I.

3.7 Data quality

3.7.1 Credibility

To enhance the study's credibility and ensure its findings accurately reflect participants' socially constructed realities, the authors implemented several measures. First, they built trust with participants by obtaining informed consent and adhering to ethical principles (Section 3.6). Second, both authors attended all but two interviews, where only one was available, familiarized themselves individually with the data, and continuously assessed their agreement, aligned with constant comparison (Saunders et al., 2019). Third, by returning transcripts to participants for review, correction, and validation, the authors strengthened their understanding of participants' perspectives. This practice of respondent validation further reinforced the study's credibility (Bell et al., 2022; Saunders et al., 2019).

3.7.2 Transferability

Given the use of semi-structured interviews, the qualitative nature, and interpretivist philosophy, the research emphasizes the specific social context under investigation, posing challenges to its transferability (Saunders et al., 2019). In such studies, transferability of findings to other contexts is left for others to assess (Bell et al., 2022). To address this, the authors ensured full transparency by providing detailed descriptions of the research process, as recommended by Saunders et al. (2019) and Bell et al. (2022).

3.7.3 Dependability

The extensive descriptions of the research process, along with detailed appendices, enhance the study's dependability. Additionally, the authors documented any changes to the study's focus as part of the comprehensive descriptions. To stay informed about these changes, the authors kept notes throughout the study, recording modifications.

3.7.4 Confirmability

One author was employed by Tendium, however, the authors were not financially compensated by the firm and collaborated solely to secure participant access. While the employed author had a preexisting interest and knowledge in AI and public sector sales, the constant comparison helped mitigate potential biases. This approach ensured that new data was continuously compared with existing data, and the authors critically assessed their interpretations through ongoing discussions.

3.7.5 Authenticity

The authors ensured fairness by adhering to ethical research practices (Section 3.6). The coding and constant comparison process provided a balanced representation of diverse viewpoints, as highlighted by Bell et al. (2022). Participant validation further enhanced the authenticity of perceptions, ensuring accurate representation (Shannon & Hambacher, 2014). Additionally, some participants gained new insights into their AI adoption during the interviews, contributing to the study's authenticity by helping them better understand their situations (Bell et al., 2022).

4. Empirical Results

4.1 AI Technologies of the Study

This study explores AI technologies that support suppliers throughout the public sector sales process, focusing on AI tools discussed in interviews. Central is Tendium's integrated platform, which combines natural language processing, information retrieval, and machine learning to automate tasks like opportunity discovery, qualification, bid writing, and analysis. The scope also includes general-purpose generative AI (e.g., large language models) and bespoke solutions developed to specific organizational needs. Adopting a holistic perspective, the study reflects how suppliers increasingly combine multiple AI tools. By studying the interplay between these technologies, the research provides a more accurate and comprehensive view of how AI is reshaping public sector sales. A summary of results is available in Appendix J.

4.2 Preliminary AI Adoption

4.2.1 Motivations for Adopting AI

Participants revealed multiple motivations for initiating the adoption of AI in their bidding process. Often, adoption was initiated by a need to improve and simplify specific tasks within the bidding process, aiming to reduce the time and effort involved.

> *"The reason is that we've read many requests, and they're not all structured the same way. You have to scroll through a lot of text to find the requirements and actual needs. Having an analysis engine to assist with that sounded like a great idea"* - F

The digital systems that supported the participants in their bidding work before starting to use AI were commonly conveyed as rigid and lacking functionality, motivating the move to newer AI tools.

> *"Tool X has become a bit more rigid over the years since it hasn't evolved much. It (AI) sounded like a useful feature, making it easier to access all procurements without only using human eyes to read or review the requests. Also, it helps ensure CPV codes and keywords are correct while identifying relevant procurements. It's a more innovative and new tool. You need to move towards 2025 rather than staying in an outdated system"* - M

Further, participants frequently worked across multiple supplier portals with a lack of integration to find active public procurements. Thus, a need to streamline the bidding process emerged as a motivator for investigating and initiating AI adoption.

> *"Considering we had at least six to ten different platforms for finding procurements... when we heard that AI could compile everything, we had no other alternative" - H*

In addition, competitive pressures, and a need to follow market trends were, by some participants, highlighted as a motivational driver.

> *"It's the market pressure. You can't ignore doing it. If we don't do it, our competitors will, and they'll do it faster and better. So, we have to be first, fastest, and best at this" - K*

4.2.2 Initiator(s) for Adopting AI

Participants conveyed how the early phase of AI adoption was unstructured, marked by quick decisions and a lack of formal implementation plans. This approach was linked to flat organizational structures and decentralized decision-making, characteristics often found in SMEs.

> *"We saw the potential and made quick decisions. We're a flat organization, and decision processes are rarely long. I ran the idea by a few colleagues in sales and large deals, and they found it exciting and promising. That was all there was to it" - L*

Rather than adhering to a structured approach, the participants emphasized the necessity of one or a few individuals initiating the AI adoption process. This process often began with raising awareness among colleagues about AI's potential or actively encouraging them to try using AI in their work.

> *"The person responsible for our bid forum took charge, gathered as much information as possible, and then shared it with different teams as they wanted to better understand the process" - H*

Participant H continues:

> *"We have a very open atmosphere at the company, and whenever someone feels they have something to share or pitch to the management that could elevate the company or an individual, we're receptive to it. There's no "this is how we've always done it" attitude" - H*

The formal organizational position of the initiator was not a determining factor in the adoption process, as initiators ranged from top managers to bid team members. However, what appeared important was management's interest in new technologies and AI, coupled with a general openness to exploring innovative tools.

> *"To a large extent, it was the founder and the management team's personal strong interest in AI development. Simply a curiosity about what was coming and how it could be used. In the beginning, it was mostly curiosity and a fearlessness to try it and see what it could be used for" - J*

> *"It was driven partly by two people who told the management, this is what we believe in, because of this and that. Then management said, Go ahead. Since new solutions constantly emerge, it has spread throughout the business. "This looks really good; I want to test it." So, we've purchased it so they can try and see what works and what doesn't" - K*

4.3 Facilitators of AI Adoption During AI Engagement

4.3.1 Mobilization

During AI integration, several participants emphasized the benefits of leveraging existing internal knowledge. Specifically, the presence of superusers with expertise in AI and data management was perceived as valuable in inspiring others and driving technology adoption.

> *"Superusers are key. Someone who leads the way, gets familiar with the platform, can see the usefulness of the tool, and where to use it to create value. That's something we've focused on…having one or two superusers who are passionate about the platform" - L*

Possessing domain-specific business skills, such as expertise in public bidding, was also highlighted as contributing to more effective and context-aware AI adoption.

> *"We knew how to do procurements. Otherwise, it would have been difficult to know where to start. There were some previous procurements to review and reuse as material for training the AI. This allowed us to quality-check, ensuring that when we tested it, we got similar or better results. I'd say the most important was that we had a foundational knowledge" - G*

Further, the ability to preserve and manage internal knowledge was highlighted as an important aspect of the AI adoption process.

"AI works great if you keep feeding it more data. I think of it like sourdough; it's good if you feed it, but if you don't, it doesn't turn out well at all" - O

At the same time, some participants lacked prior knowledge to support AI integration in the bidding process. This absence of internal expertise challenged adoption efforts, as illustrated by Participant C, noting difficulties implementing AI soon after its introduction to bid managers.

"There was more uncertainty about how the company viewed AI. Of course, we could have proofread a text, but we didn't even consider it when we first started. So, I think a lack of knowledge is the clearest answer" - C

4.3.2 Intellectual Diffusion

Participants emphasized that sharing information was a crucial aspect of AI adoption. Some highlighted the value of disseminating information repeatedly through various channels, primarily meetings, digital channels, and educational sessions.

"In the team, weekly meetings are important. It's very intense every day, but having structure with regular meetings, depending on the role, is key. Information always needs to be available and shared. Just sending out a PDF or posting it on the website doesn't work. You also need to repeat it. It's important that information is diffused in many ways" - Q

"Everyone is on top of things..."I've tested this. What have you tested?" We have Slack channels where we share things we've come across, and trend spotting. "Have you seen this?" It's a hot topic everywhere. We also had a training session for about 30 people" - K

In addition to formal information sharing, informal exchanges among colleagues were highlighted as important for AI adoption. Participant J, for example, described discussions that took place among employees during coffee breaks.

"We've discussed business value, how it (AI) has been used in customer projects, and the lessons learned. Early on, before we fully understood what could and couldn't be done, we thought ChatGPT was a source where all the information provided was correct. We quickly learned that wasn't the case. That was a natural conversation we had a lot in the beginning, about how to use it and how not to use it" - J

While participants perceived different narratives of the provided information, a common theme was the emphasis on AI's functionality, which helped empower the bid team and enhance their understanding of AI.

"Every time we meet, we highlight, "Now we've done this with AI." It's everything from creative dialog with AI to creating things…it's about showcasing good examples. In the beginning, it was more about basic orientation, "what can we do and not do, what should we do". Now, it's more about "this is what I've done." There's a big difference" - F

Furthermore, many participants emphasized that communication often focused on the value and benefits AI would bring to the bid team, which helped facilitate AI's integration into the bid process.

"Not everyone sees the value. When communicating with those I work with, I emphasize, "Why do we want to do this? Why are we showing this?" It's to free up time for things that AI can't do, build relationships with students, participants, customers, things that can't be replaced by AI. But for that, you need a strong vision: freeing up time for what?" - P

Some participants suggested that downplaying AI and instead framing it as another digital support tool could help reassure the bidding team during the adoption process.

"You should not underestimate the fear of losing one's job. But then it's important to convey that this is just a tool, like any other tool. No one would say that a business system or your email is meant to make you lose your job. This is to give you a tool that makes your daily work easier" - N

Participants also experienced active knowledge dissemination through demonstrations of AI's functionality and value for individuals or small groups within the bid team. These demonstrations were seen as helping develop a personal and deeper understanding of AI's role and benefits in their specific work context.

"We've demonstrated how many different use cases there are and what we're doing internally... When they develop a personal connection to it, not just hearing about it, but actually being able to use it for their own personal benefit, then they see it as valuable support" - F

When discussing intellectual diffusion, participants also highlighted the importance of internal openness for asking questions about AI and encouragement to support colleagues and learn from each other.

"You sit next to each other and try to convey some calmness and energy, that it's going to go well. We have an open office environment, and we're very close to each other. So if you

ever have a question, you just stand up and go to that person. That closeness is positive" - S

4.3.3 Individual Mastery

A key theme for facilitating AI adoption was for the bid team members to build mastery of the AI tool. Multiple participants perceived this as being achieved through experiential learning, specifically, through direct interaction with the tool and iterative use during practical application.

"You get far with learning by doing and trying to use it as much as possible, and understanding how you can adapt and work with the tools. It's also about challenging old working methods and patterns to the extent possible. Like we've done, letting everyone try things out for themselves" - J

"Dare to give a task and let go of control. Don't provide a 1-10 manual, but instead let them figure it out on their own. They might not do it in exactly the same way to reach the goal, but they'll learn and improve over time" - Q

Participants discussed several facilitators for driving and supporting the experiential learning process. Easy access to AI tools and encouragement to actively test them were commonly highlighted as key factors.

"If someone wants to test a relevant tool, we'll fund a two-month trial. After that, we'll decide if it's something we want to implement. Even if it is playful, we're open to it. We support those who want to lead the way, and over time, the majority will follow" - G

Additionally, participants noted that self-leadership, along with its encouragement, often rooted in the organizational culture, played a key role in facilitating the experiential learning process.

"No one waits around for something to happen. If you want something, you make sure to get it or do it. It's up to each individual. We wouldn't have come this far if we didn't have this culture. It's entrepreneurial, driven by personal initiative and curiosity. If everyone had waited for training six months down the line, we would be way behind" - K

4.4 Inhibitors of AI Adoption During AI Engagement

4.4.1 Cognitive Barriers

Participants highlighted, at times, challenges in adopting AI, with many noting that existing routines and habits created inertia, making it hard to embrace AI. The comfort of established workflows led to resistance against deviating from familiar practices.

> *"Many bid managers who have been working for a while tend to lean back. It feels comfortable when things stay the same. This change is quite scary. Some may not want to change, or they're not interested. Others may see that things are happening but don't want to take action themselves" - B*

A second cognitive barrier was a lack of trust in the quality, reliability, and professionalism of AI-generated content. Participants expressed discomfort with fully relying on AI, especially for tasks that required high control and accuracy, such as bid writing.

> *"I don't want to fully relinquish control to AI because it feels somewhat unprofessional. I think my biggest barrier with AI as a tool is trust" - O*

> *"How do we know that AI captures everything? For example, if we let AI identify what should be included in a bid, and then we send it to the customer asking them to provide those items for the bid, and later realize that things were missing" - D*

Lastly, several participants noted a perceived mismatch between AI's offerings and their role's specific demands. Without a clear connection between AI functionality and tangible work benefits, motivation to engage may stagnate.

> *"That's where I struggle. I don't clearly see what AI would add. If I knew how it could help me, I'd probably be more open to using it. I know it can answer questions in a procurement, but beyond that, I don't see how it could help me. Maybe it can do more. I would appreciate it if someone showed me how to use it better. I'm just not there yet" - M*

4.4.2 Emotional & Ethical Challenges

A recurring emotional concern was the perceived risk of AI replacing human labor. Participants noted that while automation could be helpful, it raised existential questions about the future of their roles and personal value within the organization.

"You don't want to automate away your own job. If it becomes so easy that AI can do my bids, then I'm no longer needed. So, in a way, you start thinking that maybe we don't want to optimize everything just for the sake of it. I still need to bring value to the company" - O

Participants also raised ethical concerns, feeling that using AI might be seen as taking shortcuts. These concerns were often intertwined with professional identity, pride in their craftsmanship, and a fear of being perceived as less competent.

"...But also the fear of cheating. You have a strong work ethic, you feel like you've done everything right, feeling good after writing the document with my own hands. And then, when AI does it, suddenly you're like… you might feel a bit like a fraud. What do I do now? I didn't actually create this, AI did" - P

Additionally, some participants expressed concerns rooted in broader societal narratives about AI. These concerns were less about the tool's direct impact on their roles or organizations and more about AI's evolution globally, raising issues of control, truth, and technological overreach.

"I would say most people over 50 probably find it a bit scary. We read George Orwell when it actually was relevant. That's just how it is. Even though we're also the Star Wars generation. There's a certain skepticism, just like there is toward new social media" - A

"...there's that feeling of...you know, what's really happening in the world? And also, who controls what comes out? Who knows that the output is actually true?" - M

4.4.3 Organizational Constraints

Participants also perceived organizational constraints as challenges to AI adoption, particularly the pressure of daily responsibilities, which limited the time and effort available for the adoption process.

"Fundamentally, it's about finding the balance between driving the business and making time to invest (in AI)" - O

"We have gone from handling 20 million a few years ago to handling 140 million last year. We have grown from nine employees to 32. So it's absolutely not a conscious choice, but rather that there has been so much else to focus on that has taken strength, time, and energy" - R

A recurring challenge among participants was the lack of structured and accessible data, which made it difficult to supply the volume and quality of data needed for effective AI use.

> *"That was also when we realized that we need to feed it with such enormous amounts of data for it to be useful. And that meant we never got it over the finish line. We did a trial run. We thought we have to test and see what happens. Sent in some data. But the answers were so far off. That's when we realized this would require an enormous amount of data from us. And the time and work it would take to extract that data felt a bit overwhelming." - R*

Further, participants highlighted the crucial role of managerial engagement, noting that a lack of understanding, interest, and time among decision-makers stalled AI adoption.

> *"There are some in management you can talk to, some you can't, and half of them won't give it any time. Because they don't understand it and can't grasp it. Also, they don't have the time" - A*

4.5 Outcomes Following the AI Adoption

4.5.1 Efficiency

Several participants emphasized that AI-supported systems offered a more centralized and cohesive structure for managing bid-related information. Previously scattered and unstructured data, across emails, documents, and spreadsheets, was now consolidated in a single platform, allowing for a greater overview and predictability.

> *"Before, when having tons of requests with different requirements from various buyers, it was hard to go through each request and then see the timeline, content, and requirements. With AI, everything is centralized, and there are already headings if you want to check the requirements. You click and see what the buyer is asking for and which buyers they are. It's like a well-organized drawer" - H*

Another identified improvement was AI's ability to quickly and accurately identify relevant opportunities. Rather than manually reviewing procurement documents, AI-driven pattern recognition, summaries, and keyword filtering support early bid/no-bid decisions.

> *"By using AI to go through procurement documents and extract data from them, we can quickly identify if certain keywords appear. These keywords can be relevant based on what we want to respond to or what we can't respond to. For example, if we want to respond to a*

licensing procurement and it says that being a Microsoft Licensing Solution Partner is required, that might appear in many different ways in the procurement documents. (AI) will immediately tell us, okay, this isn't for us. Since it is found (by AI) in the documents, we can discard it and move on to the next one. This saves lots of time compared to downloading and opening all the documents, searching through all the text, and looking for it. We're talking about a factor of 10 in terms of time saved" - L

A common benefit of AI adoption was a significant reduction in time for bid writing and submission. Participants noted that AI-assisted drafting tools allowed them to produce supporting texts and complete tasks much faster than before.

"It's like night and day. We can provide supporting texts for our consultants in various contexts in a fraction of the time. We've become much more productive" - F

4.5.2 Effectiveness

It was emphasized that the time saved through AI-driven efficiency allowed teams to focus on higher-value activities that more directly influenced results. In some cases, AI-supported analysis enabled earlier, more strategic engagement with public buyers. By analyzing past requirements and tailoring early outreach accordingly, organizations improved their chances of success when procurements went live.

"There's more focus on new customers. For instance, talking to the municipality before the procurement comes out. It's much about lobbying around that" - G

"We use AI a lot to analyze past procurements. What were the requirements they set? We try to start a year and a half before we know a tender will be released. Because often, we try to meet with the management of the buyer and ask what they've been satisfied with under their current agreement, and what hasn't worked. Then, when it comes to a request for information, something all regions and larger municipalities have, we want the arguments that will resonate, based on what's important to that specific client. And that means we need to analyze what differentiates us from our competitors regarding what they've found important" - N

In addition, increased speed was conveyed to contribute to higher productivity and allow teams to manage more bids in parallel.

"It's much faster to respond to a procurement now. Both going through it and, especially, answering the procurement and preparing the documents. It used to take days to complete

a tender, but now it only takes half a day if you can generate responses (with AI)…We have time to respond to many more tenders than we did before" - G

Another frequently mentioned benefit was related to quality improvement in bid writing and submission. AI-assisted drafting enhanced the linguistic and professional standards of final deliverables, especially in technical or compliance-heavy industries.

"There's an increased professionalism in our responses, better formulations, and shorter lead times. This is closely tied to information security, where, as a layperson, I have a limited vocabulary and practical knowledge. I can't really...But what comes out of the language model is pure poetry. The result is incredibly good, and as a bonus, I don't need to take time away from my colleagues" - E

Relatedly, one participant described advanced AI usage, involving multiple AI models in a feedback loop to simulate the bid evaluation process. By configuring one model to simulate a procurement officer and the other model to act as a bid writer, they were able to iteratively refine responses, ensure they met requirements, and improve their bid quality, potentially increasing their contract win rates.

"It leads to better responses and submissions of the texts… We've started feeding the procurement document into AI... we upload the documents and have our own AI that helps us write the bid. Once it's done, we send it to the critical municipality (acting as a procurement official) which gives us feedback...Then we go back and say, "This is the feedback...Fix it." So we let two bots send things to each other...That way, we get higher quality." - G

Following the integration of AI and its improvements in efficiency, some participants reported enhanced well-being, including reduced stress and a better work-life balance.

"It's less to do in the procurement processes. A lot of time used to be spent on procurement when not being out in the field or doing regular work. Therefore, we often had to work on tenders during weekends. And we've moved past that now. There's more free time in most cases. That's the benefit... I'm not as tired anymore" - I

4.5.3 Negative Externalities

Several participants pointed to unintended consequences of AI adoption, including difficulties in preserving a distinct human voice in bid writing and challenges in ensuring their submissions stood out from those of competitors.

"Everyone responding to a procurement document is selling the same thing. How do you differentiate yourself there? You're not on-site to present, so you can't personally show the things that make you stand out. All you have are the words and the documentation. If the responses also are too similar, you could lose. So, I need to make it sound human" - B

Additionally, some participants expressed concerns about a potential overreliance on AI-generated output without proper quality control.

"The negative effect is a trust that AI can do everything. We've had an employee in the past who used AI and then interpreted everything as being set and done. There should be a balance between ensuring quality, optimizing, and automating" - O

5. Analysis and Discussion

5.1 Anticipation

5.1.1 Unstructured Anticipation

The preliminary phase of AI adoption in SMEs was brief and unstructured. AI implementation decisions were made rapidly, without onboarding procedures or structured plans to support public sector sales teams before integrating AI. Additionally, there was no formal assessment of employee uncertainty or pre-entry knowledge. This contrasts with Makarius et al. (2020), who emphasize addressing employee uncertainty and pre-entry knowledge and providing formal onboarding and training. However, despite the absence of such measures, none of the studied SMEs perceived their AI adoption as unsuccessful.

Several participants noted that the SMEs' small size enabled flat decision-making and rapid idea-sharing between employees and management. An open, experimental culture and a "just-do-it" mindset further encouraged an emergent, unstructured approach to early AI adoption. This is noteworthy, as the finding diverges from the structured adoption processes suggested by Makarius et al. (2020) and Nowicki (2020) as crucial for successful adoption. However, their focus on organizations in general may explain the discrepancy, reiterating the importance of how organizational size might influence the adoption process.

SMEs were motivated to adopt AI by the potential to improve job-specific tasks such as opportunity recognition and information structuring, and to enhance the overall sales process. Furthermore, dissatisfaction with rigid digital systems, characterized by low functionality and poor integration, along with competitive pressures, prompted firms to explore AI. This supports Rodriguez and Peterson (2024), who highlight that strong intent and belief in AI's benefits increase adoption likelihood. It also extends the framework of Makarius et al. (2020) by emphasizing the need to consider motivations and pressures underlying adoption to fully understand how the anticipation phase practically unfolds.

5.1.2 Informing Employees in Anticipation

Early AI adoption was often initiated by one or a few individuals who played a key role in disseminating information, hence raising awareness and helping others understand the new AI systems. This supports Makarius et al. (2020) and Chen and Zhou (2022), who argue the importance of managers to inform employees about AI to reduce ambiguity and build understanding of the technology. However, unlike Makarius et al., the findings show that this role was not limited to managers; it could also be fulfilled by team members. Nevertheless, managerial support, often driven by an interest in technology and a willingness to explore innovation, remained vital in the early phase of AI adoption to enable AI investment. This nuance adds depth to Makarius et al., who emphasize managers' importance but do not examine what drives their support.

5.2 Encounter

5.2.1 Role Clarity

The next phase of AI adoption focused on ensuring employee engagement with AI and the gradual integration of AI into daily tasks. This relied on repeated information-sharing via meetings, digital channels, educational sessions, and informal conversations. Often, superusers with foundational AI and data knowledge, regardless of managerial or employee status, led the information provision. This contrasts with Makarius et al. (2020), who emphasize the necessity of primarily managerial involvement in supporting employee comprehension and actions of using AI. The findings suggest that during the encounter phase, an initiator's AI expertise is more influential for adoption than their formal organizational position.

One common narrative of information emphasized how AI supports the sales process, helping employees understand AI's functionality and relevance to their roles. This resonates with Makarius et al. (2020) on the importance of role clarity, that is, building role expectations and knowing how AI reshapes tasks. Further, several SMEs held individual or small-group demonstrations of AI's functionality and value, fostering personal, task-specific insights, hence improving employees' role clarity. This extends understanding of how role clarity is actively established, rather than merely affirming its importance during adoption. Furthermore, it aligns with the arguments of Chen and Zhou (2022) and Rodriguez and Peterson (2024), who emphasize the importance of cultivating positive perceptions of AI's usefulness and ease of use for successful adoption.

In addition, fostering an internal culture where employees felt comfortable asking questions about AI and supporting peer learning promoted effective knowledge and information sharing. This finding extends the framework of Makarius et al. (2020) by highlighting dimensions that underpin effective intellectual diffusion.

5.2.2 Task Mastery and Social Interaction

The provision of information and demonstrations empowered employees, increasing their comfort with AI use. This supports Makarius et al. (2020), who argue that fostering task mastery, and thereby employee confidence in performing duties with AI, is important for adoption. Further, experiential learning through direct interaction with AI during practical application enhanced employees' task mastery. This aligns with Rodriguez and Peterson (2024), who argue that salespeople's experiences with AI influence their usage and engagement. Experiential learning was facilitated by easy tool access, encouragement to experiment, and a curious, entrepreneurial culture promoting self-leadership. This extends Chen and Zhou (2022) by showing how culture shapes internal locus of control and self-efficacy, key to AI adoption. The findings elaborate on Makarius et al. (2020) by identifying actions that foster task mastery, rather than merely affirming its importance.

The experiential learning implies a social interaction with AI, which played a role in participants' adaptation and reflects early signs of adjustment (Makarius et al., 2020). However, identified challenges suggest some participants had not sufficiently socialized with AI to develop an identity enabling deeper integration (Makarius et al., 2020).

5.2.3 Resistance and Trust

Resistance mainly occurred in the encounter phase, driven by cognitive, emotional, and ethical concerns. As Makarius et al. (2020) suggest, resistance could be expected given the influence of individual traits, context, and prior experiences on employees' propensity to trust and engage with AI. Participants also had customer-facing roles, which could deepen the resistance (Makarius et al., 2020). Contrary to Makarius et al., resistance was not due to reduced human interaction but, in line with Paschen et al. (2020b), stemmed from fears of job displacement and ethical concerns, such as a sense of cheating. Further, while AI's broader potential was acknowledged, it was sometimes seen as misaligned with roles, reinforcing hesitation.

Resistance was also tied to workflow inertia and doubts about the quality, reliability, and professionalism of AI outputs. Unlike Rodriguez and Peterson (2024), transparency, bias, and privacy were not key concerns. These findings nuance Makarius et al.'s framework by showing how sources of resistance challenge the adoption process.

While the study does not establish causality between facilitators and challenges of AI adoption, it shows that sharing information about AI's value, benefits, and functionality helped reduce barriers and support integration. Consistent with Makarius et al. (2020), this information provision enhanced trust among employees, facilitating integration. Demonstrations and experiential learning further built trust by enhancing participants' understanding and mastery of AI, aligning with Chen and Zhou (2022), who emphasize the role of training and information provision to build understanding and engagement whilst reducing uncertainty. Moreover, framing AI as a familiar digital tool eased concerns like job displacement, extending Makarius et al.'s framework, which does not address the role of framing in AI adoption.

5.2.4 Contextual Influence

Broader societal narratives about AI raised concerns among participants regarding control, truth, and technological overreach. Additionally, organizational constraints such as the pressure of daily responsibilities, unstructured and inaccessible data, and insufficient managerial support challenged adoption. This demonstrates that AI's development within societal and organizational contexts was perceived to influence adoption, dimensions that the framework of Makarius et al. (2020) is lacking.

Further, foundational expertise in AI and data management was perceived as valuable in inspiring others and driving the adoption of the technology. This corresponds with the findings of Makarius et al. (2020), suggesting that organizations with digital infrastructure and expertise are better positioned for AI integration. Additionally, specific business skills, like public sector sales, supported more effective adoption, extending Makarius et al., by showing that business skills influence adoption.

5.2.5 Job Design

As AI increasingly integrated, employee tasks shifted toward higher value-adding activities, such as strategic work and customer engagement, aligning with Makarius et al's. (2020) suggestion of shifting tasks toward those requiring human expertise. However, the study did not find that managers formally redesigned jobs. This suggests that AI in the studied cases, which generally exhibited moderate novelty and limited scope, has not been sufficiently transformative to necessitate structured job redesign. The tools tended to enhance specific tasks rather than fundamentally alter organizational roles. This limited transformative capacity may explain the absence of more formal organizational change, contrasting the findings of Paschen et al. (2020b) and Rane et al. (2024) in that AI fundamentally transforms sales processes.

5.3 Metamorphosis, Outcomes, and Navigating SME Challenges

5.3.1 First-Order Effects

The most immediate outcomes following AI adoption were process-oriented, reflecting first-order effects (Enholm et al., 2021). These effects primarily manifested as process efficiency gains in the public sector sales process. AI centralized previously fragmented information, creating a single point of access to critical data. This reduced the need to manually reconcile information from multiple sources, in turn simplifying collaboration and clarifying task ownership. This expands the findings of Rodriguez and Peterson (2024) by showing that AI can generate administrative efficiency improvements via data centralization.

AI tools also accelerated opportunity qualification through document parsing, keyword extraction, and filtering, reducing time spent assessing opportunity and organization fit and enabling quicker bid/no-bid decisions. Further, AI-assisted content generation cuts drafting time for standard bid responses. This elaborates on Rodriguez and Peterson (2024) by displaying how specific benefits of AI generate efficiency.

5.3.2 Second-Order Effects

AI freed up time and cognitive resources from repetitive administrative tasks, enabling professionals to focus on early buyer engagement, identifying opportunities and trends, and crafting personalized communication strategies. This strategic shift, a key second-order effect (Enholm et al., 2020), aligns with Rodriguez and Peterson (2024) and Han et al. (2021), showing AI's role in reallocating time from performing administrative tasks to sales, decision-making, and customer relations. This reinforces that despite the regulatory complexity of procurement, AI's core benefits of process efficiency, automation, and insight generation remain largely consistent across public and private B2B settings.

Additionally, AI-driven analysis of procurement data helped firms understand previous buyer requirements, anticipate procurements, and engage in pre-bid lobbying, reflecting improved market performance, proactive bidding strategies, and enhanced competitive positioning.

Further, AI allowed firms to manage more public procurements simultaneously without compromising quality. AI-assisted bid writing enabled handling more submissions in parallel while maintaining or improving delivery standards, driving operational performance gains through improved operational efficiency. Additionally, cultural and psychological benefits, such as reduced stress, fewer overtime hours, and better work-life balance, were observed. These effects could have long-term implications for employee retention and productivity, contributing to sustainable performance over time.

Some unintended second-order effects also emerged. A common concern was the loss of human distinctiveness in AI-generated content. Participants feared responses could become overly generic and lack the nuanced tone that differentiates their organization as competitors use similar AI tools. Therefore, in the standardized, competitive context of public sector sales, where differentiation is vital, such homogenization was seen as a strategic liability. Additionally, several participants warned of growing over-reliance on AI outputs, with some employees treating its suggestions as definitive rather than advisory, mirroring Rodriguez and Peterson's (2024) findings that some salespeople accept AI outputs unquestioningly. This reduced critical reflection of final submissions, raising concerns about bid quality and accountability. These findings suggest the need for deliberate human oversight in AI integration to preserve quality, critical thinking, and character of its submissions.

The study did not yield clear evidence of a direct impact on financial performance. While AI adoption improved operational, market-based, and possibly sustainability performance, the connection to financial outcomes remains ambiguous.

5.3.3 Metamorphosis and Developing Sociotechnical Capital

The first- and second-order effects suggest firms are developing what Makarius et al. (2020) call sociotechnical capital: the integration of human capabilities and AI that can generate sustained competitive advantage. As seen in Section 4.5, firms that move beyond experimentation can see improvements related to productivity and trigger psychological and cultural shifts. Such outcomes are not merely side effects but essential conditions for consolidating sociotechnical capital (Makarius et al., 2020). Similar to the literature on AI among buyers in public procurement (e.g., Andersson et al., 2025; Nowicki, 2020; García-Rodríguez et al., 2019), AI thus seem to pose extensive benefits and improvements for suppliers in their public sector sales process as well.

However, while many firms report process and strategic gains, sociotechnical capital development remains uneven. Empirical evidence points to emerging signs of metamorphosis, where AI is not only altering tasks but also influencing how employees relate to their work and each other. Yet, cognitive barriers, emotional and ethical challenges, and organizational constraints left some firms in an experimental rather than integrative phase.

Whether AI becomes a sustained competitive advantage for SMEs, through sociotechnical integration, depends on aligning technical capabilities with human experience and continuously adapting routines, culture, and infrastructure (Makarius et al., 2020). Thus, investment in employee training, leadership commitment, data infrastructure, and management of the emotional and cultural dynamics emerge as particularly important. However, further research is needed to determine which of these areas offers the greatest impact and how organizations can most effectively prioritize their efforts. Without sustained attention to these factors, AI adoption risks plateauing at the process support level, rather than becoming a lasting competitive advantage.

Makarius et al.'s (2020) AI integration model help contextualize these findings. Regarding novelty, the AI applications discussed in this study generally fall into the category of moderate novelty. This as many SMEs adopted existing generative AI platforms or integrated third-party solutions designed specifically for public sector sales, representing a departure from traditional tools but do not radically alter the organizational architecture. In terms of scope, the adoption was largely limited to specific tasks within the public sector sales process, such as document parsing, summarization, and content generation, rather than full-scale automation of strategic or managerial functions. This indicates that, while adoption was meaningful, it was functionally bounded. Hence, per the model, firms may experience immediate process-level benefits, but need deeper integration for transformative impact. This raises the question of whether the limited level of integration is solely due to SME-related constraints or also reflects limitations in the technology itself, thus creating a sociotechnical imbalance. As Xu and Gao (2025) argue, joint optimization of social and technical subsystems is essential for successful technology adoption and organizational performance. To better understand the relative influence of these factors, longitudinal studies are needed to track how AI adoption and its effects evolve as both the technology and the organizations using it mature.

5.3.4 Addressing SME Barriers with AI

The findings suggest that successful AI integration helps SMEs overcome barriers in the public market, supporting the view of AI as a self-help strategy that enables SMEs to navigate public sector sales challenges (Akenroye et al., 2020; Loader, 2013).

First, AI technologies that automate opportunity detection and document parsing mitigate barriers associated with limited information access. Participants described how AI enabled faster, more reliable identification of relevant procurements by extracting keywords, analyzing requirements, and highlighting disqualifying criteria. This supports SMEs in overcoming challenges such as the inability to determine appropriate contacts, limited procedural knowledge, and difficulty identifying contract opportunities (Akenroye et al., 2020; Loader, 2013). Moreover, AI's ability to centralize and systematize information reduces dependency on fragmented platforms and manual searches, addressing issues related to administrative burden and procurement information (Calderón et al., 2018) and bureaucracy (Loader, 2013).

Second, AI enables SMEs to assess fit for complex contracts and framework agreements by analyzing historical procurement data and drawing parallels with organizational competencies. This helps firms make informed decisions about contract size, duration, and risk (Loader, 2013). By providing timely insights, AI empowers SMEs to strategically select public procurements that align with their capacities and minimize risk exposure.

Third, automating bid writing and standard content generation reduced the time and resources required for proposal preparation (Loader, 2013), supporting the findings of Rane et al. (2024) that AI adoption led to process efficiencies. This is particularly impactful for smaller firms with limited administrative capacity or those lacking formal bid-writing skills (Loader, 2013). Participants noted that AI-assisted drafting improved both speed and quality of submissions, enabling compliance and enhancing professionalism in bids (Loader, 2013). The time savings also suggest that SMEs may perceive bidding as less time-consuming, improving their commitment to developing competitive proposals (Akenroye et al., 2020).

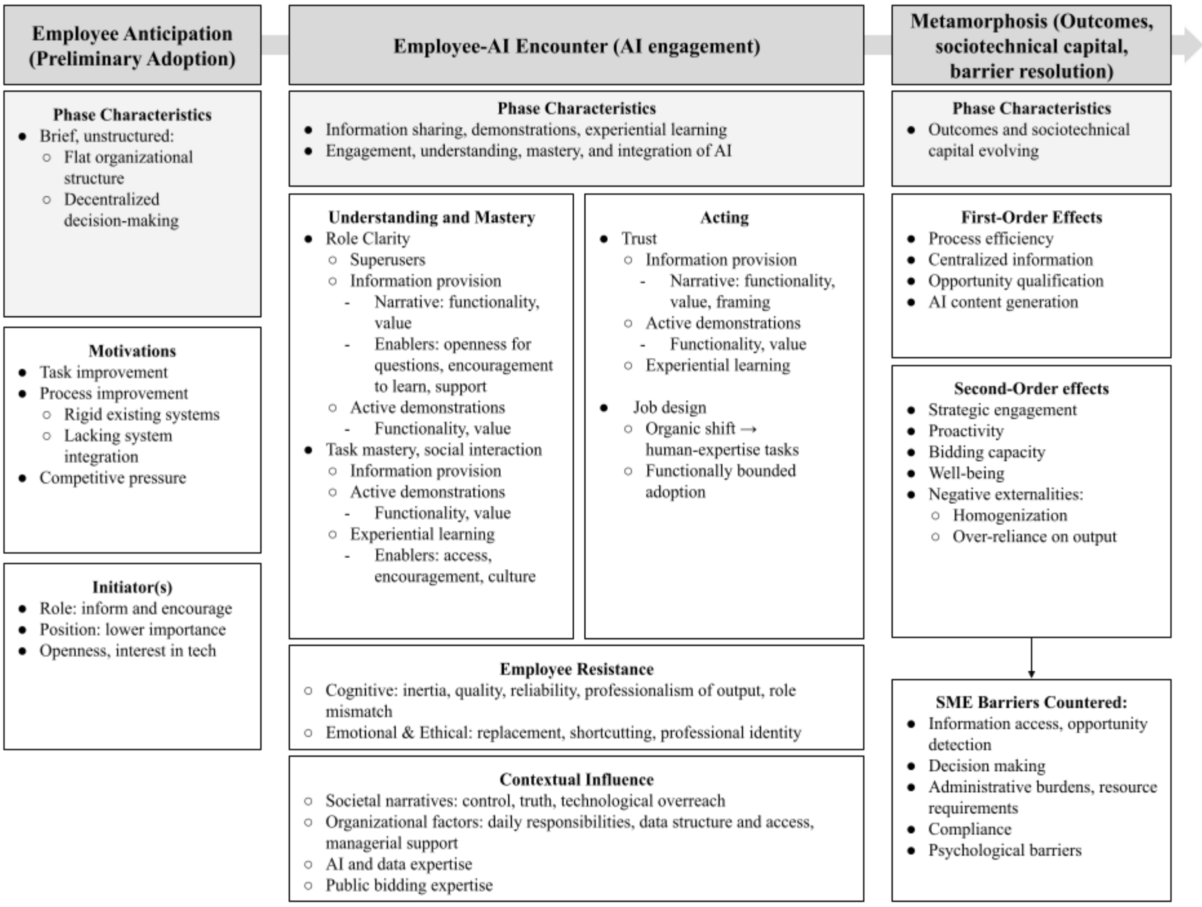
Beyond process efficiency, AI may also reshape the psychological dynamics of SME participation in public sector sales. While AI helped some feel more capable of producing professional, compliant bids, others experienced ethical and cognitive discomfort, such as feelings of cheating, impostor syndrome, and distrust in AI outputs. These concerns suggest mixed psychological outcomes: AI may reduce competence gaps for some, while creating doubt, vulnerability, and value misalignment for others. However, with hands-on learning, peer exchange, and a practical framing of AI, many reported less anxiety and increased openness. In this way, AI helps SMEs overcome structural and internal barriers, fostering more confident and sustained engagement with a public market often perceived as complex and exclusionary (Akenroye et al., 2020).

6. Conclusion

6.1 How SMEs Adopt AI and the Outcomes of the Adoption

This study examined how Swedish SMEs adopt AI as a sociotechnical process in public sector sales and the resulting organizational outcomes (Figure 5).

Figure 5. *Overview of SME AI Adoption and Its Outcomes*



Findings show that preliminary AI adoption unfolds rapidly and informally through informal, decentralized, and human-centered processes. Early adoption was driven by initiators open to digital experimentation and motivated by operational inefficiencies and competitive pressure.

In the later phase of AI engagement, internal superusers with expertise in AI and data often played a central role in driving adoption and experimentation, mobilizing the organization. Continuous information sharing across multiple channels, emphasizing AI functionality and value, and active demonstrations contributed to enhanced and individualized role clarity during the adoption process. This was reinforced by a culture of openness for questions and sustained encouragement for learning about AI. Further, Experiential learning, facilitated by AI access, encouragement to try AI, and an entrepreneurial culture, along with information sharing and demonstrations, fostered task mastery among employees, enabling them to effectively integrate AI into their work contexts.

During the adoption, managers did not formally redesign employee roles. Instead, employee tasks organically shifted toward activities requiring human expertise, particularly strategic work and customer engagement. Thus, AI primarily enhances specific tasks rather than fundamentally transforming organizational roles.

Adoption was marked by resistance rooted in cognitive, emotional, and ethical concerns. The process was also shaped by societal narratives, organizational constraints, AI/data expertise, and public sector bidding capabilities. To mitigate resistance, findings highlight the need to build trust through information dissemination, active demonstrations, and experiential learning.

Sociotechnical integration remains incomplete in many firms due to ethical, emotional, cognitive, and organizational barriers. Nevertheless, successful AI integration yields first-order effects such as increased bid-writing efficiency, enhanced information flow, and improved opportunity qualification. Over time, these lead to second-order effects, including higher bid quality, more proactive public sector sales, broader participation, and reduced employee stress. However, negative externalities also emerge, such as overreliance on AI outputs and diminished human distinctiveness in submissions. The limited integration of AI in some firms may also reflect some constraints in the technology itself, given the emergent state of AI in public sector sales.

Connecting outcomes to public sector sales barriers, findings show that successful AI adoption directly addresses challenges SMEs face, such as information asymmetries, opportunity detection, administrative burdens, decision-making, and compliance. Through automation, information structuring, and increased public sector sales capacity, AI enables SMEs to participate more consistently and strategically, thereby lowering barriers within public sector sales.

6.2 Theoretical Contribution

First, while public procurement presents distinct regulatory, procedural, and operational complexities (Fountoukidis et al., 2023; Morcov and Puiu, 2023), the supplier-side adoption of

AI within this domain remains underexplored. Consequently, this study develops the literature by providing insights into how SMEs adopt AI technologies under these specific constraints, addressing the gap in existing AI adoption within sales literature.

Second, this study advances AI adoption research in sales by detailing how successful integration of humans and technology generates first- and second-order effects, along with negative side effects. It deepens understanding of AI's adoption, application, and impact in public sector sales.

Third, this study advances SME self-help literature by conceptualizing AI adoption as a self-help strategy. Prior research has focused on external interventions such as policy change and buyer-side reforms (Akenroye et al., 2020; Loader, 2013; McKevitt and Davis, 2013), as well as dynamic capabilities (e.g., Akenroye et al., 2020; Calderón et al., 2018), with limited attention to supplier efforts (Rejeb et al., 2023). By showing how SMEs use AI to autonomously lower public sector sales barriers, the study extends the role of SME agency.

Fourth, this study nuances STS theory by showing that AI adoption and sociotechnical alignment in SMEs emerge without formal change management programs. Unlike traditional STS frameworks, which assume structured, organization-wide adoption processes (Makarius et al., 2020), this study presents a more decentralized and experiential view, driven by individual agency and contextual experimentation in resource-constrained environments. It extends STS theory by emphasizing the role of information provision, demonstrations, and experiential learning in adoption and what enables these processes. Further, societal narratives, organizational constraints, and expertise are identified as novel contextual factors that shape adoption. Additionally, while existing literature focuses on technological, operational, and managerial challenges (Chen and Zhou, 2022; Makarius et al., 2020), this study extends this literature by demonstrating how cognitive, emotional, and ethical concerns can hinder AI adoption, advocating for a more human-centered approach to sociotechnical change.

6.3 Managerial Implications

This study identifies five key managerial implications for SMEs seeking to adopt AI technologies to improve public sector sales performance.

First, managers should recognize that AI adoption in SMEs is often informal and individually driven. Rather than relying solely on formal change programs, managers should enable decentralized exploration by allowing employees the flexibility to experiment with AI tools in their daily work, in line with the informal and opportunistic adoption processes identified in this study. Additionally, facilitating information sharing and active demonstrations via encouragement and establishing an openness for questions is crucial.

Second, managers must acknowledge and proactively address employee concerns regarding AI adoption as such barriers may inhibit engagement with new technologies. Managers should create spaces for open discussion about these concerns and frame AI as a complement to, rather than a replacement for, human expertise.

Third, the findings show that AI adoption can play a critical role in public sector sales, resulting in tangible positive outcomes. Thus, managers should actively invest time and resources into AI technologies that align with their strategic objectives in public sector sales to improve their performance.

Fourth, managers need to be attentive to differences in technological competence across employees. The study highlights that adoption levels vary based on prior experience and confidence with digital tools. Managers should consider offering continuous support and providing information to ensure that adoption is not limited to the most technologically advanced individuals but is accessible across the organization.

Fifth, managers should engage actively in AI adoption processes. The findings suggest that when leadership is passive or disengaged, adoption momentum slows. Managers should signal their commitment to AI initiatives by remaining involved in early adoption activities, communicating expectations clearly, and reinforcing the relevance of AI-supported work practices.

6.4 Limitations

This study is confined to the Swedish context. While Sweden’s public procurement legislation aligns with EU directives, suggesting that the findings may carry relevance for SMEs across the European Union, certain national characteristics may shape AI adoption in distinct ways. Factors such as institutional frameworks, levels of digitalization, and the structure of Sweden’s procurement market may influence how AI is perceived, implemented, and integrated by SMEs. As such, while the study offers insights of potential value beyond Sweden, its conclusions should be interpreted with attention to these contextual specificities.

6.5 Future Research

As AI adoption in public sector sales continues to develop, three areas for future research are identified. First, further research should investigate the relationship between operational improvements from AI adoption and direct financial outcomes, as this connection remains ambiguous. Second, given the emergent state of AI in public sector sales, longitudinal studies are needed to examine how the adoption and its effects evolve as organizational routines and strategies mature. Third, future studies should explore how AI-to-AI communication may reshape the public market as buyers and suppliers increasingly adopt AI technologies and how suppliers can leverage such dynamics in their public sales process.

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8. Appendices

Appendix A. SME Barriers. Adapted from Loader (2013)

Category	Associated Barriers
A. Public sector	
A1. Public sector environment	
Policy	(1) Competing procurement objectives, with lack of clear priorities (2) Supplier rationalization leading to a reduced supplier base and marginalization of small suppliers
Culture	(3) Risk-averse attitudes (4) Pro-large-business attitudes
Organization	(5) Devolved processes produce complexity, confusion, and inconsistency
A2. Procurement process	
(1) Identify opportunities that are available	(6) Inability to determine appropriate contact (7) Lack of knowledge about procedures and opportunities
(2) Determine contract requirements and decide whether or not to tender	(8) Size of contract - volume prohibitive (9) Contract length prohibitive (10) Uncertainty of work within a framework contract
(3) Take part in tender process either: (a) Open procedure: return tender by set date (b) Restricted procedure: two-stage process:	(11) Difficulty getting onto approved supplier list (12) Need to demonstrate a track record (13) Prohibitive resource requirements associated with preparing bids: cost and time (14) Overly prescriptive requirements

- prequalification stage (prequalification questionnaire) - invitation to tender	(15) Bureaucracy (16) Procurers' lack of professionalism: lack of training, technical expertise
(4) Contract awarded on basis of value for money	(17) Narrow definition of value for money/cost focus
(5) Supplier outcome: success; contract awarded; failure; feedback on request	(18) Slow payment (19) Lack of/poor feedback
B. Small business sector	
Capacity	(20) Lack of appropriate resources (management, administrative, marketing, language skills, legal, electronic)
Skills	(21) Poor completion of bids (22) Lack of required standards
Attitudes	(23) Reluctance to engage with a process perceived to be unfair

Appendix B. Pre-study Information

Participant	Role	Time	Place	Date
Ronny Ågren	Head of Sales, Tendium AB	24:12	Online: Teams	2025-01-30
Maria Hägnander	Educator, IHM & Public Bid	26:59	Online: Teams	2025-02-06
Magnus Johansson	Bid & Competition Expert, Företagarna	24:54	Online: Teams	2025-02-24

Appendix C. Permission to Contact

Email: First outreach

Subject: Research Collaboration with Stockholm School of Economics

Hello [Name],

Tendium is currently conducting a research project in collaboration with the Stockholm School of Economics on how Swedish small and medium-sized enterprises (SMEs) use AI in public sector sales. The aim of the study is to understand how SMEs can lower the barriers to participating in public tenders and what role AI plays in this process.

We are reaching out to ask for your permission to allow the Stockholm School of Economics to send you more information about the study and, if you are interested, contact you for an interview. Participation is completely anonymous, and all information is handled confidentially in accordance with GDPR.

If you agree to be contacted directly with more information and would like to learn more, please reply to this email or reach out to us at +46 ** *** ** **.

Thank you in advance!

Best regards,

Tendium Team

Appendix D. Second Outreach to Prospective Interviewees

Email: Follow up, if the first request was approved

Subject: Re: Research Collaboration with Stockholm School of Economics

Hello [Name],

Great to hear that you're interested in learning more! Here's some additional information about the study.

About the study: In addition to my work at Tendium, I'm currently pursuing a Master's degree in Business & Management at the Stockholm School of Economics. Together with my classmate Arvid Nygård, we're writing our master's thesis on how small and medium-sized enterprises (SMEs) can use AI to overcome barriers in public sector sales. Although SMEs make up 98.2% of all suppliers in the public sector, they only account for about half of the total payments. We want to understand how it can be made easier for more SMEs to participate in tenders and win more contracts through the use of AI.

Your anonymity will be preserved in the study, and all collected data will be handled confidentially in accordance with GDPR. If you wish, you will also receive a copy of the final study once it's completed!

Would you be interested in participating? It would be incredibly valuable to us. The interview takes a maximum of 60 minutes and can be done digitally or in whatever format suits you best. We're flexible with dates, but ideally, we'd like to schedule it sometime between February 10th and 28th.

Looking forward to your response!

All the best,

Appendix E. Interview and Participant Characteristics

Nr	Code	Time	Date	Place	Role	Gender
1.	A	1:07:52	2025-02-10	Online: teams	Bid manager	Male
2.	B	1:00:08	2025-02-11	Online: teams	Bid manager	Female
3.	C	49:04	2025-02-11	Online: teams	Bid manager	Male
4.	D	55:16	2025-02-12	Online: teams	CEO	Male
5.	E	1:08:01	2025-02-12	Online: teams	Bid manager	Male
6.	F	44:46	2025-02-13	Online: teams	CEO	Male
7.	G	50:12	2025-02-19	Online: teams	CEO	Male
8.	H	40:48	2025-02-21	Online: teams	Business Manager	Female
9.	I	51:24	2025-02-21	Online: teams	CEO	Male
10.	J	45:44	2025-02-24	Online: teams	Bid Manager	Male
11.	K	46:21	2025-02-26	Online: teams	Bid Manager	Female
12.	L	46:22	2025-02-28	Online: teams	CEO	Male
13.	M	51:54	2025-03-03	Online: teams	Bid Manager	Female
14.	N	54:04	2025-03-07	Online: teams	CEO	Male
15.	O	55:29	2025-03-12	Online: teams	Bid Manager	Male
16.	P	1:00:29	2025-03-13	Online: teams	Bid Manager & Business Coordinator	Female
17.	Q	50:55	2025-03-25	Online: teams	Bid Manager	Male
18.	R	30:12	2025-03-28	Online: teams	Bid Manager	Male

19.	S	46:25	2025-04-03	Online: teams	Bid Manager & Architect	Female

Minimum	30:12
Maximum	1:08:01
Average	51:20
Median	50:55

Appendix F. Interview Guide

Ethics

Participation in this study is entirely voluntary, and you have the option to pause or end the interview at any time without needing to provide a reason. You are also free to choose not to answer a question without offering any further explanation.

If you decide to withdraw from the study, all data collected from you will be deleted. In our research, which is part of our master's thesis in Management at the Stockholm School of Economics, both you and your employer will remain anonymous.

We will not disclose any information about other participants to anyone. We would like to ask for your permission to record the interview so that we can transcribe it later.

Do you have any questions before we continue?

Introduction

- Can you briefly tell us about yourself and your experience in public procurement?
- Can you briefly describe your current role?
- How do you use AI in your current role and in your work with selling to the public sector?

Adopting AI

- What motivated your organization to start exploring AI?
- What considerations were made before the decision to implement AI was taken?
- How was AI perceived and discussed within the organization before the implementation?
- Can you describe how AI was implemented in the organization?
- Can you describe how you worked on integrating AI into the organization and its processes in the long term?
- Did you perceive any issues of adopting AI, personally or among colleagues?
- Can you share if it was something particular that facilitated the AI adoption?

Effects

- What changes have you experienced from the AI adoption in your work with public sector sales?
- What changes have you experienced from the AI adoption in relation to the organization as a whole?
- Have you noticed any problems or negative effects?

Outro

- When you look back on your experience with AI adoption, what are the key lessons learned?
- Is there anything else you would like to share about your experience with AI adoption or anything else?

Appendix G. Example of Coding Process

I'm pretty rock'n'roll, and then I talked to our CEO and said that I need sharper tools than what we have. He said, we can have both if you want. And then we try AI. It's not harder than that.

But AI is basically just instead of XX (old tool) if you will. The procurement sites will still be there. I'll be submitting all the tenders, and all municipalities and regions will need to do so too. So no, it just felt fresher and more modern. Easier to understand. XX isn't ugly graphically, but it was very... yeah, clunky. It felt like there was cable programming behind it. They were very, very old-fashioned

They're probably going to come up with something, they have to, otherwise they'll lose their customers. And they've already started chasing. But we'll see what happens. So, we had to do something. I wanted sharper documents.

Codes:

Motivation: better tools

Consideration: brief, quick decision

Motivation: replace old tool

Public sales: rigidity

Motivation: simple functionality of AI

Motivation: rigid old systems

Motivation: improved bid-writing

Appendix H. Coding File

1st order concepts	2nd order themes	Aggregate dimensions	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
Simplifying tasks, responding to competition, and replacing outdated systems	Motivations of Adopting AI	Preliminary AI-adoption	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Informal, individual-driven adoption supported by flat structures and curiosity	Initiator(s) for adopting AI	Preliminary AI-adoption	X	X			X		X	X			X	X				X	X		X
Superusers and domain knowledge as drivers of adoption	Mobilization	Facilitators of AI adoption during AI engagement	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X		
Repeated knowledge sharing and demonstrations enabling adoption	Intellectual Diffusion	Facilitators of AI adoption during AI engagement	X	X		X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Experiential learning and self-leadership accelerating adoption	Individual Mastery	Facilitators of AI adoption during AI engagement	X		X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Habitual routines, distrust, and unclear value limiting adoption	Cognitive Barriers	Inhibitors of AI adoption during AI engagement	X	X	X	X				X		X	X		X		X	X	X	X	X
Fear of job loss, professional identity concerns, and broader societal anxieties	Emotional & Motivational barriers	Inhibitors of AI adoption during AI engagement	X	X		X				X		X	X		X	X	X	X	X		
Workload, data challenges, and lack of leadership	Organizational constraints	Inhibitors of AI adoption	X	X	X		X	X					X		X		X		X	X	X

support as barriers		during AI engagement																			
Centralized information, faster qualification, and productivity gains	Efficiency	Outcomes following the AI-adoption		**X**						**X**	**X**			**X**	**X**	**X**	**X**				**X**
Strategic engagement, higher bid quality, and improved well-being	Effectiveness	Outcomes following the AI-adoption		**X**	**X**	**X**	**X**	**X**	**X**	**X**	**X**	**X**	**X**	**X**		**X**	**X**	**X**	**X**	**X**	**X**
Loss of human voice, generic outputs, and overreliance risks	Negative externalities	Outcomes following the AI-adoption		**X**				**X**								**X**	**X**	**X**	**X**	**X**	**X**

Appendix I. Disclosure of AI Usage

AI tools were used in selected parts of the thesis process to support administrative tasks, language improvements, and translation, always with critical human oversight. The use of AI was in accordance with the Stockholm School of Economics' guidelines, and AI served as an aid rather than as a substitute.

For transcription, Klang.AI was used to transcribe interview recordings. This was approved by course director Karl Wennberg. Before uploading, all recordings were anonymized to remove personal information. Once transcription was completed, the audio files were deleted, and the transcripts were stored securely on OneDrive, following SSE's data management policies. Potential risks, such as transcription inaccuracies were managed by sending the transcript to the interview subject for approval, and text revisions were managed by manual review and critical judgment. AI assistance was also used to translate selected interview quotes and questions, as well as email outreaches from Swedish to English. These translations were carefully compared against the original Swedish versions to ensure that nuances and intended meanings were maintained. Using AI in this way contributed to increased efficiency, allowing more time to be spent on analysis and interpretation.

In the writing process, generative AI (specifically OpenAI's language models) was used to correct grammar, academic tone, structure, and readability of the text. This was approved by supervisor. Suggestions produced by AI were critically reviewed and manually edited to ensure that meaning, argumentation, and academic standards were preserved.

Prompt examples include:

> *"Can you help me correct the grammar and academic tone of this paragraph while keeping the original meaning intact?"*
>
> *"I need help shortening this section while retaining clarity and flow. Please suggest edits accordingly"*

Overall, the use of AI highlighted the importance of seeing these tools as supportive rather than decisive in the research and writing process. AI offered meaningful help with administrative tasks and improving the language in the thesis, but all core academic work including research design, reviewing literature and theory, interpretation of results, analysis, and conclusions was conducted independently by the authors.

Appendix J. Summary of Results

Aggregate Theme	Second Order Theme	Summary of Findings	Participants
Preliminary AI Adoption	Motivations of Adopting AI	AI was adopted to simplify and reduce time spent on public sector sales tasks. They also used AI to respond to market competition and improve operational efficiency by replacing outdated systems and integrating multiple supplier platforms into a single, streamlined solution.	A, B, C, D, E, F, G, H, I, J, K, L, M, N, O, P, Q, R, S
Preliminary AI Adoption	Initiators for Adopting AI	The early phase of AI adoption was informal and unstructured, often lacking official plans and marked by quick decision-making. Adoption was typically initiated by individuals, regardless of formal position, who raised awareness and encouraged use among colleagues. Flat organizational structures, decentralized decision-making, and active managerial interest in innovation supported this flexible and rapid adoption approach.	A, B, E, G, H, K, L, M, N, O, P, Q, R, S
Facilitators of AI Adoption During AI Engagement	Mobilization	Superusers with AI and data expertise inspired adoption. Domain-specific business knowledge, particularly in public bidding, helped contextualize AI use and improve results. Managing and expanding internal knowledge was seen as critical for sustaining adoption, while the absence of foundational expertise created challenges in early implementation.	A, B, C, D, E, F, G, H, I, J, K, L, M, N, O, P, Q,

Facilitators of AI Adoption During AI Engagement	Intellectual Diffusion	Repeated information sharing through meetings, digital channels, and informal discussions, along with demonstrations showing task-specific benefits, were critical for adoption. Peer support and an open environment for questions further lowered barriers to using AI.	A, B, D, E, F, G, H, I, J, K, L, M, N, O, P, Q, R, S
Facilitators of AI Adoption During AI Engagement	Individual Mastery	Building individual mastery of AI tools through experiential learning was key to adoption. Hands-on practice, easy access to AI tools, and organizational encouragement to experiment supported skill development. A culture of self-leadership and personal initiative further accelerated learning and integration into daily work.	A, C, D, E, F, G, H, I, J, K, L, M, N, O, P, Q, R, S
Inhibitors of AI Adoption During AI Engagement	Cognitive Barriers	Cognitive barriers to AI adoption included resistance to changing established routines, lack of trust in AI-generated content, and difficulties linking AI functionality to tangible work benefits. Without clear value or confidence in AI outputs, motivation to adopt new tools often weakened.	A, B, C, D, H, J, K, M, O, P, Q, R, S
Inhibitors of AI Adoption During AI Engagement	Emotional and Ethical Challenges	Emotional barriers to AI adoption included fears of job displacement, concerns about undermining professional identity, and feelings of imposter syndrome. Ethical worries about "cheating" by using AI and broader societal anxieties about control, truth, and technological overreach also influenced perceptions of AI.	A, B, C, D, H, J, K, M, N, O, P, Q

Inhibitors of AI Adoption During AI Engagement	Organizational Constraints	Organizational barriers included heavy workload that limited time for learning, lack of structured and accessible data, and insufficient managerial support. Unclear communication and leadership disengagement further slowed adoption efforts and reduced momentum.	A, B, C, E, F, K, M, N, P, Q, R, S
Outcomes Following AI Adoption	Efficiency	AI centralized scattered bid-related information, improving overview and organization. AI tools also accelerated opportunity qualification by enabling faster filtering and analysis of procurement documents. Additionally, AI-assisted drafting significantly reduced the time needed for bid writing, leading to major productivity gains.	B, H, I, L, M, N, O, S
Outcomes Following AI Adoption	Effectiveness	AI-driven efficiency gains enabled a shift toward more strategic activities, such as earlier buyer engagement and tailored outreach. Increased speed also allowed teams to manage more bids simultaneously while improving the quality and professionalism of submissions. Advanced use cases, like AI feedback loops, further enhanced bid quality. Additionally, greater efficiency contributed to reduced stress and improved work-life balance.	A, C, D, E, F, G, H, I, J, K, L, N, O, P, Q, R, S

Outcomes Following AI Adoption	Negative Externalities	Unintended challenges from AI adoption, including difficulties in maintaining a distinct human voice in bids and risks of submissions becoming too generic. Concerns were also raised about overreliance on AI outputs without sufficient quality control.	B, D, N, O, P, Q, R, S