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The Effectiveness of Artificial Intelligence in Public Procurement Corruption

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The Denotation

Name of student

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List of Abbreviations

AI- Artificial Intelligence

AI-ACT-AI-based anti-corruption

ALICE -Análise de Licitações e Editais (Analysis of Biddings and Call for Bids)

CGU- Comptroller General of the Union

GDP-Gross Domestic Product

GDPR-General Data Protection Regulation

ICO- Information Commissioner's Office

ICPC -Independent Corrupt Practices and Other Related Offences Commission

ISO- International Organization for Standardization

MARA -Mapeamento de Risco de Corrupção na Administração Pública Federal (Mapping Corruption Risk in the Federal Public Administration)

OECD- Organisation for Economic Co-operation and Development

OHCHR-Office of the United Nations High Commissioner for Human Right

RPA- Robotic Process Automation

SALER- Sistema de Alertas Rápidas (Rapid Alert System)

UN ECOSOC - United Nations. Economic and Social Council

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This Master's Thesis was prepared during the studies for the distance master's degree at Neapolis University and was approved on…..…………………………… [date of approval] by the members of the Examination Committee.

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Dedication

To my sister Kopano Dhlula; you may only be present in spirit, but I know how proud you would have been.

To my daughter; I hope I have made you proud.

To myself; Thank you for having the courage to take a leap of faith in pursuit of your goals.

Abstract

Public procurement is a major part of global GDP, making it very vulnerable to corruption. This has led governments to use Artificial Intelligence (AI) as a key tool for oversight. However, the shift from technical possibilities to real-world effects is often overlooked. This dissertation looks into the factors that influence how well AI-based Anti-Corruption Tools (AI-ACTs) work in public procurement. The effectiveness is assessed through the lens of the ISO 9000 standard, focusing on the extent to which planned anti-corruption outcomes are achieved.

The research uses an Explanatory Multiple-Case Study approach, relying on qualitative methods through Secondary Data Analysis. It examines three specific AI tools: ALICE and MARA in Brazil, and SALER in Spain. These examples create a comparison between a well-established AI environment in Latin America and a developing regulatory system under the EU AI Act. The study tests three hypotheses: (1) that transparency in algorithm design, (2) data quality, and (3) human oversight are key factors that affect AI effectiveness.

The results validate all three hypotheses. The findings show that AI greatly improves detection speed and volume, but its effectiveness is limited by institutional, legal and ethical factors. Transparency (H1) is necessary for legal acceptance, as black box systems encounter considerable judicial pushback. Data quality (H2) serves as a functional limit; biases in training data can reproduce existing administrative issues instead of resolving them. Lastly, human oversight (H3) is crucial for connecting digital alerts to corrective actions, turning algorithmic results into practical integrity measures.

The research concludes that AI is not a quick-fix but rather a socio-technical approach. AI functions as a decision-support tool, with its success relying on strong data governance, legal clarity, human oversight, closing skills gap and respect for human rights. Policy recommendations highlight the importance of explainable AI and breaking down organizational data obstacles to fully realize the benefits of digital oversight. Finally, This study offers a strategic guide for policymakers and future researchers aiming to establish tailored safeguards in the digital battle against public procurement corruption.

Keywords: *Artificial Intelligence, Public Procurement, Corruption Detection, ISO 9000, Algorithmic Transparency, Human-in-the-Loop, Alice, Mara, Saler*

Chapter I - Introduction

The rapid adoption of AI in the public sector is seen as a significant turning point for governance (Vasconcelos and Santos 2024, 110). However, as global public procurement spending continues to involve large amounts of public funds, it remains the government function most vulnerable to corruption. This is why the use of AI to tackle public procurement corruption in the public sector is on the rise (Adobor and Yawson 2023, 355). These AI-based Anti-Corruption Tools (AI-ACTs) referring to algorithms designed specifically for corruption detection, represent this rising trend (Resimic 2025, 24). In spite of this rise, a number of factors have been recognized that need to be addressed when implementing AI (Jankovski et al. 2025, 13). Therefore, grasping its transformative potential in public procurement requires a closer look at its technical, legal, and ethical complexities that hinder its real-world effectiveness.

Brazil and Spain are key examples for studying how systemic corruption affects the use of AI in the public sector. In Brazil, ongoing corruption involving top government officials and large companies has severely damaged institutional trust (Velascocoa 2020, 2). This issue is highlighted by the 2024 Corruption Perceptions Index (CPI), where Brazil received a score of 34 out of 100, a recorded lowest ever, indicating a major drop in the perceived integrity of the public sector (Transparency International 2025a, 5). As a result, the country’s long-term efforts to implement AI in public administration have turned into a continuous struggle, marked by a constant conflict between the potential of technology and the weakness of governance systems (Zick et al. 2024, 1).

Spain serves as a key European contrast; its push for AI adoption is driven by the need to tackle high-level, systemic corruption (Jiménez Sánchez 2023, 4). While Spain outperformed Brazil, its CPI score of 56 out of 100 in 2024 still indicates ongoing institutional risks (Transparency International 2025a, 40). Despite these internal challenges, Spain has become a significant player in shaping AI policy in both the European Union and Latin America. Analysis of secondary sources shows that major issues in Spain's implementation reflect the institutional difficulties found in Brazil (Jiménez Sánchez 2023, 5). Together, these countries offer a dual-hemisphere view on whether AI can genuinely serve as a transformative tool against corruption or whether it simply adopts the biases of the systems it aims to change.

This dissertation explores the critical moderating factors namely transparency, data quality, and human oversight; as determinants of whether AI serves as a powerful tool for public procurement anti-corruption efforts or a hollow technological promise

The existing discourse focuses on the technical capabilities of AI; this research adopts a socio-technical perspective, suggesting that the core problem is the "implementation gap" in anti-corruption technology. The theoretical potential of AI to detect corruption patterns is immense; its practical application is not merely a coding failure but an institutional one. This failure is frequently rooted in a lack of transparency, poor data quality, and the absence of meaningful human oversight (Andersson, Arbin, and Rosenqvist 2025, 128).

Accordingly, this study is guided by the following research question:

What factors moderate the real-world effectiveness of Artificial Intelligence (AI) tools used for detecting corruption in public procurement?

By examining these moderators, this research aims to identify ways to address unclear algorithms and professional doubts hindering the use of AI as an anti-corruption solution in public procurement. To move beyond subjective measures of success, this study evaluates effectiveness through the lens of the ISO 9000 standard, defining it as the extent to which planned anti-corruption activities are realized and intended results are achieved (ISO 2015).

To investigate this question, the study tests three primary hypotheses:

H1: Transparency in algorithmic design moderates the relationship between AI tools and their real-world effectiveness in detecting public procurement corruption.

H2: The quality of the data used moderates the relationship between AI tools and their real-world effectiveness in detecting public procurement corruption.

H3: The presence of human oversight mechanisms moderates the relationship between AI tools and their real-world effectiveness in detecting public procurement corruption.

According to the OECD (2025), despite reviewing 200 AI use cases, only 43% reach full implementation, which explains the institutional failures mentioned earlier. The focus of this study is driven by the urgent need to ensure that the implementation of AI tools is no longer subject to pilot purgatory but achieves global adoption. This study provides empirical case-study evidence from Brazil and Spain, moving beyond theoretical warnings to practical moderation effects. It offers a roadmap for governments, policymakers, and anti-corruption organizations by identifying why some AI tools achieve full implementation in certain contexts while others struggle during implementation. In essence, this study offers insights to enhance global efforts in fighting public procurement corruption through the effective integration of AI tools.

This dissertation is framed within the parameters of Public Procurement and Anti-Corruption technology. It distinguishes itself from broader AI research by focusing on AI-ACTs. It examines the socio-technical obstacles that hinder technical alerts from turning into corrective measures.

The structure of this study begins with an exploration of the global challenges of public procurement corruption, the transformative potential of AI, and the theoretical foundation for the three moderating hypotheses. It is followed by details on the qualitative research, case study methods, and cross-case analysis of the ALICE, MARA, and SALER systems. Next, the study synthesizes findings with secondary sources against the hypotheses and global trends. Finally, it summarizes key issues, addresses study limitations, and offers policy best practices.

Chapter II – Literature Review

2.1. The Global Challenge of Corruption in Public Procurement

Corruption is a global reality, commonly defined as the abuse of entrusted power for private gain (Adam and Fazekas 2021, 3; Köbis, Starke, and Rahwan 2022, 3; Fitriyanah and Yanti 2025, 1561). This widespread misconduct manifests in diverse forms, including bribery, fraud, extortion, embezzlement, nepotism, kickbacks, and unlawful beneficial ownership (Adam and Fazekas 2021, 2; OECD 2022, 13; Fitriyanah and Yanti 2025, 1561). The consequences of corruption are deemed to be devastating, as it erodes public trust, weakens both the functioning of public institutions and the rule of law, and diverts public funds (Adam and Fazekas 2021, 6). In addition, its direct costs include significant financial losses through misallocations or higher expenses, often resulting in inflated prices, lower quality of goods or infrastructure, and a failure to meet contract standards (OECD 2022, 10). Furthermore, corruption perpetrated by corrupt elites, who design and control the system, poses significant challenges to anti-corruption efforts (Adam and Fazekas 2021, 6).

Public procurement, among these challenges, is the buying of goods, services, facilities, and construction works from public or private entity suppliers (Potin et al. 2023, 1; Andhov, Darnall, and Andhov 2025, 2). It is a comprehensive government activity involving four key elements: supplies, works, facilities (utilities), and services. This process is not limited to buying, but includes leases, rentals, and various contract types to obtain goods and labour (Hidayat, Syaukat, and Harianto 2023, 2861). Beyond mere transactions, procurement helps to meet social, economic, and technological goals (Ribeiro et al. 2018, 4; Hidayat, Syaukat, and Harianto 2023, 2861), while also supporting businesses (Patil 2017, 391). As a fundamental mechanism of modern governance, governments globally allocate about US$9.5 trillion annually for public contracts, which accounts for roughly 15% to 22% of GDP in many developing nations (World Bank 2020).

Corruption in public procurement significantly hinders good governance and fair service delivery. It appears in various ways, including bid rigging, collusion, and conflicts of interest (Ayobami et al. 2023, 131). For context, bid rigging occurs when competitors collude to decide who will win a bid, thereby eliminating fair competition and driving up procurement costs. Research further shows that collusion frequently happens between suppliers or between officials and suppliers, damaging the competitive nature of the procurement process. This results in contracts being awarded to a limited number of companies, a situation worsened by weak oversight. Conflicts of interest worsen these problems, as decision-makers may use their power to benefit from businesses with which they are secretly connected, highlighting even deeper systemic weaknesses (Ayobami et al. 2023, 131).

According to Sharma, Sengupta, and Panja (2019), the public procurement environment is complex, involving significant public spending and a variety of stakeholders, which makes it vulnerable to corruption. Procurement vulnerabilities include structural weaknesses, such as complicated processes and insufficient organizational controls against corruption. Frequent interactions between public officials, businesses, and third parties, meanwhile, create opportunities for misconduct, often manifesting as collusion or other complex schemes that traditional audits cannot effectively detect. These procedural flaws are further worsened by organizational and behavioral weaknesses, such as the acceptance of improper practices within institutions, a lack of knowledge among staff, and widespread unethical behavior. Sharma asserts that this web of weaknesses has allowed the system to be exploited, leading to negative outcomes like cost and time overruns, poor project performance, and project failures (Sharma, Sengupta, and Panja 2019, 957).

Further research by Abdou et al. (2022) identified the duration of submission periods and a need for real-time monitoring (a key issue during the COVID-19 era) as critical public procurement corruption vulnerabilities. Their study found that a key systemic weakness is the absence of digital infrastructure, necessitating the urgent implementation of e-procurement systems and machine-readable public contract databases to reduce corruption. The authors not only recommended e-procurement systems that run metrics and utilizes AI for future initiatives (Abdou et al. 2022, 11-12), but previous scholars like Neupane et al. (2012) had also explored how public e-procurement tools could reduce corruption in the public procurement process. This is shown in Figure 1 below:

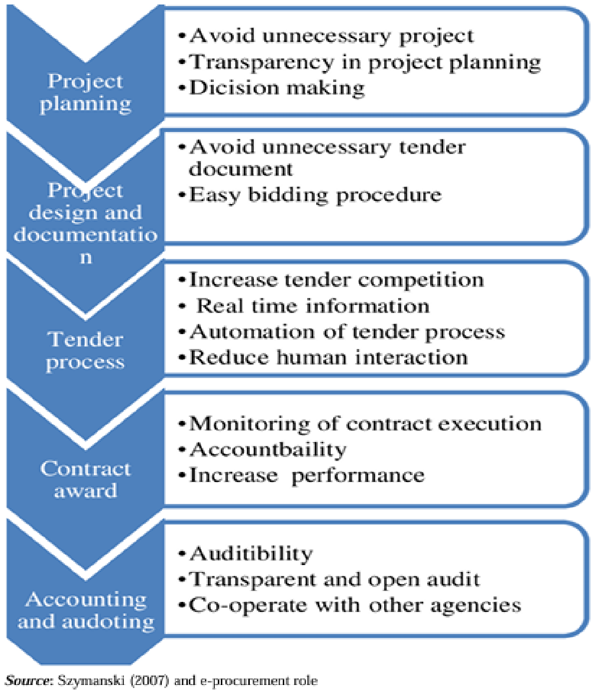

Figure 1: Anti-corruption Role of E-Procurement in Procurement Process Source: Szymanski 2007, cited in Neupane et al. 2012, 307

Overall, the fight against corruption has traditionally involved a combination of systemic reforms, such as strengthening legal frameworks and increasing transparency, and behavioral approaches, like encouraging ethical conduct, to create a synergy that reinforces compliance (Komakech 2024, 145-46). Other conventional methods, such as organizational audits and whistleblower systems, while important, tend to respond to corruption rather than prevent it proactively, which limits their ability to discourage possible wrongdoing (Ayobami 2023, 131). Moreover, traditional detection methods have significant limitations. Human monitoring techniques, for example, frequently fail because actors continually find ways around them. Similarly, rule-based systems cannot detect evolving or sophisticated schemes like money laundering (Del Rey-Puech, Balabanova, and McKee 2025, 1342). In countries with weak governance, existing law enforcement mechanisms may be insufficient, necessitating preventative actions to supplement enforcement (OECD 2022, 13). Critically, traditional methods fall short against modern schemes, making innovative solutions essential for public procurement anti-corruption efforts.

2.2. AI and Anti-Corruption Opportunity

This is where AI, defined as the use of computers to mimic human intelligence for problem-solving, reasoning, and pattern recognition (Guida et al. 2023, 2), presents a transformative opportunity to enhance public procurement oversight (Ayobami et al. 2023, 132). According to Transparency International (2025b, 3), AI is expected to handle large amounts of data rapidly, while minimizing human errors and providing timely responses. Thus, AI contributes to anti-corruption efforts by enhancing service delivery, reducing the risks of human abuse, and enforcing compliance. It has particularly strong potential to achieve specific goals, such as reducing corruption and expenses while enhancing transparency (Gadour 2024, 12).

In essence, the rise of AI has brought significant changes to decision making, offering improved capabilities in prognostic analytics, optimization, and automation (Menke, Gomes, and Xavier 2024, 277). This remarkable progression is shown in Figure 2 below, tracing the path from early AI in the 1950s to today's generative AI models.

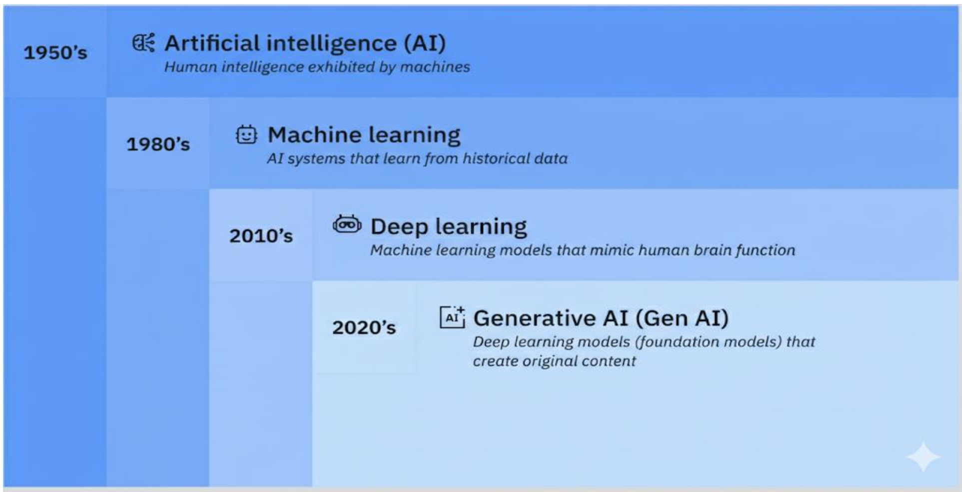

Figure 2: How Artificial Intelligence, Machine Learning, Deep Learning, and Generative AI Are Related
Source: Stryker and Kavlakoglu 2024.

The significance of this evolution for procurement lies in the modern machines' learning capability to build models that predict and make decisions based on complex data (Stryker and Kavlakoglu 2024). Recent studies confirm AI's significant impact, particularly in areas like procurement integrity and fraud detection (Zinnbauer 2025, 7). Machine learning models can uncover anomalies or malfeasance. An anomaly generally describes deviations from expected behavior in public procurement processes, such as unusual purchases or transactions that may signal irregularities. Malfeasance, meanwhile, encompasses various types of misconduct, including favoritism, collusion, and cost overruns (Schneider dos Santos et al. 2025, 14-15). Deep learning, a subset of machine learning, employs multilayered neural networks known as deep neural networks; better mimic the intricate decision-making processes of the human brain (Stryker and Kavlakoglu 2024). These deep learning models excel at pattern recognition, using algorithms highly effective at uncovering complex patterns hidden in large volumes of unlabeled and unstructured data (Schneider dos Santos et al. 2025, 12). These capabilities enable the flexible adjustment of red flag indicators, making it harder for criminals to manipulate the system (Zinnbauer 2025, 7).

Moreover, AI-driven contract analysis tools can identify risks and inconsistencies before project initiation (Ayibam 2023, 411) and enable officials to shift from reactive measures to predictive insights (Ayobami et al. 2023, 132). As a result, identifying anomalies in public procurement can enhance buying power, ultimately improving citizens' quality of life through the proper use of public funds (Niessen, Paciello, and Fernandez 2020). In practice, AI's influence has evolved both politically and within corporate settings, as it offers new techniques for transparency and accountability while also providing significant opportunities for anti-corruption efforts (Transparency International 2025b, 3).

2.3. Factors that influence AI's effectiveness in public procurement

This section now turns to defining AI's potential effectiveness; the core outcome variable, measured via ISO 9000 standards as the extent to which planned anti-corruption activities achieve intended results (ISO 2015), examining the institutional factors that influence AI's success. The literature identifies three critical factors affecting AI's effectiveness:

2.3.1. Algorithmic Transparency

The growing reliance on algorithmic systems; defined as self-contained, step-by-step operations for calculation, data processing, and automated reasoning signify a fundamental change in government functions, especially those aimed at combating corruption (Association for Computing Machinery 2017, 1). Studies have found that AI is increasingly utilized to examine large data sets, process natural language (for example, in procurement contracts), identify conflicts of interest, and automate decisions to reduce corruption risks (Ageh 2019, 567, 582; Ponti, Cerrillo-i-Martínez, and Di Mascio 2021, 110). Yet, the success of these AI-ACT tools hinges significantly on algorithmic transparency, a crucial element shaping their reliability, fairness, and overall effectiveness in public procurement. Indeed, transparency must be better integrated at every stage of AI development, from initial design to auditing, rather than treated as an afterthought (Kossow, Svea, and Jenkins 2021, 18)

A key theme in the literature is the inherent lack of clarity surrounding government algorithms, with some researchers describing them as “black boxes” that are hard for outsiders to understand, thereby limiting insight into how decisions are made (Pasquale 2015, 3; Burrell 2016, 1). This opacity, referring to the public or officials' inability to know which algorithms are employed, how they function, and what basis underpins decisions, primarily arises from the complexity of advanced machine learning models (Ponti, Cerrillo-i-Martínez, and Di Mascio 2021, 112). Such opacity presents direct threats to both AI success and public sector values. It undermines auditability and substantially heightens the risk of bias (Odilla 2024, 30). In complex systems like neural networks, this absence of transparency shifts power from human evaluators to data-driven models, making it difficult for public officials to justify procurement decisions during legal or ethical scrutiny (Mutangili 2025, 50). Moreover, such opacity makes it particularly challenging to detect harmful code or data tampering, thereby reducing accountability for corrupt actors (Transparency International 2025b, 10).

Algorithmic transparency remains an essential requirement for reliable and effective AI (Kossow, Svea, and Jenkins 2021, 18). It enhances AI's effectiveness across several key areas, beginning with procurement and design. The authors encourage policymakers to adopt strategies that boost transparency during procurement, perhaps favoring explainable statistical approaches over opaque black-box systems. Transparency also proves vital for reducing bias and discrimination. Bias may arise from algorithm designers or, more commonly, from low-quality, outdated, or poorly curated data that perpetuates existing inequalities (Ponti, Cerrillo-i-Martínez, and Di Mascio 2021, 113). Reinforcing this, Odilla (2024, 30-31) positions transparency as a key strategy to eliminate systematic bias. This view aligns with Transparency International's (2025b, 10) warning that opacity in training datasets makes it difficult to identify and correct such inequalities.

Transparency further shapes both the quality of decisions and human accountability. Research shows that algorithm type and features directly affect the quality of human judgments (Janssen et al. 2020, 490). Their findings warn against indiscriminate reliance on data-driven models like machine learning for decision-making, as they often reduce explainability compared to simpler rule-based algorithms. Explainable AI (XAI) here refers to a machine learning model's capacity to provide clear explanations for its predictions or choices (Sampaio et al. 2024, 54), while rule-based approaches derive rules from data to predict outcomes or make decisions (Abediniangerabi et al. 2022, 544). Although explainability often yields more accurate decisions, Janssen et al. clearly state that it alone does not guarantee transparency or improved decision-making, signaling a persistent risk that even partially explainable algorithms may still conceal errors from users (Janssen et al. 2020, 490).

The demand for algorithmic transparency stems from essential ethical and legal requirements. Legal due process requires XAI (Sanchez-Graells 2021, 10). Since analyzing data to uncover corruption often implicates basic rights, like data protection and privacy; systems must comply with legal standards guaranteeing the right to information about automated decision-making (Ponti, Cerrillo-i-Martínez, and Di Mascio 2021, 114). Consequently, interdisciplinary approaches are essential, blending technical expertise with policy frameworks to audit, identify, and correct algorithmic bias while upholding legitimacy (Ayobami et al. 2023, 132; Odilla 2024, 30-31).

Ultimately, by effectively combining advanced technology with robust ethical governance, algorithmic integrity offers a practical path to reimagining public procurement as a transparent, fair, and resilient system. In the end, transparency ensures that machine intelligence supports human accountability, thereby boosting efficiency and public trust while systematically reducing corruption risks in public financial management (Ayobami et al. 2023, 137).

2.3.2 Data Quality in AI systems

Governments are increasingly adopting sophisticated algorithmic systems, especially those powered by machine learning, to analyze vast data volumes for detecting irregularities and corruption cases in public procurement (Ponti, Cerrillo-i-Martínez, and Di Mascio 2021, 110; Ageh 2019, 568). By processing aggregated and interconnected data, these systems aim to identify subtle patterns or profiles indicative of conflicts of interest or fraud patterns that would otherwise go missed (Ponti, Cerrillo-i-Martínez, and Di Mascio 2021, 110).

The primary challenge in using AI for anti-corruption efforts is the data itself: obtaining valid and reliable information to reveal a true picture of corruption, which remains often hidden (Köbis, Starke, and Rahwan 2022, 5; Forjan, Köbis, and Starke 2024, 245). This embodies the "garbage in, garbage out" (GIGO) principle, stating that AI's effectiveness depends heavily on the accuracy and completeness of its training data (Sanchez-Graells 2021, 8; Adam and Fazekas 2021, 11). Indeed, poor data quality, along with inconsistent publication practices, creates significant obstacles to AI integration while undermining its accuracy and reliability (OECD 2024, 74). For instance, Soylu (2022, 8) notes that data providers often release information that is incomplete, poorly formatted, or difficult to analyze, thereby limiting further analysis.

Consequently, AI's success hinges directly on the quality of the data it processes (Adam and Fazekas 2018, 24). In Albania, for example, the government's ambitious 95% AI-based model failed due to particularly acute needs for robust data management and high-quality data, a major problem in Albanian public administration. Such research also highlights how data issues have prompted urgent calls for policymakers to improve procurement database management and scope, steps necessary to enable AI implementation (Sanchez-Graells 2021, 12; Sqapi 2024, 264, 266-67).

Without a doubt, when AI systems are trained on flawed, incomplete, or biased data, they risk reinforcing existing biases within procurement frameworks (Uduwage-Don et al. 2023, cited in Ayobami et al. 2023, 132). Such systematic bias undermines AI fairness, as humans embed their values in the data they collect, often favoring one group's values over those of others (Hickok 2022, 1216). Consequently, AI-ACTs often reflect societal inequalities and biases from previous anti-corruption initiatives, thus perpetuating historical injustices. For instance, a system might flag Black women from lower educational backgrounds as suspicious candidates, revealing how data reflecting past discrimination leads algorithms to produce statistically valid yet discriminatory outcomes (Odilla 2024, 30).

Ultimately, the success and reliability of AI against corruption in public procurement depend largely on both the quality of and ethical management over its training data. Research indicates that both training and testing data must be high quality, appropriate for the task, and ethically sourced (Kossow, Svea, and Jenkins 2021, 18). Accordingly, scholars urge greater focus on improving data quality, including through semi-automated methods and techniques designed to address such problems (Ezeji 2024, 69). This emphasis on trustworthy data governance and robust data management proves crucial to ensuring AI truly benefits the public while minimizing harm, demanding clear regulations to uphold accountability and fairness (Ayobami et al. 2023, 135).

2.3.3. Human Oversight and Capacity

Although AI has great potential to improve efficiency and reduce corruption in public procurement, its effective use and overall success depend heavily on strong human oversight and institutional capacity. The literature's main takeaway is that governance in the digital era needs a balanced strategy: fully utilizing AI’s powerful capabilities while preserving human oversight (Mutangili 2025, 54). Sanchez-Graells (2021, 3) argues that AI systems should enhance current oversight mechanisms rather than replacing the institutional checks that regulate government spending. Thus, the key challenge for policymakers is to ensure that AI-driven solutions prioritize the public good, rather than merely optimizing financial results without considering ethical and social implications (Mutangili 2025, 54).

Effective human oversight mechanisms play a vital role in the relationship between AI and corruption-detection effectiveness. Experts strongly advocate for a “human-in-the-loop” approach, in which human participation is essential to build public trust and ensure ongoing engagement (Forjan, Köbis, and Starke 2024, 245; Sanchez-Graells 2021, 10). Yet, the design of this oversight matters, as the human element can also introduce new governance risks. Most AI-ACTs are created primarily to support human efforts in investigating suspicious cases, but this often leads to human overload and insufficient attention to algorithmic insights (Odilla 2023, 382). For instance, early machine learning models analyzing over two million Colombian public procurement contracts from 2011 to 2015 proved beneficial to authorities, primarily in prioritizing contracts for auditing and monitoring. This demonstrates that AI’s value lies in guiding human focus and preventing overload, thereby enhancing oversight effectiveness (Gallego, Rivero, and Martínez 2021, 374-75).

Notably, the successful implementation of AI in government relies heavily on a public administration's ability and willingness to embrace such technologies (Budak and Škrinjarić 2024, 40). However, a significant institutional capacity gap, often caused by insufficient skilled personnel acts as a detrimental factor, thus, greatly restricting AI's potential benefits. Government agencies frequently lack staff with the necessary skills to engage in AI research and development. Even when developers supply code, public officials often find themselves “unable to assess technological design” resulting in the struggles to develop AI (Rowe and Prior 2022, 344). Similarly, a study in Albania revealed that the main systemic issue was a substantial institutional capacity gap due to insufficient skilled personnel, which rendered advanced AI tools ineffective, despite their technical potential (Sqapi 2024, 266-67).

In contrast, studies warn that simply including human involvement is not enough. The human element can actually heighten the risk of corruption by diffusing responsibility and enabling individuals to blame “faulty” AI systems when errors occur (Transparency International 2025b, 11). Therefore, strong governance and political will are essential; a weak institutional framework can make even the most advanced AI tool ineffective (López-Iturriaga and Sanz 2018, 994). Ultimately, the future of AI in public financial management will depend not just on the technology itself, but also on commitment to organized, effective human oversight and strategic resource allocation to build human capacity (Sanchez-Graells 2021, 12–13).

Chapter III: Research Methodology

This chapter outlines the research framework developed to address the study's main research question. The research design first defines the main aims, then provides a thorough explanation of the qualitative methodology employing a case study approach. Case studies from Brazil and Spain provide relevant data to identify documented AI-ACTs in public procurement management.

3.1. Research Design

The core structure of this study is based on an explanatory multiple-case study design, utilizing a qualitative approach. It was selected to fill a significant research gap: the absence of empirical analysis examining the combined and comparative moderating effects of institutional factors on AI.

This multiple-case study method enables the researcher to gain the depth needed to explore complex organizational dynamics. As Adams et al. (2022) state, this method is well-suited for achieving a thorough understanding of complex systems that cannot be easily separated from their context. Therefore, this study allows for a detailed examination of how institutional frameworks, human decisions, and legal constraints, beyond just technical code impact AI performance in real public procurement environments. Here, effectiveness follows ISO 9000 standards, defined as “the extent to which planned activities achieve intended results” (ISO 2015).

As Goundar (2012, 19) emphasizes, a qualitative research approach aims to reveal how people or organizations perceive and think about a specific topic, making it ideal for examining the socio-technical complexities of anti-corruption tools. To carry this out, the study employs secondary data analysis, particularly comparative document/case analysis, as its main method. This method entails a thorough examination of existing documents and case studies without any evidential influence. By concentrating solely on documented AI-based anti-corruption tools, this research can analyze the “how” and “why” of complex issues within their particular real-world settings, a process deemed robust by Yazan (2015, 148) and Adams et al. (2022). In the end, this design supports cross-case analysis, which is crucial for analyzing how the three moderating factors interact across various geographical and institutional contexts to produce different results in corruption detection.

3.2. Sampling and case selection

The chosen countries are regarded as prominently affected by public procurement corruption (Odilla, 2024; Jiménez Sánchez, 2023). Brazil offers a mature AI anti-corruption ecosystem with robust transparency laws (Odilla (2024, 11), while Spain serves as a strategic benchmark for European AI policy and regulatory compliance under the EU AI Act (Ruvalcaba-Gomez 2025, 6).

The unit of analysis includes three specific AI ACTs: ALICE, MARA (Brazil), and SALER (Spain). The study relies on Secondary Data Analysis, concentrating on a detailed document analysis of official records and technical performance reports. These purposively sampled tools illustrate developing and transitional economies that are making strides to advance AI adoption against corruption.

3.3 Ethical Approval

In accordance with the guidelines of the Cyprus National Bioethics Committee and Neapolis University Pafos, this research does not involve human participants, interviews, or the collection of non-public personal data. Since the study relies exclusively on publicly available secondary documents and official government portals, it is exempt from full Bioethics Committee review. All data sources are cited in compliance with academic integrity standards.

3.4. Data Collection and Analysis Process

Data collection involved a systematic secondary analysis of official government white papers, policy reports (OECD, EU), and academic records. The research was conducted through academic databases (Google Scholar, EBSCOhost), web search engines using keywords such as “public procurement,” “corruption,” “Artificial Intelligence,”’ “ALICE bot Brazil,” “SALER AI,” “MARA AI,” and “AI public procurement corruption”, from November 2025 to January 2026.

Analysis is performed using thematic analysis, guided by three deductive codes based on the research hypotheses: (1) Transparency, (2) Data Quality, and (3) Human Oversight.
As Adams et al. (2022) suggest, this leads to the final stage of cross-case synthesis, where findings from Brazil and Spain are systematically compared to identify which factors serve to validate or contradict the hypotheses, providing actionable insights for context-specific institutional safeguards.

Chapter IV - Presentation of data /Results

The main goal of Chapter III was to create the methodological framework and the qualitative, explanatory multiple-case design needed to explore the research question. This chapter shows the empirical results that came from that framework, proving that the systematic data collection and analysis methods outlined in the previous chapter were applied.

4.1. Case Study: Brazil

4.1.1. Brazil's Public Procurement Landscape

The foundation of public administration in Brazil is found in Article 37 of the Constitution of the Federative Republic of Brazil (CF). This article requires that Public Administration follow key principles: legality, impersonality, morality, publicity, and efficiency (Jankovski et al. 2025, 2). Today, AI has emerged as an essential tool for maintaining these principles, offering opportunities to improve the quality of services and resource-management efficiency (Jankovski et al. 2025, 3).

Public procurement plays a significant role in the Brazilian economy, comprising about 12% of national GDP (Brasil 2022, cited in Cabral et al. 2025, 204). This substantial economic role positions procurement at the heart of Brazil's commitment to the United Nations' 17 Sustainable Development Goals (SDGs), particularly Goal 12 Target 7, which emphasizes sustainable public procurement (SPP) practices (UN 2015; Tribunal de Contas da União n.d.). These practices represent public policies aimed at promoting economic efficiency, social justice, and environmental protection. However, implementing these policies necessitates coordinating a complex array of technical, financial, and human resources (Cabral et al. 2025, 204).

Despite its crucial role, the Brazilian procurement system suffers significant losses due to widespread corruption and poor coordination. Corruption in procurement contracts raises costs by 20% to 30% above expected prices, resulting in annual losses of approximately 200 billion reais (Lyra 2022, 1). This reflects a broader global pattern where 2% to 5% of global GDP is lost to money laundering and corruption, which undermines public services, hinders private sector growth, and bolsters organized crime (Velasco et al. 2020, 2).

The size and complexity of the Brazilian federation create major challenges. These challenges arise from difficulties in defining the scale of public contracts owing to insufficient inter-federative coordination when compiling national databases. This federal structure separates transparency over spending on bids and contracts, which complicates obtaining a comprehensive view of public expenditure (Fenili 2023, 73). Additionally, the procurement framework is often viewed as complex and restrictive, leading officials to adhere to rigid “reverse-bidding” methods that discourage innovation and thorough project evaluation (Langevin, Fassio, and Pigot 2022).

4.1.2. ALICE Tool (Analyzer of Bids, Contracts, and Notices)

To address these challenges, Brazil has incorporated AI into public management to transform both the evaluation of public policies and citizen services (Vasconcelos and Santos 2024, 110). Central to this initiative is the ALICE (Análise de Licitações e Editais) tool; Analyzer of Bids, Contracts, and Notices (Odilla 2023; OECD-OPSI 2024). Created by the Office of the Comptroller General of the Union (CGU) in 2014, ALICE aims to assist auditors both in preventing and detecting corruption in federal bidding documents (Menke, Gomes, and Xavier 2024, 278). The tool functions by cross-referencing procurement information with 27 government databases through network analysis algorithms (Ayibam 2025, 61).

ALICE operates through a structured process, beginning with automated data collection and culminating in human oversight, thus ensuring a smooth transition from raw data to actionable intelligence. First, the system's algorithms automatically collect data from key sources, including the Federal Government Procurement Portal (Compras.gov.br), the Banco do Brasil Procurement Portal, the Caixa Econômica Federal Procurement Portal, and the Federal Official Gazette. After data collection, AI employs advanced text mining and data analysis methods to examine procurement documents and detect risk indicators like fraud, irregularities, and violations of Brazilian laws and regulations. Following analysis, the system automatically generates alerts for identified risks. These alerts populate a dedicated database and generate specific investigative tasks for human auditors, who then conduct targeted investigations and liaise with purchasing unit managers to resolve issues, striking a balance between machine efficiency and human judgment (Menke, Gomes, and Xavier 2024, 278-79).

Through Robotic Process Automation (RPA), ALICE enables continuous auditing. The ALICE bot assists auditors by analyzing tenders, bid submissions, and public contracts, flagging potential issues like embezzlement and anti-competitive behavior to notify assessment teams before final procurement decisions (Nicaise and Hausenkamph 2025). In 2023, the tool evaluated 190,923 acquisitions, generating 203 audit cases valued at R$27 billion (OECD-OPSI 2024). By early 2024, ALICE's interventions had suspended more than R$9.7 billion in questionable purchases (Menke, Gomes, and Xavier 2024, 279)

Studies show a clear link between ALICE alerts and procurement actions. A 1% rise in alerts from the previous month is associated with a 0.389% increase in procurement notices, suggesting that managers respond quickly to AI-driven monitoring to mitigate risk (Menke, Gomes, and Xavier 2024, 284). This enhancement led to a 30% decrease in financial losses among audited cases and reinforced protections for public funds (Nicaise and Hausenkamph 2025).

Despite these achievements, full AI integration faces substantial obstacles. For instance, ALICE's success depends heavily on data standardization, requiring all public organizations to adopt consistent data formats (Ayibam 2025, 61). Without this, cross-referencing capabilities are compromised. Additionally, many Brazilian government agencies struggle with outdated technological infrastructure unable to support contemporary machine learning demands. This inadequate infrastructure also poses risks to information security and data integrity (Jankovski et al. 2025, 9).

Brazil is also navigating complex legislative development to balance AI ethics and data privacy with existing legal frameworks. A major obstacle remains judicial acceptance, as Brazilian courts have often rejected algorithmic outputs as valid legal evidence (Ayibam 2025, 61). This conflict between technological progress and legal customs reached a pivotal moment in the significant case REsp 1.878.959, where the Superior Court of Justice blocked an AI-based bidding platform. The court ruled that the provider's refusal to share its scoring algorithm, which the vendor claimed was a trade secret, led to a black box method that seriously breached the constitutional principle of administrative transparency (Ayibam 2025, 63). Beyond transparency and evidentiary issues, all AI systems in the public sector must comply strictly with the General Data Protection Law (LGPD) to protect sensitive judicial data, ensuring that the pursuit of efficiency does not undermine citizens' fundamental rights (Jankovski et al. 2025, 13).

Ethical AI use faces additional risks from algorithmic bias, as systems may perpetuate unfair patterns embedded in flawed historical data (Jankovski et al. 2025, 13). This problem is worsened by severe shortages of AI experts in Brazilian public institutions, which cannot compete with private-sector salaries (Vasconcelos and Santos 2024, 119; Jankovski et al. 2025, 10). During ALICE's initial rollout, ‘captcha’ challenges on government portals required temporary human intervention until automated solutions were developed (OECD-OPSI 2024). Compounding these technical issues, cultural resistance remains strong: many civil servants perceive AI as a threat to their job security and established power dynamics, making them reluctant to pursue essential training (Vasconcelos and Santos 2024, 116, 119; Jankovski et al. 2025, 12).

4.1.3. The MARA System (Mapping Corruption Risk in the Federal Public Administration)

Developed between 2014 and 2015 by the CGU, MARA (Mapeamento de Risco de Corrupção na Administração Pública Federal) originated as a master's dissertation project in computer science designed to address a critical organizational challenge: severe staffing shortages in the intelligence unit responsible for background checks (Odilla 2024, 12–21). MARA sought to automate decision-making and minimize human bias through machine learning, delivering faster, more precise corruption prevention than manual methods (Odilla 2024, 21).

MARA operates as a machine learning tool that calculates corruption risk scores for civil servants. Users input a social security number to receive a probability score indicating that person's likelihood of engaging in “corrupt” behavior, displayed on a simple gauge (Aarvik 2019, 8). MARA's core strength lies in scalable risk scoring for understaffed units, analyzing over 100 factors (salary, connections, networks) through Adaptive Lasso and Ridge regression, achieving 81% precision and 83% accuracy, ideal for resource-constrained teams (Odilla 2024, 12). By ranking individuals according to their potential for corrupt behavior, whilst considering career history and project participation, this tool provides early warnings of misconduct (Nicaise and Hausenkamph 2025).

Additionally, combining diverse data sources like business connections, electoral contributions, enables the CGU to conduct background checks infeasible at manual scale. MARA earned international recognition as a pioneering example of data-driven corruption prevention (Odilla 2024, 12). However, MARA's success hinges critically on data quality. Political affiliation data from the Electoral Court was frequently outdated or required extensive cleaning to resolve inconsistencies and missing values (Odilla 2024, 28). Similarly, sanctions data and electoral donation records suffered timing and funding discrepancies. These technical challenges indicate that the effectiveness of AI in predicting corruption is closely linked to the dependability of a country's core databases

A critical limitation arises because MARA was trained on civil servants previously caught and penalized for corruption (Nicaise and Hausenkamph 2025). This creates a “ground truth” dilemma: the model only captures detected corruption, potentially overlooking undetected corrupt activities. Consequently, MARA over-target agencies with strong internal controls while ignoring corruption in departments where investigations are less common (Nicaise and Hausenkamph 2025; Köbis, Starke, and Rahwan 2022, 5).
Moreover, the algorithm's design incorporated subjective choices like including political affiliation while excluding gender, age, and educational background (Odilla 2024, 29). This selection risks reinforces existing biases, particularly if politically motivated prosecutions shaped the training data.

Concerning the ethical and organisational challenges, the “algorithm challenge” presents a trade-off between false positives and false negatives. In corruption cases, a false positive labeling an innocent person as corrupt can lead to severe social and professional repercussions (Köbis, Starke and Rahwan 2022, 6). The absence of internal guidelines to manage this trade-off has raised concerns about MARA's practical application.

Organizationally, MARA lacks transparency. Not all CGU personnel reported awareness of the tool, and some expressed concerns that it operates secretly or remains under-implemented due to legal limitations (Odilla 2024, 21). Given its sensitive nature, access remains restricted to few employees, with no clear indication whether it integrates into CGU's daily operations (Odilla 2024, 13).

4.2. Case Study: Spain

4.2.1. Spain’s Public Procurement Landscape

The drive to use AI in Spain's public sector stems from a never ending public procurement corruption issue. Unlike other countries where corruption may show up as minor bribery at service counters, Spain deals with systemic, high-level corruption that mainly impacts political and economic elites. This type of corruption seldom affects the civil servant at the counter; rather, it targets users of vital public services such as health, education, or policing by diverting resources through illegal commissions for public contracts (Jiménez Sánchez 2023, 4). The extent of this issue was clearly illustrated in 2015, when an article in El País reported that around 150 senior elected officials were facing trials for corruption-related crimes (Barbería 2015). More recently, arrests linked to alleged manipulation of SEPI contracts (a government holding company) involving public procurement kickbacks implicated Prime Minister Pedro Sánchez's Socialist Party (PSOE), referred to as the "Koldo case" (Fernández-Pontes 2025).

This rich environment for corrupt activities arose from a weak institutional structure that had difficulty managing the behavior of administrative leaders, especially in territorial and institutional administrations (Jiménez Sánchez 2023, 5). Experts have pinpointed significant shortcomings at four different levels: regulatory, bureaucratic, political, and judicial. For an extended period, political leaders neglected to tackle the fundamental causes of these problems, frequently choosing superficial reforms that barely affected the core systems of corruption (Jiménez Sánchez 2023, 5-7).

Recognizing this, Spain has emerged as a key player in shaping AI public policies in both the European Union (EU) and Latin America. During its 2023 EU Council Presidency, Spain pioneered approval of the landmark EU AI Act in March 2024 (Ruvalcaba-Gomez and Garcia-Benitez 2025, 16). Spain also established the Agencia Estatal para la Supervisión de la Inteligencia Artificial (AESIA) in 2023; the EU's first dedicated public AI oversight body. Although there are currently no state-level registries for AI algorithms, regional governments in Madrid and Castilla-La Mancha have started to integrate AI skills into their digital transformation agencies to enhance efficiency and citizen services (De la Sierra 2025, 127).

4.2.2. The SALER System (Rapid Alert System)

Spain's primary AI anti-corruption application is the SALER system (Sistema de Alertas Rápidas), established in 2018 by the Valencian Parliament through Law 22/2018. Overseen by the General Inspection of Services, SALER predicts potential corruption cases within the Generalitat of Valencia. Unlike reactive traditional auditing, SALER proactively cross-references digital administrative records to identify risks like conflicts of interest, collusion, double funding, procurement manipulation before financial losses occur (European Commission 2021; Digital Future Society 2023, 31).

SALER's effectiveness derives from its ability to aggregate and analyze diverse public data sources. It examines direct payments, contract records (all bidding and execution phases), subsidy details (grantors, beneficiaries, invoices), plus notary records, property registries, and business registries to uncover hidden relationships (European Commission 2021; Digital Future Society 2023, 32). When risks are detected, General Intervention Service inspectors receive alerts to initiate investigations, which may escalate scrutiny or dismiss cases. Inspectors then determine whether alerts represent errors, negligence, poor practices, or suspected fraud requiring formal investigation (Digital Future Society 2023, 34).

To enable this, the General Inspection contracted IT providers to develop custom algorithms executing automated queries targeting:

- Split contracts: detecting when a project is split into multiple smaller contracts with the same or different suppliers to bypass stricter bidding limits.
- Recurrent awardees: Identifying possible oligopolies or lack of competition.
- Collusive biddings: patterns where the same group of bidders frequently appear in various calls.
- Conflicts of interest: non-compliance with legal incompatibility standards (European Commission 2021).

Even with its difficulties, SALER signifies a major change in European public administration:

- Legal Legitimacy: It was the first algorithmic control system in Spain to gain approval through a specific law, establishing a strong legal basis for its function (Capdeferro 2025, a3.7).
- Preventative Deterrence: Functioning as an “early-warning” system, it supports officials in their duties, theoretically discouraging wrongdoers who are aware their actions are being monitored in real-time (Digital Future Society 2023, 32).
- Regional Leadership: Valencian model has paved the way for other regions like Galicia, which are now taking prominent roles in AI legislation (De la Sierra 2025, 147).

Despite its innovative design, SALER has encountered significant challenges during implementation. A key issue is the slow digital transformation in the public sector; for the system to function properly, it needs high-quality, accurate, and consolidated data, which many departments find hard to provide. Technical difficulties were worsened by political changes, such as the reassignment of the system's original champions within the Ministry of Transparency (Digital Future Society 2023, 33). Additionally, there was initial pushback from public organizations who were concerned that SALER would mainly serve as a surveillance tool, highlighting the need for clear communication and collaborative design to foster institutional trust (European Commission 2021; Digital Future Society 2023, 38).

A critical issue remains pertaining to AI transparency deficits in Spanish governance. National disclosure about AI decision-making remains inadequate; absent public registries obscure systems affecting rights and services (Capdeferro 2025, a3.6; De la Sierra 2025, 132). SALER embodies transparency dilemmas: excessive disclosure risks exploitation, while insufficient transparency erodes trust (Digital Future Society 2023, 35).

SALER's development also brought to light the tension between AI advancements and data protection regulations. In 2017, the Spanish Data Protection Agency criticized the system for possibly violating Article 23 of the General Data Protection Regulation (GDPR), which led to the implementation of stricter definitions concerning the purpose and duration of data collection (Digital Future Society 2023, 35).To tackle these ethical and legal issues, the system enforces a strict “human-in-the-loop” policy. According to Article 31 of Valencian Law 22/2018, the system does not make final decisions; rather, it produces alerts that must be manually classified by human inspectors to distinguish false positives, errors, or fraud warranting investigation (Digital Future Society 2023, 37; Capdeferro 2025, a3.11).

4.3. Cross-Case Synthesis: Brazil vs. Spain

Although Brazil and Spain possess distinct legal systems and diverse procurement landscapes, their AI implementations reveal striking similarities among the moderating factors influencing tool success or failure.

4.3.1. Transparency Paradox:

A key observation across both cases is the tension between transparency and effectiveness. Spain's SALER faces a transparency dilemma: excessive disclosure enables bad actors to exploit the system (Digital Future Society 2023, 35). Similarly, Brazil's black box problem, exemplified by Case REsp 1.878.959 demonstrates that insufficient transparency can trigger judicial termination of AI tools (Ayibam 2025, 63). Furthermore, civil servants perceive these tools as opaque: CGU personnel often lacked awareness of MARA (Odilla 2024, 21), while SALER raised surveillance concerns due to unclear decision-making processes (European Commission 2021). Additionally, in these states, data protection regulations demand transparency to safeguard human rights (Digital Future Society 2023, 35; Jankovski et al. 2025, 13).

4.3.2. Data Integrity:

Furthermore, both cases confirm that AI-ACTs analyze massive datasets from diverse departmental sources (Menke, Gomes, and Xavier 2024, 278; European Commission 2021; Odilla 2024, 12). Brazil's ALICE requires data standardization to ensure consistent formats (Ayibam 2025, 61). MARA suffered missing data and inconsistencies', proving its effectiveness depends on Brazil's core databases (Odilla 2024, 28). Similarly, SALER relies on high-quality public data to detect corruption patterns (Digital Future Society 2023, 32).

4.3.3. Human-in-the-loop

Beyond transparency and data quality, both countries emphasize human oversight as essential while AI serves as a supporting tool. In Brazil, ALICE and MARA send alerts to human auditors who then investigate to resolve any alerted issues. It recognizes the importance of human investigation to validate algorithmic findings (Menke, Gomes, and Xavier 2024, 278-279; Nicaise and Hausenkamph 2025). While in Spain, Law 22/2018 and practice requires that human inspectors classify alerts to prevent black box legal issues (European Commission 2021).

4.4. Emerging moderating factors.

Cross-case analysis revealed additional factors beyond the initial hypotheses that significantly influence AI effectiveness.

4.3.4. Legal Acceptability and Regulatory Shortcomings

Effectiveness in detecting corruption is meaningless if that detection cannot be converted into a legal prosecution according to Nicaise and Hausenkamph (2025). Their argument is that algorithmic evidence can easily be rejected by a judge, basically the tool's effectiveness drops to zero for approval if it lacks legal acceptability even if it yields high results for detection. For example, the judicial resistance in Brazil and the Regulatory Lag mentioned in the Spanish case (SALER) saw an instance where GDPR concerns almost halted data cross-referencing (Digital Future Society 2023, 35).

4.3.5. Institutional Culture and Professional Resistance

In addition to technical challenges, officers often exhibit resistance which poses a significant obstacle on the use of AI-ACTs. An example in Brazil, there is a strong cultural resistance, as AI is seen as a threat to job security (Vasconcelos and Santos 2024, 116) even SALER was believed to serve as surveillance, because it lacked transparency and technical know-how by most workers (European Commission 2021; Digital Future Society 2023, 38).

4.3.6. Digital Infrastructure and Technological problems

The success of ALICE and SALER depends on how advanced the government is in digital technology. The presence of captcha barriers on Brazilian government portals and outdated servers in Spanish regional departments act as physical moderators that slow down the planned activities of AI (OECD OPSI 2024; Digital Future Society 2023, 33). This shows that the AI's real-time advantage disappears if disadvantaged by low quality and slow government portals.

4.3.7. Political Interference

In the case of SALER, the reassignment of original political supporters within the Valencian Ministry of Transparency acted as a negative moderator, slowing down the system's integration despite its strong legal foundation (Digital Future Society 2023, 33). This political instability fueled surveillance fears, further distancing public organizations (European Commission 2021; Digital Future Society 2023, 38) (European Commission 2021; Digital Future Society 2023, 38).

Chapter V: Discussion and Interpretation of Results

This chapter interprets the empirical findings from Chapter IV relative to the study's three hypotheses and theoretical framework. This analysis confirms that transparency, data quality, and human oversight significantly moderate AI's real-world effectiveness in detecting public procurement corruption, as measured by ISO 9000 standards (ISO 2015).

5.1. H1: Transparency in Algorithmic Design

Hypothesis: Transparency in algorithmic design moderates the relationship between AI tools and their real-world effectiveness in detecting public procurement corruption.

Result: H1 is validated. The following findings share its validation;

- Legal validation (Spain): In the SALER case, Law 22/2018 established transparency, giving the tool legal legitimacy. This transparency in the tool's purpose enabled institutional support and provided inspectors with a clear legal framework to respond to alerts (Capdeferro 2025, a3.6).

- The Black Box Issue (Brazil and Spain): On the other hand, the MARA tool encounters a "transparency paradox." Due to its internal secrecy, where even some CGU staff are unaware of its daily operations, it struggles with widespread acceptance and raises concerns about hidden activities (Odilla 2024, 21). Even though, with SALER, maintaining levels of operational secrecy could be to prevent bad actors from exploiting the system (Digital Future Society 2023, 35).

This study finds that the effectiveness of AI is limited when users cannot understand its design logic. Transparency is found to go beyond just having open code; it involves clear legal status and operational guidelines, which directly affect how much auditors trust and utilize the system's results. In this case, transparency serves as an important moderator on the effectiveness of AI to achieve intended results to curb public procurement corruption.

4.4. H2: Data Quality

Hypothesis: The quality of data used moderates the relationship between AI tools and their real-world effectiveness in detecting public procurement corruption

Result: H2 is validated. The following findings share its validation;

- The Ground Truth Limitation (MARA): The effectiveness of MARA is greatly limited by its training data, which only includes civil servants who have already been caught. This circularity implies that the tool may struggle to identify new corruption patterns, thus restricting its practical effectiveness to what is known and creating bias (Nicaise and Hausenkamph 2025; Köbis, Starke, and Rahwan 2022, 5).

- Technical Restrictions (ALICE & SALER): ALICE encountered infrastructure issues and captcha challenges that initially necessitated human help to overcome (OECD OPSI 2024). Likewise, SALER's effectiveness is hindered by the slow digital transformation of different departments, resulting in inaccurate or fragmented data inputs (Digital Future Society 2023, 33).

AI cannot imitate human intelligence if the data foundation is biased or incomplete. The reliability, standardization, and scope of the data (for instance, cross-referencing notary and business registries) directly influence the accuracy of the corruption alerts produced. Data quality emerged as the strongest technical moderator across all cases, confirming the Garbage In, Garbage Out principle in AI effectiveness (Sanchez-Graells 2021, 8; Adam and Fazekas 2021, 11).

4.5. H3: Presence of Human Oversight Mechanisms

Hypothesis: The presence of human oversight mechanisms moderates the relationship between AI tools and their real-world effectiveness in detecting public procurement corruption

Result: H3 is validated. The findings below share its validation;

- The human-in-the-loop: In Brazil, the effectiveness of ALICE is evaluated based on its assistance to human auditors. Data indicates a direct causal relationship: a 1% rise in AI alerts results in a 0.389% increase in corrective notices led by humans (Menke, Gomes, and Xavier 2024, 284). This implies that without a human auditor to investigate and contact, the AI alert stays as an inactive digital record. MARA and SALER also rely in human interpretation received from system alerts (Digital Future Society 2023, 33; Nicaise and Hausenkamph 2025), which affirms that its effectiveness to deliver rapid alerts influence the auditor's promptness to take necessary action

- The Legal Mandate (SALER): Spanish Law 22/2018 clearly requires a Human-in-the-Loop framework. Article 31 mandates that human inspectors manually classify each alert to prevent the professional stigma associated with false positives (Capdeferro 2025, a3.11).

- Institutional Trust; in every instance, existing literature shared human oversight was recognized as the primary way to reduce the professional stigma of false positives and enhance stakeholder trust (Digital Future Society 2023, 37; Köbis, Starke, and Rahwan 2022, 6). For MARA, human interpretation is essential but requires quality training data and transparency to avoid bias amplification (Nicaise and Hausenkamph 2025).

It is evident that AI tools did not function as autonomous judges but rather as decision supporting systems. Their effectiveness is influenced by their ability and willingness to allow specialized human individuals to interpret, validate, and act on the algorithmic results. A caution is relevant on system exploitation to fully acknowledge human oversight as a crucial operational moderator that transforms a technical alert into a real-world outcome.

5.2. Comparing of Findings

5.2.1. Transparency as the Foundation of Trust

My initial hypothesis (H1) suggested that transparency in algorithm design influences the connection between AI and its effectiveness. The findings from Brazil and Spain strongly support this hypothesis, but with important nuances. In Spain, the effectiveness of the SALER system is enhanced by Valencian Law 22/2018, which grants it clear legal legitimacy (Capdeferro 2025, a3.6). This aligns with existing literature arguing that algorithmic transparency preserves legal legitimacy (Sanchez-Graells 2021, 10; Ayobami et al. 2023, 132; Odilla 2024, 30-31). This finding is consistent with the UN ECOSOC (2025, 5) claim that AI can foster public trust only when it is built with explainable algorithms.

In addition, a major issue highlighted in this research is algorithmic opacity. As Andhov, Darnall, and Andhov (2025, 12) point out, although AI platforms are created to predict market trends, they frequently lack transparency about their data sources and design. This lack of clarity hinders a procurement official's ability to examine decisions, thus diminishing accountability in AI systems. The Transparency Paradox discovered in this research, where tools like MARA function in a black box to prevent bad actors from manipulating the system, represents a crucial observation. While Studman and Machirori (2024, 26) contend that transparency is important for local government, the Brazilian judiciary's dismissal of black box evidence (REsp 1.878.959) demonstrates that without transparency, the tool's results are legally ineffective (Ayibam 2025, 63).

5.2.2. Data Quality and the GIGO Reality

H2 focused on the quality and application data used. This research across the three tools, ALICE, MARA, and SALER, shows that data quality is the most significant technical factor. The UN ECOSOC (2025, 5) points out that a "lack of data availability and accessibility" continues to be a major issue. Andersson, Arbin, and Rosenqvist (2025, 131) further clarify that procurement managers have serious worries about data quality, security, and confidentiality, a concern also raised by Andhov, Darnall, and Andhov (2025, 10), who highlight that gathering bidder information for AI training raises important concerns about data minimization and purpose limitation.

Furthermore, a key finding of this study is the recognition of circular bias in MARA's training data. Since MARA was trained solely on civil servants who had previously been caught (Nicaise and Hausenkamph 2025), its effectiveness is negatively impacted by its limited perspective. Resimić (2025) asserts that deficiencies in training data worsen skewed historical patterns. Thus, when AI is trained solely on previously detected corruption, it perpetuates blind spots, making it less capable of recognizing new or previously unnoticed fraud schemes. This argument aligns with ICO (2024) findings that unbalanced training data can lead to discriminatory outcomes.

Additionally, the technological challenges caused by slow digital transformation across departments (Digital Future Society 2023, 33) indicate that the impact of AI is limited by the infrastructure of government-wide data governance (Andersson, Arbin, and Rosenqvist 2025). As RAND authors Ryseff, De Bruhl, and Newberry (2024) and Ryseff and Narayanan (2025) observed, data-related problems, such as insufficient suitable data and the low prestige of data cleaning activities, are major factors in unsuccessful AI initiatives.

Likewise, the situation in Africa reflects these challenges, marked by a combination of inadequate digital infrastructure and fragmented policy frameworks (Duja Consulting 2024). While the African digital economy was projected to hit $180 billion by 2025, the continent represents less than 1% of global AI research and development, mainly due to insufficient high-quality local data (Khasru and Anik 2025).

5.2.3. The Importance of Human Oversight

H3 indicated that mechanisms for human oversight enhance the effectiveness of AI. The data from Brazil's ALICE tool serves as strong evidence: a 1% rise in AI alerts results in a 0.389% increase in human-led corrective actions (Menke, Gomes, and Xavier 2024, 284). This demonstrates that AI does not replace auditors; instead, it helps focus their limited attention.

The need for Human-in-the loop approach has become a global standard. During the 59th session of the Human Rights Council, Lyra Jakulevičienė (OHCHR 2025) emphasized that using AI without proper human rights considerations can negatively affect all human rights, including discrimination and privacy breaches, especially for vulnerable groups like women, children, and minorities. Public sectors are advised to conduct thorough impact assessments and provide access to remedies (OHCHR 2025). This research shows that human supervision is essential for transforming a digital alert into an actual recovery of funds, all while safeguarding basic rights. As noted by Duja Consulting (2024), experienced forensic specialists need to verify results and establish the legal case

A typical example is the significant result of ₦1.6 billion saved by Nigeria's ICPC using AI to analyze procurement data. This success was only possible through teamwork between technical agencies and human investigators (Duja Consulting 2024).

5.2.4. Ethical and Human Rights Implications

The use of AI in public procurement raises ethical issues related to bias and fairness, which are important because of societal demands for government transparency (Andhov, Darnall, and Andhov 2025, 11). Research findings support Sanchez-Graells (2024, 4), who cautions that poorly designed digital solutions can lead to widespread harm, such as exclusion and a decline in the legitimacy of the state. This is especially pertinent in the case of MARA, where subjective decisions in algorithm design reflect the concerns highlighted by the UN about algorithmic profiling (UN ECOSOC 2025, 6).

5.2.5. The Skills Gap

The skills gap noted in the research cases from Spain and Brazil is a common issue (De la Sierra 2025, 127; Jankovski et al. 2025, 10). According to Salesforce (2024), 60% of IT professionals in the public sector report that a lack of AI skills is their biggest challenge. Interviews conducted in Sweden (Andersson, Arbin, and Rosenqvist 2025, 128) supported this, highlighting insufficient resources, low AI knowledge, and siloed work as significant barriers. Africa is also still experiencing limitations due to lack of skills, although it also faces issues like poor digital infrastructure, funding limitations, and scattered AI policies (Khasru and Anik 2025). The European Commission (2025) also found that the integration of AI is challenged by lack of skills and disjointed administrative systems that hinder the expansion of solutions.

5. Conclusion and Recommendation

The main aim of this study was to identify the factors that moderate the real-world effectiveness of AI tools in public procurement. By analyzing the implementation of ALICE, MARA, and SALER, this study finds that the effectiveness of AI is not a fixed technical measure, but rather a changing result influenced by institutional, legal, and ethical factors. The research reveals that technical excellence alone is insufficient to curb public procurement corruption.

The findings validated all three hypotheses in this study. This study has found that transparency influences the Legal acceptability of a tool. Without it, judicial resistance prevents real-world effects (Ayibam 2025). Further, the research shows that Data Quality is the main technical obstacle. ALICE's success relied on its access to 27 different government databases, while MARA’s performance was limited by circular training biases which is supported by Köbis, Starke, and Rahwan (2022, 5). The study strongly confirms the GIGO principle discussed by Sanchez-Graells (2021) and Adam and Fazekas (2021). The finding that AI projects fail primarily due to data issues is supported by Ryseff and Narayanan (2025), RAND authors, who emphasizes that data cleaning and management are often overlooked but critical drivers of success. Moreover, the study indicates that AI functions as a decision support system. The 0.389% rise in corrective notices for every 1% increase in ALICE alerts demonstrates that the human-in-the-loop is the actual engine of effectiveness (Menke, Gomes, and Xavier 2024).

Although much of the literature emphasizes efficiency, this research incorporates the cautions of Lyra Jakulevičienė (OHCHR 2025). By pointing out how biased data in MARA or SALER can result in the exclusion of minorities or suppliers with limited data, this study advances the discussion on anti-corruption AI technicalities and human rights.

In summary, for AI to progress from pilot purgatory to actual effectiveness (ISO 9000), it needs to be part of a socio-technical system that prioritizes legal transparency, data integrity, and human agency as essential elements for global adoption.

5.1. Limitations of the study

The study analysis depended on case studies and secondary analysis, the lack of transparency in these tools meant that some technical details were not available for direct review in order to make an observational conclusion. The study does not include real-time interactions between auditors and AI tools.

This cross-sectional analysis cannot evaluate long-term effectiveness or the impact of political interference over time. The rapid evolution of AI after data collection (tool upgrades) may change the results.

Furthermore, even though Brazil and Spain offer strategic contexts for this study, they are considered on middle to high-income contexts. The results might not completely consider the specific challenges of very low-resource environments or authoritarian situations. This may result in findings falling short of effectively offering solutions for global adoption.

5.2. Recommendations for Policy and Best practice

I propose that governments avoid AI-ACTs that are black boxes to prevent legal and data protection pushbacks as seen with Brazil's ALICE and MARA. These are effective tools, yet there is a need to embrace algorithmic registries. This way, sources of training data and intended applications of AI-ACTs are openly available, guaranteeing legal validity and fostering trust.

In addition, adopting explainable AI (XAI) can help prevent the black box trap experienced with judicial issues in Brazil; therefore, developers need to make AI scoring decisions clear and legally justifiable while still deterring bad behavior.

Additionally, there is a need to incorporate the presence of human oversight (human-in-the-loop) in the design of AI usage. This means that there is a requirement that AI-generated alerts can be assessed by qualified auditors prescribed by law, as shown by the Valencian Law 22/2018.

Furthermore, governments need to standardize current procurement records, thus enhancing data standardization. ALICE, MARA, and SALER rely on varied databases; thereby, this recommendation is relevant to improve data quality.

Further, taking note that anti-corruption tools need complete data to succeed, governments should focus on unified data governance plans that eliminate work silos.

In addition, there is a need for the public sector to invest in technical civil service expertise. Establishing specific roles that mandate AI expertise is crucial in connecting algorithmic warnings with legal justification.

Lastly, public sector systems should align with OHCHR (2025), which requires that human rights are prioritized. Thereby, it should be a requirement that anti-corruption tools are regulated, periodically inspected, and programmed to monitor bias and discrimination against small businesses owned by minorities.

To conclude, this thesis refers governments to the AI Accountability Framework developed by the U.S. Government Accountability Office in 2021. With the assistance of AI experts, GAO (2021) revealed that this framework identifies essential practices to promote accountability and responsible AI usage by national agencies and other organizations engaged in the design, development, deployment, and ongoing monitoring of AI systems. This thesis finds this framework timely and relevant to AI-ACTs to effectively curb public procurement corruption (see Appendix A).

5.3. Future research

This thesis work needs to be expanded to analyze the specific data-governance challenges in Africa and Asia.

In addition, future research should look into the possibilities of human oversight bias and system exploitation, a valid fear that was observed in Spain's SALER. Specifically, the research can determine if the human-in-the-loop principle is not a flaw that encourages corrupt practices.

Moreover, researchers can explore the advantages of AI-ACT legal frameworks that govern usability in a state. The same research could explore how the law can protect legal acceptability of these tools, protect against bias and discrimination, and preserve human rights.

Lastly, future researchers should further explore political interference as a moderating factor to AI-ACTs in public procurement corruption. This was a rare finding on SALER's implementation despite the fact that the Valencian Law had been passed

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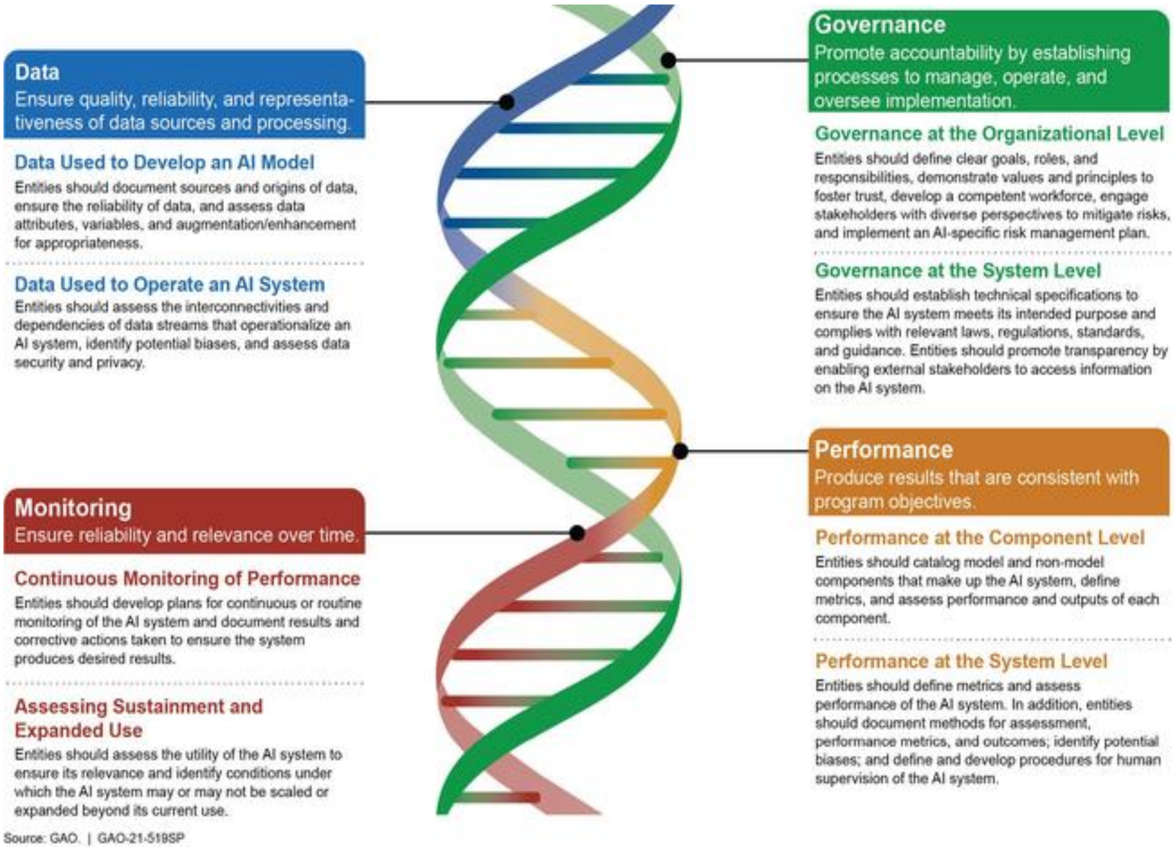
7. Appendices

Appendix A: Artificial Intelligence (AI) Accountability Framework



Source: GAO 2021