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FUTURE
STUDIES RESEARCH JOURNAL

e-ISSN: 2175--5825

ARTIFICIAL INTELLIGENCE ADOPTION IN PUBLIC ORGANIZATIONS: A CASE STUDY

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ABSTRACT

Purpose: The study explores the key factors influencing AI adoption by public organizations, and sought to understand the dynamics of AI adoption, aiming to identify the potential challenges of integrating AI with ESG considerations.

Originality/value: This research addresses the gap in understanding AI adoption in the public sector at the firm level, emphasizing the challenges and risks of technology integration. The study discuss how AI can be used effectively, contributing to societal appropriation of technological progress.

Methods: Methodology employs a multi-stage analysis of literature, followed by ten interviews and a case study on Brazil's Federal Revenue Service. Empirical data was probed through rigorous coding and thematic analysis, selecting the most impactful factors influencing AI adoption.

Results: The conclusions highlight the role of AI in elevating public services performance and reach. However, the deployment of AI calls for vigilant oversight to mitigate adverse effects and inequalities and demands a multidisciplinary strategy addressing an interplay of challenges.

Conclusion: The study provides a framework for effective AI adoption, offering insights for decision-makers on strategizing AI adoption, emphasizing the importance of factoring ESG concerns into de decision to adopt this technology.

Keywords: Artificial Intelligence. Public sector. Strategic leadership. Innovation. Technology adoption.

FUTURE STUDIES RESEARCH JOURNAL
Scientifc Editor: Renata Giovinazzo Spers
Evaluation: Double Blind Review, pelo SEER/OJS
Guest paper
Received: 06/03/2024

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ADOÇÃO DE INTELIGÊNCIA ARTIFICIAL EM ORGANIZAÇÕES PÚBLICAS: UM ESTUDO DE CASO

RESUMO

Objetivo: O estudo explora os principais fatores que influenciam a adoção da IA por organizações públicas e discute a dinâmica da adoção da IA, com o objetivo de identificar os potenciais desafios da integração da IA com considerações ESG.

Originalidade/valor: O estudo aborda a lacuna na compreensão da adoção da IA no setor público no nível da firma, enfatizando os desafios e riscos da integração dessa tecnologia. O estudo contribui sensivelmente para a apropriação social do progresso tecnológico.

Métodos: A metodologia selecionada emprega a análise da literatura em múltiplas etapas, seguida de dez entrevistas e um estudo de caso na Receita Federal do Brasil. Os dados empíricos foram analisados por meio de codificação rigorosa, selecionando os fatores mais impactantes que influenciam a adoção da IA.

Resultados: As conclusões destacam o papel da IA no aumento do desempenho e do alcance dos serviços públicos. No entanto, clama para que a adoção de IA tenha supervisão vigilante, para mitigar os efeitos adversos e as desigualdades potenciais.

Conclusão: O estudo fornece uma estrutura para a adoção eficaz da IA oferecendo insights para os tomadores de decisão sobre a estratégia de adoção e enfatizando a importância de levar em consideração as preocupações ESG na decisão de adotar esta tecnologia.

Palavras-chave: Inteligência artificial. Setor público. Liderança estratégica. Inovação. Adoção de tecnologia.

1. INTRODUCTION

According to Grandhi et al. (2021), the current business environment is characterized by an unparalleled level of uncertainty, leading to many intricate and unpredictable trajectories. This presents a particular challenge for public sector entities, as they must strive to maintain or even improve operational efficiency while expanding their operations (Williams et al., 2021).

There is growing social interest in encouraging innovation in the public sector as a discipline to improve efficiency, quality, and accessibility and address pressing societal challenges (Arundel et al., 2019). This is especially true in Brazil, where public sector spending accounts for 19% of its GDP (BCB, 2022), surpassing the global average of 17% (World Bank,

2023) and notably outpacing the contribution of its manufacturing sector to the GDP by roughly 10 percentage points (World Bank, 2023).

Among the strategies used by public sector companies to improve quality and performance are adopting new technologies (Gong et al., 2021), upskilling staff (Sikdar, 2018), and changing organizational design (Emre et al., 2019).

Artificial intelligence (AI) has begun to significantly impact public sector companies after decades of frustrating false starts and costly disappointments. Futurists have long predicted this impact, which is now becoming a reality (Chalmers et al., 2021; Obschonka & Audretsch, 2020).

The interaction between AI-based technology and humans is fluid and expected to develop over time (Pandurangan et al., 2021; Liu & Kim, 2018). This evolution may exacerbate a problem highlighted by Agarwal (2018, p. 1), suggesting that the

> public administrators are unprepared for the challenges they must face in order to cope with this non-incremental and exponential changes, as many of the existing government structures and processes that have evolved over the last few centuries will likely become irrelevant in the near future.

Although research on the private sector's implementation of self-learning algorithms is extensive, ranging from supply chain management (Pournader et al., 2021) to material discovery (Cai et al., 2020) and energy management (Ahmad et al., 2021), studies on government digitalization have mostly focused on classifying AI technologies and addressing ethical, legal, and policymaking-related challenges. Few studies have explored the role of governments as sophisticated AI adopters beyond traditional ICT projects.

For example, AI has been used to enhance the capacity of public servants to efficiently process and respond to citizen feedback by identifying prevalent sentiments and topics within large volumes of communications, as discussed by Alamoodi et al. (2021) when analyzing data from the COVID-19 outbreak.

This allows for a more nuanced understanding of public opinion, enabling the development and implementation of policies and services that are more closely aligned with citizens' needs and expectations.

Given this scenario, this study aims to investigate the key factors that drive artificial intelligence adoption in public organizations, including potential economic, social, and environmental impacts, and to elaborate a set of practical recommendations to support public agents implementing AI-based solutions.

This study addresses a gap in the academic literature on AI adoption in the public sector at the firm level. The challenges and potential benefits of integrating AI into public sector companies highlight the significance of this study.

2. LITERATURE REVIEW

According to the System of National Accounts (2008), the public sector consists of publicly owned corporations at all levels that provide services such as education, health, and security to all members of a community. The primary objective of the public sector is to design and improve laws and policies continuously, provide public services to citizens, and deliver and manage necessary resources and infrastructure to enable civil servants to perform their responsibilities (OCDE, 2019).

Citizens expect the same level of efficiency and user experience for government transactions such as online banking or shopping. Gobble (2018) argues that digitalization can yield certain advantages, predominantly via efficiency enhancements and diminished error frequencies. However, this does not fundamentally alter the operational dynamics. In contrast, authentic digitalization instigates a fundamental change in the organizational setup, as various authors such as Vial (2019), and Gong et al. (2020) refer to as “digital transformation.”

Factors that hinder innovation in the public sector include a lack of intra-organizational coordination (Arundel et al., 2019), insufficient incentives (Clausen et al., 2019), lack of agility (Hansson et al., 2012), resistance to change (De Vries et al., 2016), shortage of staff (Weber et al., 2014), risk-averse culture (Brown and Osborne 2013), inadequate IT infrastructure (Clausen et al., 2019), rigid hierarchy (Susha & Gronlund 2014), and poor organizational learning culture (Vial, 2019).

2.1 Artificial intelligence principles

AI systems possess a remarkable trait in that they can improve the outcomes of their predictions and analyses without requiring direct human intervention (Blackwell, 2020; Newell and Marabelli, 2020). They achieve this by assimilating various techniques to draw diverse conclusions and adapting their understanding to various contexts (McCarthy et al., 1955).

Despite its widespread use, there is currently no universally agreed upon definition for AI. McCarthy et al. (1955, p. 12) elaborated one of the first propositions, defining AI as "The study is to proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it."

Giving computers the ability to learn and interact swiftly with humans without the need to be explicitly programmed to do so is a complex endeavor (Zou et al., 2009) that involves different approaches to dealing with multiple nuances (Enholm et al., 2022) by relying on inferences (Dobrescu and Dobrescu, 2018). AI problem domains encompass communication, knowledge representation, perception, planning, and reasoning (Enholm et al., 2022; McCarthy, 2007), and involve interactions with humans or machines, processing sensory inputs, simulating outcomes, and solving complex problems.

AI systems use various techniques (AI HLEG, 2019). According to Chui et al. (2018), classification, estimation, and clustering are the most widely used techniques. Classification involves categorizing new inputs into predefined categories based on a training dataset (Fogel 2006). Estimation entails assessing the subsequent numeric value in a sequence by leveraging a training dataset (Omitaomu & Niu, 2021), and clustering classifies data into internal coherent categories (Ezugwu, 2022).

Machine learning approaches often "teach" machines how to reach an outcome by showing them many examples of correct outcomes, a process called "training" (Dobrescu & Dobrescu, 2018). Machines can "learn" how to generate useful conclusions by analyzing vast datasets using linear regression techniques (Ezugwu et al., 2022; Fogel, 2006).

Deep learning is a machine learning technique in which algorithms take multiple steps between the input and output, interacting with different layers of neurons to classify input features in a complex and abstract form (Schmidt et al., 2020).

Given the novel nature of AI applications and its growing interplay in everyday life, technology leaders have recently issued an open letter asking to "immediately pause for at least six months the training of AI systems more powerful than GPT-4" (Bengio et al., 2023, p. 1). This call-to-action centers on pivotal concerns regarding the responsible development of AI and key issues, including the urgent need for AI systems to be rigorously tested for biases and irregularities, ensuring fairness and transparency, as well as the imperative to safeguard sensitive information against unauthorized access. Furthermore, the manifest claims a comprehensive assessment of the human impact of AI's widespread adoption, emphasizing the necessity of considering societal and economic implications. This collective stance seeks to navigate the complexities of AI development, advocating a balanced approach that prioritizes ethical considerations, security, and the well-being of society at large.

2.2 AI for social good

The economic and societal implications of AI are complex and can substantially affect diverse sectors of society. The introduction of AI and automation technologies has both advantages and disadvantages. AI can positively augment labor productivity, generate novel employment prospects, and significantly elevate an individual's quality of life through its contributions to healthcare, education, and personalized services (Davenport & Ronanki, 2018; Dobrescu & Dobrescu, 2018). However, there are also concerns about the social impacts of AI, which are mainly associated with job losses and structural changes in the nature of work, potentially contributing to income inequality and economic disparities (Tomaev et al., 2020). To some extent, AI-driven technologies have a pattern of entrenching social divides and exacerbating social inequality, particularly among historically marginalized groups. Low- and middle-income countries may also be more vulnerable to the negative social impacts of AI and are less likely to benefit from its gains (Hwang, 2018).

Notwithstanding, the seminal work of Acemoglu and Restrepo (2018) suggests that countervailing forces can mitigate the displacement effect of automation on labor demand. As the cost of producing automated tasks declines, the economy expands, increasing the demand for labor in non-automated tasks. This effect can manifest as an increase in labor demand in the same sectors undergoing automation or in non-automating sectors.

It is also important to acknowledge that the ability of machine learning to perform tasks proficiently does not guarantee successful automation implementation. Notably, business practices often exhibit resistance to change in the face of technological advancements (Manyika et al., 2017), underscoring the sociotechnical nature of work (Rosenblat et al., 2016) where a multifaceted interplay of factors, including historical context and cultural norms, significantly influences employment patterns and work processes. Consequently, automation adoption alone might be less dependent on the immediate economic benefits offered by the technology, and more influenced by a complex interchange of local historical and cultural factors (Rosenblat et al., 2016).

From a sustainability perspective, the quest for improved model quality incurs substantial energy and environmental costs, primarily stemming from the processes of algorithm training, management of the application learning life cycle, and infrastructure required for data storage (Zhao et al., 2021; Tomaev et al., 2020). The carbon footprint of training a large ML model can be equivalent to driving an average passenger vehicle for more than 242,000 miles (EPA, 2023). A holistic AI ecosystem environmental impact assessment must include data collection and processing, model development, optimization, and inference.

The integration of AI with environmental, social, and governance principles is a significant advancement in the contemporary landscape of societal welfare (Ahmad et al., 2021). The synergy between AI and ESG factors facilitates a more nuanced and comprehensive approach to address complex societal challenges. Typical AI capabilities enhance decision-making processes, enabling public sector entities to tackle a wide array of issues. Specifically, AI's application in environmental management demonstrates its potential for social good (Tomaev et al., 2020; Campion et al., 2020; HAI, 2023). Botelho Jr. et al. (2022) illustrate that applying AI for climate modeling and satellite-based deforestation data can positively contribute to energy management and natural resource conservation.

In workforce management, AI offers promising avenues for enhancing inclusivity and fairness. By analyzing hiring and promotion data, AI tools can identify and mitigate biases, fostering a more diverse and equitable workplace. This application underscores AI's role in promoting social justice and governance excellence within public sector organizations (Wirtz et al., 2019).

Moreover, the democratization of access to services represents a pivotal area in which AI can positively contribute to society. Advances in AI technology have the potential to improve access to healthcare, create new commercial opportunities, and enhance fairness in service delivery (Mikhaylov et al., 2018; Lopes et al., 2019; Emre et al., 2019). Nevertheless, this potential comes with the caveat that such technologies could also introduce new forms of inequality and bias, if not managed responsibly.

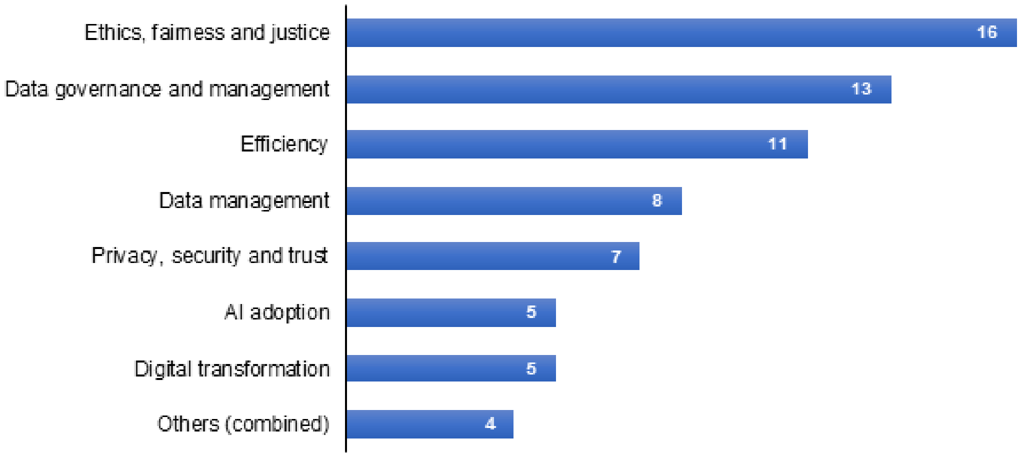
AI presents a multifaceted toolkit for public services aimed at achieving the social good, particularly when guided by ESG principles. However, the realization of AI's full potential for the social good hinges on a balanced approach that amplifies its benefits while mitigating inherent risks and challenges (Agarwal, 2018; van Noordt & Misuraca, 2022).

2.3 AI adoption in public sector research

This study used a dataset from EBSCO Academic Search Complete, comprising peer-reviewed English articles published between 2013 and 2023, to examine AI research in public administration. An initial review identified 67 relevant studies. After filtering out articles that focused on the methodology, technical aspects, and general use cases, 44 studies were selected for analysis. These studies encompass various topics and applications, collectively indicating that AI can improve public services. However, the ethical and technical issues require further investigation.

To classify the publications, the topical area of each study was coded using multiple labels, reaching ten categories. Figure 1 shows the number of citations in each category. The total category frequency count exceeded the total number of articles because each article may address more than one category.

Figure 1 – Number of citations in each category in selected publications



Source: Elaborated by the authors

Some studies have examined AI applications (Kouziokas, 2017; Ransbotham et al., 2017), whereas others have explored the theoretical foundations of AI (Sikdar, 2018; Zou et al., 2009) and public value generation (Criado et al., 2019). However, only 5 studies were labeled as “AI adoption” (about 7% of the universe). Not surprisingly, less than 4% of AI publications between 2010 and 2021 have focused on the adoption of AI in public service issues (HAI, 2023).

Further examination of the AI literature has revealed that publications have adopted a sub-area-focused approach, resulting in a fragmented view of AI applications and the challenges they pose.

A study on the factors that influence an organization's decision to adopt AI requires a comprehensive theoretical framework that encompasses not only the firm's strategy, but also the capability to manage dynamic factors (Alsheibani et al., 2020). Table 1 presents a list of the factors commonly associated with innovation adoption. These factors were the starting points for a better understanding of the adoption of AI artifacts.

Table 1. Innovation adoption drivers

Innovation adoption drivers	References
Competitive pressure	Yang et al. (2013); Oliveira & Martins (2011); Pan & Jang (2008); Criado et al. (2019)
Consumer trust, and regulatory acceptance	Ransbotham et al. (2017)
Corporate culture	Teece, et al. (1997); Bughin et al. (2017)
Compatibility	Davenport & Ronanki (2018); Rogers (1995)
External influence	Yang et al. (2013); Lopes et al. (2019)
Interoperability	Rogers (1995)
IT infrastructure	Pan and Jang (2008); Zhu et al. (2003)
Perceived benefits and barriers	Rogers (1995); Criado et al. (2019)
Security and privacy issues	Brynjolfsson & Mcafee (2018); Bughin et al. (2015)
Structure and processes	Campion et al. (2020)
Technical expertise	Yang et al. (2013); Ransbotham et al. (2017); Chui (2017); Oliveira & Martins (2011)
Technology readiness	Pan and Jang (2008); Ransbotham et al. (2017)
Top management support	Ransbotham et al. (2017); Chui (2017)

Source: Elaborated by the authors

Recognizing such factors can lead to more sophisticated adoption strategies, resulting in increased innovation usage and social appropriation of its value.

3. RESEARCH METHODS AND DATA

This study follows a recent trend in practitioner-focused investigations (e.g. Williams et al., 2021; Sakhnyuk & Sakhnyuk, 2020; Vial, 2019) that emphasize empirical data and the examination of patterns in the adoption of cutting-edge technologies. To do so, authors first conducted a scoping review of existing AI adoption corpus. This methodology is particularly suitable for complex or heterogeneous areas of research (Arksey, O'Malley, 2005), and is defined by Munn et al. (2022, p. 950) as:

> a type of evidence synthesis that aims to systematically identify and map the breadth of evidence available on a particular topic, field, concept, or issue, often irrespective of source (ie, primary research, reviews, non-empirical evidence) within or across particular contexts. Scoping reviews can clarify key concepts/definitions in the literature and identify key characteristics or factors related to a concept, including those related to methodological research.

This initial phase of the methodology identified the breadth of the literature on the emergent topic of AI adoption by public companies, in accordance with the Joanna Briggs Institute's guidelines for scoping review development (Peters et al., 2020). Subsequently, a multi-stage screening strategy for coding and analysis was conducted based on the procedures suggested by Saldaña (2021).

Following this stream of research and based on the European Commission's "Ethics Guidelines for Trustworthy AI" (EU 2022), ten semi-structured interviews were conducted during Aug-22 and Jan-23 with experienced executives from both the public and private sectors. This approach allowed the interviewer to address predetermined topics, while admitting interviewees to consider additional topics. The protocol used during the interviews was rigorously tested and refined prior to data collection following the methodology outlined by Eisenhardt and Graebner (2017).

Interviewees were selected based on their experience in developing AI-based solutions or responsibility for the organizational adoption of artifacts based on artificial intelligence, as presented in Table 2.

Table 2. Qualification of interviewees and details of interviews

Position	Experience (Years)	Company nature	Company sector	Interview duration	Method
Vice-president	12	Private	Education	1h 10min	In-Person
Director	22	Private	Telecommunications	50 min	Online
Global Product Manager	15	Private	Manufacturing	1h	Online
Senior Manager	18	Indirect public administration	ICT	1h 20min	Online
Coordinator	22	Indirect public administration	Traffic Management Authority	45min	Online
Director	25	Direct public administration	Buildings and grounds	1h	In-Person
Director	20	Indirect public administration	Urban planning and design	50min	In-Person
Senior Manager	18	Direct public administration	Urban mobility	1h 10min	In-Person
Partner	14	Private	Software	1h 40min	In-Person
Manager	8	Private	Healthcare	1h	Online

Source: Elaborated by the authors

The interview dynamics were mostly the same for both public officials and private executives, in some cases differing in the perspective from which the questions were asked. Table 3 presents an excerpt of the questions and specifies the dimensions of the innovation adoption baseline that were covered by each question.

Table 3. Excerpt of interview questions and associated adoption drivers

Interview question examples	Associated adoption drivers
How do you address consumer concerns regarding AI in terms of privacy and decision-making transparency?	Consumer trust, and regulatory acceptance
In what ways do you think AI will continue to influence competitive dynamics in the next five years?	Competitive pressure
How do you ensure the security and privacy of data in AI systems?	Security and privacy issues
Did you ensure that your system has a sufficient fallback plan should it encounter unexpected situations?	Structure and processes
Did you put in place a strategy to monitor and test that the AI system meets the goals, purposes and intended applications?	Perceived benefits and barriers
How do you ensure that new AI technologies are compatible with existing systems and processes within your organization?	Compatibility
Are there any specific processes or departments that have undergone significant transformation due to AI integration?	Structure and processes
How do you assess and develop the technical expertise required for AI implementation within your company?	Technical expertise
What role does top management play in shaping the AI vision and strategy of your company?	Top management support

Source: Elaborated by the authors

The interview transcripts underwent two rounds of manual coding in which the researchers meticulously employed an inductive approach to identify and tag all relevant information.

This resulted in 160 codes, 38 of which were later identified to pertain to the AI adoption domain. To minimize subjective bias, an associated researcher was invited to support the code mapping revision and metasynthesis (Barnett-Page and Thomas, 2009). The metasynthesis process employed two-step thematic analysis. First, individual codes were grouped into broader categories. These categories were then further refined into comprehensive thematic concepts.

The theming process employed a deductive approach tailored to the principles of AI adoption, incorporating pertinent literature on the subject. Finally, focused coding was employed as the second-cycle coding methodology. This technique is widely used for interpretive analysis and to assess the significance and frequency of identified categories (Thornberg and Charmaz, 2014). The focused coding analysis yielded 63 unique codes (see Table 3).

A case study was undertaken following Yin's (2018) guidance, which recommends this approach in situations where existing research lacks adequate information for generating specific hypotheses, and the investigation is guided by broader research questions.

The selected case aligns with the objectives of this study, namely, to investigate the key factors that drive AI adoption in public organizations. The case study was conducted during the Aug/Sep-22 timeframe with the objective of investigating the adoption of an AI-based system by the Brazilian Federal Revenue Service Agency (RFB).

A diverse set of data sources encompassing interviews, public documents, and archival records was utilized to enhance the validity of the findings. The data collection framework was structured according to Eisenhardt and Graebner (2007).

4. FINDINGS

This section presents results regarding the drivers and dynamics of AI adoption, focusing on aspects related to the public sector context.

4.1. Interviews

In accordance with Sikdar's (2018) findings, eight interviewees declared that AI adoption constitutes a strategic decision that requires explicit support from top management, particularly in addressing concerns related to safety and privacy. A public official interviewed commented: "Effective management involvement ensures that our projects align with organizational goals and adhere to ethical and regulatory standards, fostering a sense of trust in our AI initiatives."

From the perspective of implementation, there were five mentions to "compatibility" and "integration with other ICT tools already in use", as facilitators for adoption. The other four mentioned that partnerships are essential to developing robust solutions, not only for technical knowledge input, but also for accelerating the development process and mitigating risks. As one interviewee observed, "having a partner [in developing a new AI application] offers multiple benefits: it brings together complementary skills and knowledge, enhancing the product's quality and innovation potential. Second, it allows for resource pooling, such as financial, technological, and human, reducing investment and risk".

There is a general understanding amongst interviewees that the quality of an AI-based recommendation is fundamentally dependent on the quality of the training dataset and, furthermore, the quality of input data. Therefore, data lifecycle management has emerged as a core discipline for companies that intend to adopt AI. A Senior Manager of a public company commented: “although complex to develop, data lifecycle management is a fundamental discipline for AI-adopting companies”. The interviewee highlighted the necessity for the systematic management of data from acquisition to disposal, ensuring accuracy, availability, and integrity throughout the AI application's lifecycle.

From the responsibility and human accountability perspective, emerged from the interview with an experienced Director from one of the largest indirect public administration companies in São Paulo: “if a machine cannot be accountable for the outcome, it cannot make the decision”. Based on this understanding, all decisions are human decisions, and AI-based recommendation systems should play an accessory role.

The time lapse between data input and AI recommendations was a central preoccupation for the two interviewees because the AI applications they adopted required real-time or quasi-real-time interactions between company representatives and customers/citizens. This aspect was not mentioned by other respondents, underlining that there is no one-size-fits-all approach to quality.

4.1.1. Thematic analysis

To implement a systematic method to explore the underlying semantic and conceptual foundations of the interviews, a comprehensive thematic analysis was conducted, which revealed specific areas of interest. Thematic Analysis is a solid analytical technique used to identify and interpret patterns of meaning in a dataset (Braun and Clarke, 2012).

The authors followed Braun and Clarke's thematic analysis method, consisting of six steps: (1) becoming familiar with the data, (2) generating codes, (3) generating themes, (4) reviewing themes, (5) defining and naming themes, and (6) locating exemplars.

A set of 63 codes was identified, and 12 primary drivers (themes) were initially identified, four of which were consolidated into two owing to semantic and thematic similarities, resulting in ten AI adoption drivers. Table 4 presents the results of the analysis.

Table 4. AI adoption drivers and related codes derived from thematic analysis

AI adoption driver	Frequency	Codes
Efficiency	21	Productivity, factual decision making, focus, streamlining, cost-effectiveness, speed
Workload	19	Automation, capacity, optimization
Implementation AND Operations	18	Technological readiness, storage, energy consumption, technical staff, partnerships, legacy systems and applications, budget, compatibility, triability, reach
Privacy	18	Personal or private information, confidentiality
Quality	17	Accuracy, consistency, latency, robustness, data strategy, standardization, insights, flexibility, compatibility, reliability
Leadership	15	Organizational readiness, endorsement, risk management, training and development, communication, change management, data literacy, innovation culture, partnerships
Transparency	13	Explicability, understandability, disclosure, allow for contestation
Fairness AND Justice	9	Consistency, inclusion, equality, equity, (non)bias, (non)discrimination, diversity, plurality, accessibility, trustworthiness, welfare
Trust	7	Credibility, reversibility, safeguards
Responsibility	6	Accountability, liability, legitimacy, prevention

Source: Elaborated by the authors

Although “efficiency” has emerged as the primary driving force of adoption, considerations about “transparency”, “technological readiness”, “skilled labor force”, “fairness”, and “privacy” also have a substantial influence on the adoption process, according to interviewees.

4.2. Customs Selection System Through Machine Learning (SISAM) case study

SISAM is a highly sophisticated AI application utilized by the Brazilian Federal Revenue Service Agency (RFB). This agency oversees tax collection and customs operations, and combats noncompliance, smuggling, piracy, and drug trafficking within the country. SISAM is currently being used for the real-time processing of all Declarations of Import (DI) registered in the country. In 2022, there were more than 2.5 million Declarations processed by RFB agents (RFB, 2023). The objective of SISAM is to amplify exponentially the capacity of the Brazil Federal Revenue Authority to spot atypical foreign trade transactions while accelerating the clearing process.

Over 100 million entries in the Brazilian Foreign Trade System database (SISCOMEX) were used to train the system with both cleared and flagged results. The system was designed to be updated daily, and through this can quickly “learn” new forms of fraud attempts. SISAM, with its nonlinear architecture, is equipped to learn from a solitary instance of a novel type of fraud while distinguishing between recurring anomalies such as typical fraud attempts and refraining from categorizing them as normal occurrences.

The algorithm can learn from the typical behavior of importers and exporters individually, and can identify unusual transactions based on that, even if any previous fraud is detected.

SISAM's supervised and unsupervised learning features are not distinct; they emerge from the same Bayesian network and share a common knowledge base with approximately 8.5 billion data points.

SISAM performs the following actions for each DI:

- Compute the probability of tax classification errors or anticompetitive practices in real-time.
- Estimate the correct value for each identified error;
- Estimate the expected monetary return of the Federal Revenue Authority intervention;
- Generate an ordered list of DIs to be analyzed by field agents.

SISAM reports its findings in real time to field agents in natural language with a comprehensive explanation of the reasoning process. This feature allows customs officials to evaluate the system's analysis and make well-informed decisions regarding whether to follow it, while still maintaining their discretion to conduct an autonomous call to examine any DI.

4.2.1. SISAM adoption

SISAM has been successfully deployed across all customs branches, and its rapid adoption can be credited to the quality of its recommendations, real-time operation, evolving capability to identify irregularities, evaluation of the financial implications of each irregularity, and communication of the reasoning processes. All these are critical in fast-paced customs environments.

The system's user-friendly interface is also a driving force for adoption, as evidenced by the insignificant expenses incurred to train all field agents across Brazil. Furthermore, SISAM's interoperability with other RFB systems is vital for ensuring cohesive and seamless operations within the customs framework.

The value proposition of SISAM became self-evident not only for top management but also for field agents. This recognition is marked by substantial gains in process efficiency and accuracy, underscoring the system's role in enhancing the operational dynamics of Brazilian customs. SISAM adoption resulted in a decline of approximately 25% in the number of goods checked during the customs clearance process while enhancing general compliance with tax administrative requirements (Jambeiro Filho, 2015).

Three indirect benefits of system adoption were captured during the interviews: (1) cross-company consistency of the DI screening process; (2) SISAM's effectiveness in detecting deviations that induced importers to be more diligent in filling the DI, avoiding errors, and complying more frequently with regulations; and (3) leadership noticing an increase in the public perception of impartiality and professionalism of the agents, leading to a more respectful relationship between officials and traders.

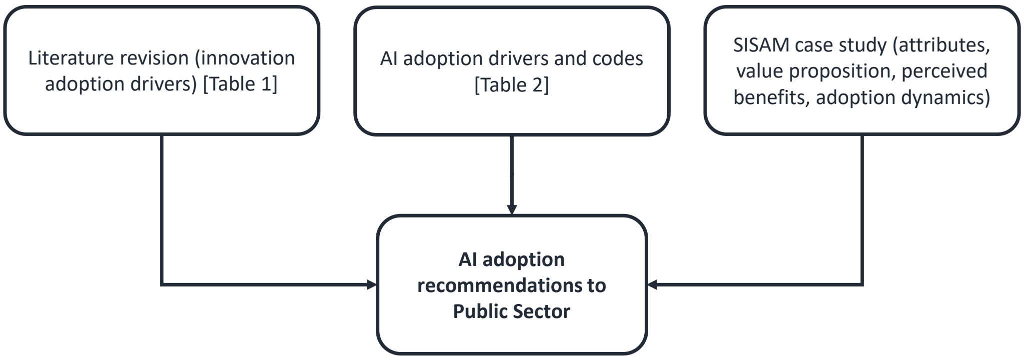
SISAM adoption shows that organizational readiness for AI adoption involves developing capabilities in areas such as programming, infrastructure, data management, and risk management. As declared by one of the interviewees, AI development in the public sector has a considerable level of risk, given the stage of the technology: "Without top management explicit support, I even consider starting an AI project".

Notwithstanding the findings of Chui et al. (2018), the development of Brazilian Customs' SISAM did not follow a formal business case. The push to develop an AI solution to assist RFB agents was made by senior leadership and executed internally. This finding suggests that some aspects of AI adoption in the public sector differ from those in private enterprises.

5. RECOMMENDATIONS

A set of 12 recommendations for AI adoption was formulated based on the following data sources shown in Figure 2.

Figure 2. Recommendations data sources



Source: Elaborated by the authors

These recommendations are intended to support public service leadership in developing a convincing argument in favor of AI adoption and provide guidance on addressing the typical challenges associated with this implementation.

Table 5. AI adoption recommendations to Public Sector

1. Analyze the legal and regulatory framework, identifying potential risks, and articulating how AI can create public value
2. Develop open and transparent accountability structures
3. Assess organizational readiness to adopt AI by mapping technical capabilities, strategic data assets, IT infrastructure, and other AI initiatives already in place within Public Administration
4. Develop a process to identify and prioritize operational hurdles that AI can overcome, collaborating with users to uncover and gain insights from "user stories"
5. Design and implement safeguards to prevent algorithmic bias
6. Guide AI development towards a human-centric path since inception
7. Create a data strategy that adheres to data protection laws and AI principles, considering data quality as the foundation for AI
8. Pursue and build a network for public-private partnerships to allow for collaborative initiatives
9. Create a clear narrative about estimated impact of Ai projects on employees' routines
10. Develop plans to foster internal technical expertise
11. Design effective public sector AI procurement processes
12. Establish funding schemes and secure the availability of resources, considering the maturity of AI initiatives within the organization

Source: Elaborated by the authors

6. DISCUSSION

The research data offer fresh insights into AI adoption at the organizational level. Called our attention that while the literature review indicates that "Ethics, fairness and justice" is a prime concern during the adoption process, this aspect received limited attention from interviewers. In addition, in contrast to previous studies (e.g., Chui et al., 2018) that stated that successful AI transformations require a solid AI business case, the SISAM case study showed that strategic alignment and leadership may be sufficient driving forces to initiate the development process in a public organization setting.

While the advantages of AI are recognized and observed in the SISAM case, uncertainties regarding top management support, the balance between value and risk, and obstacles associated with infrastructure and legacy system integration can hinder adoption.

The SISAM case also showed that investing in training to build AI literacy across the organization may reduce workplace anxiety about the implications of adoption, as previously suggested by Viechnicki and Eggers (2017).

Thirteen times during the interviews, “transparency” is one of the most prevalent principles in the current literature on AI adoption (Saura et al, 2022; Wirtz et al, 2019; Henman, 2020). Thematic analysis reveals significant variations in this construct in relation to explainability, disclosure, and the possibility of contestation.

Interviewees also emphasized the relevance of data quality. In the public sector, data is particularly subject to confidentiality issues, particularly when it relates to individuals. In this case, data management represents an important legal and technical challenge that is amplified when external suppliers are involved in developing the solution (Campion et al., 2020).

The adoption of AI by public sector companies requires managers to have more than basic technical expertise, even if the development is outsourced. When dealing with external partners, a solid technical foundation helps public administrators avoid being improperly influenced, safeguarding the interests of the public organization, particularly relating to the generation of social value and commitment to ethics.

Legacy technology integration is pivotal for AI adoption. The correlation between compatibility and the intention to adopt an innovation was first identified by Rogers (1962) and has since been supported by several other studies (Oliveira and Martins, 2011; Yang, 2015; Yan, 2009; Zahi, 2010).

Transparent AI-based recommendations are fundamental in public service settings. In this context, it is imperative that AI systems carry auditing capabilities by design to avoid black-box situations and ensure that the level of explicability relates to the context and consequences of incorrect outputs.

Public managers should adopt an integrated approach before launching AI pilots by analyzing whether AI is the correct solution for each business situation. A common issue found in this study is how enthusiastic managers look for problems to solve using a given technology. Experienced managers should otherwise use their domain knowledge to identify projects that can bring more value to the organization and use this knowledge to determine whether AI or other analytical technologies are best suited to achieve the objectives.

Finally, fostering a sustainability-oriented mindset among practitioners and researchers in the field of machine learning is crucial. This paradigm shift is essential for mitigating the substantial environmental impacts associated with the exponential growth of artificial intelligence. Leading public and private institutions can contribute by developing sustainability metrics, exploring alternative optimization strategies, utilizing energy-efficient hardware, and investing in carbon offset projects to address unavoidable emissions. Understanding the environmental and social impacts of AI is essential for the development, implementation, and monitoring of responsible and beneficial technologies.

7. CONCLUSION

AI-powered processes can assist government agents in being more efficient and making better decisions than the current baseline. AI can be particularly suitable for cases in which established analytical techniques are already in use. AI systems that perform repetitive tasks pose fewer challenges than others do because they rarely incur moral dilemmas, which might be a strategic "point of entry" for AI.

This study highlights the critical role of artificial intelligence in enhancing public services through environmental, social, and governance frameworks. AI's ability to handle vast datasets facilitates improved decision making. Although AI offers significant benefits for environmental management and social equity, its deployment requires careful oversight to avoid negative outcomes. Emphasizing responsible use and addressing potential inequalities is paramount. Ultimately, the successful integration of AI into public services hinges on balancing its advantages against risks and ensuring equitable benefits for all.

The development of AI projects requires a multidisciplinary approach, with technological, legal, ethical, and policy constraints. Clearly, AI efforts must be technologically feasible, but they must also be permissible under law and acceptable to key stakeholders.

To manage AI complexity, public services can consider partnering with the private sector through remodeled public procurement processes. Traditional "arms-length" market procurement, which relies on detailed contracts and technical requirements, may not be effective in this context. Instead, long-term collaborative relationships should be developed.

Notably, AI systems are not entirely fool-proof and may produce controversial judgements; leadership should instill the notion that AI can create a false sense of authority and confidence. Nonetheless, the role of humans must be protected, particularly in the public sector, where compliance and accountability must be ensured by design.

8. RESEARCH LIMITATIONS AND FUTURE DIRECTIONS

While this research offers valuable insights, its methodology has limitations in terms of generalizability and subjectivity, which impact the breadth and depth of its conclusions. This study's focus on a singular case of AI adoption does not provide a broad, representative sample, thus constraining the applicability of its findings across different contexts. Moreover, reliance on interviews with specialists introduces potential subjective biases in both the selection of participants and interpretation of their insights. Furthermore, this study does not encompass the full spectrum of potential implications of AI implementation within the public sector.

Future research should delve into the intricate interplay between artificial intelligence and environmental, social, and governance considerations in the domain of public companies. This includes investigating the technical hurdles, regulatory frameworks, and sophisticated procurement processes that characterize the public sector's engagement with AI technologies. Additionally, there is a critical need to examine the economic ramifications of AI adoption, particularly in terms of how government entities can socially appropriate the benefits of AI initiatives. Such explorations are vital for understanding how AI can be leveraged to advance ESG goals, thereby contributing to sustainable and responsible development in the public sector. This expanded focus will not only address the gaps identified in the current research but also provide a holistic view of the potential and challenges of integrating AI with ESG principles in public companies.

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