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Decision Support Systems for Government Auditing: The Role of AI in Ensuring Transparency and Compliance

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Abstract

In a world growing increasingly entangled in the web of data and its profound implications, Audit and compliance departments face unprecedented challenges. The sheer magnitude of data generated today necessitates access to new tools for the understanding and interpretation of such data, or simply for its effective storage. Traditionally, these departments relied upon the analysis of a small sample of transactions. However, the changing reality forces auditors to reconsider their approach. A high-impact Compliance Access Control (CAC) is to guarantee timely and extensive compliance verification of all data, as mandated by legislation. In this regard, businesses require a "Decision Support System for government auditing." The system should ensure inquiry compliance by means of automatically generating the relevant audit queries, given the transaction data and legislative input. This paper proposes a semi-automatic solution and demonstrates how a few programmatically solvable problems can give rise to the desired compliance access control tools. An implementation of the proposed system is illustrated through a case study *in financial services. When data and its associated interpretation are the core assets at stake, the lack of automated tools might jeopardize the very business model. The advent of the so-called data economy 4.0 has deeply transformed the nature of auditing and compliance assurance. Data is now a product created by clients and resold to third parties. But the data revolution comes with a twist: Legislators have caught up with its growing power as an asset and, in turn, prescribed mandates for the audit and compliance departments. In this regard, one of the most radical changes is the legislation requiring inquiry compliance with all data, and not just a sample. City financial supervisors have led the charge in promulgating such legislation, fostering an epochal shift in the audit industry towards tools capable of guaranteeing inquiry compliance with all data.*

Keywords: Decision Support Systems (DSS), Government Auditing, Artificial Intelligence (AI), Public Sector Transparency, Regulatory Compliance, Audit Automation, Machine Learning, Fraud Detection, Accountability, Risk Assessment, Data Analytics, E-Governance, Internal Controls, Digital Audit Tools, Ethical AI.

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1. Introduction

Government departments and other public sector organizations around the world are building, deploying and procuring more and more automated decision-making (ADM) systems, including artificial intelligence (AI) systems. An artificial intelligence (AI) system is a computer program that is able to perform tasks normally requiring human intelligence. AI technology includes traditional rule-based systems or expert systems, as well as statistical or neural nets. These statistical / neural net systems include the ones often referred to as machine learning (ML) systems, deep learning, or generative AI systems which can produce human-like text or imagery. ADM refers to human-made systems that initiate one or more decisions using computer programs to analyze data about the world.

The rise of new AI/ML systems has spurred hundreds of national and international governmental technology initiatives to protect outside Audit – the critical '3rd party evaluation and oversight' needed to ensure that bots and algorithms are fit for purpose, transparent, assessed and adopted with the inclusion of diverse voices and ultimately trusted . Public institutions have a duty of care to implement mechanisms, processes and anonymous channels for insiders, whistleblowers and citizens to report ethically challenging AI/ADM decision making. Effective systems are essential for trust in systems and to leverage powerful new technologies. Whatever the AI technology, additional infrastructure is needed to monitor, measure, audit and govern it across the entire organization. But if this does not happen inside public sector organizations, trust cannot be built with the outside world. It is critical that all public sector organizations work closely with independent custodians of trusted technology environments to deliver trustable AI/ADM decision-making systems.

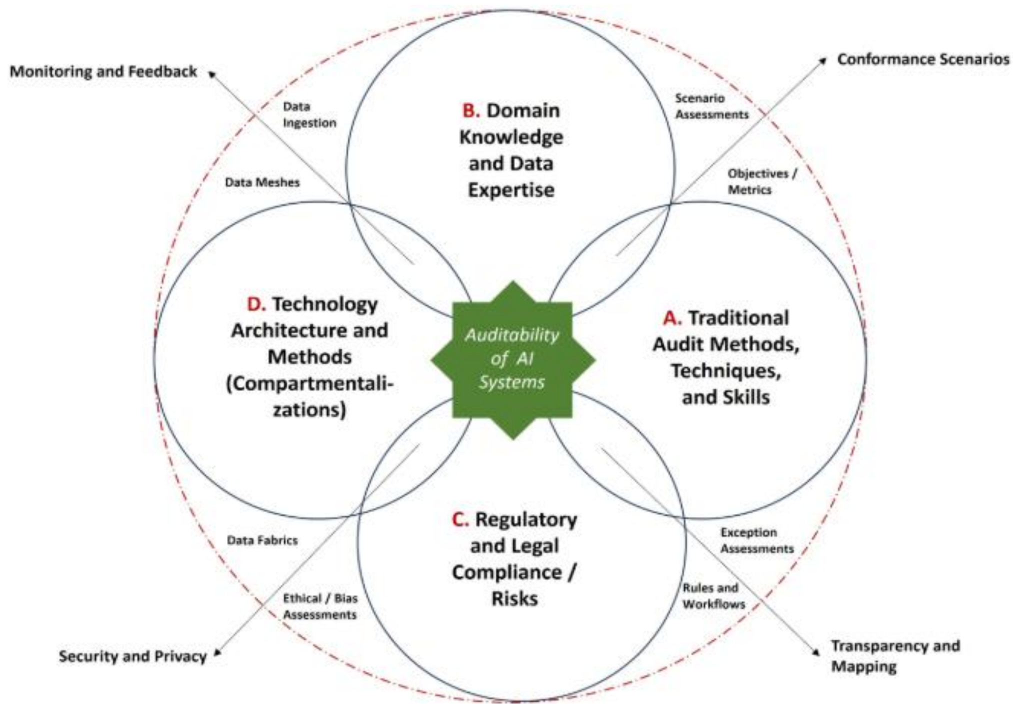

Fig 1: Decision Support Systems for Government Auditing

This approach needs governments to embrace existing technologies, processes and data standards as vital to deploying normative AI systems that meet ethical guidelines. Training safety/risk teams to speak the language of key decision makers and knowing how to interact with technology and data scientists is essential. Secondly, better oversight of elected officials, public servants and procurement practices is needed. Technology must tackle both formal and informal corruption and lobbying of all public decision making. In November/December 2021 alone, this meant delaying decisions worth billions of dollars with overt lobbying for very publicly identified outcomes.

1.1. Background and Significance

The rapid technological advancements achieved worldwide in recent decades and the increasing functionality and diversification of information and communication technologies (ICTs) have led to substantial changes in how institutions and governments operate. The ICTs' development has, without a doubt, paved the way for increased productivity and automation of resources in both private and public sectors. New technologies and software have allowed for a remarkable reduction in time taken to complete tasks, implementation of more efficient coordination systems, fast data collection, and substantially improved internal and external communications mechanisms. However, paradoxically, while advanced technologies, especially AI, could improve accountability and transparency in government auditing, better reporting, and less error-prone financial statements, they can also be used by government institutions and agencies for strategic reasons to diminish and obfuscate accountability. This paper provides a systematic literature review of the current trends, opportunities, and challenges in applying AI-based Decision Support Solutions (DSSs) for government auditing.

As denoted by the title, the paper's primary focus is on how the direct applications of DSSs enhance government accounting compliance and assist government auditors in increasing audit efficiency, effectiveness, and accountability. On the flip side, attention is given to the inherent flaws of current DSSs that may impede audit accountability by limiting understanding, opaque algorithmic processes, and information asymmetry. The literature review is classified into two main themes. The first theme focuses on how AI-based DSSs enhance auditors' capabilities in meeting governmental accounting compliance, with specific applications in examining compliance conditions and generating audit findings, conclusions, and opinions. In this respect, a taxonomy of the DSSs is provided based on the governing agencies, the forms and scales of DSSs, and the types. The second theme concentrates on the possible adverse impacts of both direct and potential AI-based DSSs in government auditing. Concerns are raised regarding potential impairments to audit accountability due to limited understanding, undisclosed application processes, and information gaps associated with current and future DSSs.

The ultimate aim of the paper is to lay the groundwork for future research on how to enhance audit accountability while enjoying the benefits of advanced AI-based DSS. The widespread phenomenon of the declining amount of audit findings and resulting sanctions across disparate countries raises worries among the general public in the years before the COVID-19 pandemic, especially when billions of dollars in public funds are being spent for relief supplies and recovery projects. Given the increasing complexity of accounting estimates, fraud and corruption are growing concerns. For government auditors, both out-stripping regulatory compliance and greater transaction complexity pose sizable challenges in performing effective audits. Hence, opportunities are discussed on how to tackle challenges in government audits from the perspective of implementing DSSs.

Equ 1: Anomaly Detection (Z-Score)

$$Z = \frac{X - \mu}{\sigma}$$

- X: observed value
- μ: mean of dataset
- σ: standard deviation

2. Overview of Decision Support Systems

Decision Support Systems (DSS) are computer-based systems that help organizations make decisions by aggregating information from multiple sources and providing analysis tools for better understanding. The term DSS encompasses a wide range of computer-based information systems, from simple dumb code to intelligent systems capable of reasoning and processing complex information. DSS design is not only highly interdisciplinary, involving research areas such as modern software engineering, artificial intelligence, empirical studies on human behavior in the decision-making process, but also highly context-dependent, as DSSs are often designed for specific organizations, including private companies and public institutions. DSS have evolved to accomplish more difficult and complex tasks, often requiring the processing of dissimilar information. Incorporating new capabilities, such as multi-source aggregating, identifying experts or informants, dialog support, and peer-to-peer source reputation learning support, makes designing a successful DSS even more difficult. Nevertheless, more difficult tasks are usually not associated with the fuzziness of the information being processed, which, together with the complexity of the information landscape, is a huge challenge. Successful DSSs must account for the diverse and sometimes non-cooperative nature of information sources and ensure that they provide credible and relevant information to the decision-making process. They should support the decision-making process through a set of well-defined steps while ensuring individual decision makers that the suggestions made by the DSS are credible and achievable. Although DSS was originally limited to the business domain, it has gained acceptance in other areas, including finance, government, healthcare, and agriculture, and DSS tools are offered for various domains. These applications assist people in making decisions by processing domain information to ensure quality choices, and the DSS implementations are characterized according to the complexity of the decision being made, the decision type, or the level of automation. The automated decision types by the most autonomy refer to fully justified decisions, semi-automated systems, and Cook Decision Support Systems (CDSS).

2.1. Definition and Purpose

Decision support systems (DSS) are information technology applications that support decision-making processes and problem solving activities. In a strict sense, DSS refers to systems that support complex decision making and problem solving, which are not easily fixed or predetermined. The term DSS means different things to different people in the DSS community; it is used broadly to refer to virtually any computer system that supports decision making, and it is used narrowly to refer to a specific class of systems that meet specific criteria. According to one of the broad definitions of DSS, it includes all computer systems that support managerial decisions, or to be even more broad, any system that supports individual and group decision making at any organization level, thus also including, for example, personal productivity systems and computerized telecommunication systems.

A more focused DSS definition provided earlier says that DSS is an interactive computer-based system that aids decision makers in using data and models to solve unstructured problems. They added an important qualification of DSS with respect to computer systems and applications: “A fully PC-based DSS is an integrated system which includes hardware, software, data, and manual files, and is used for any decision-making activity”. As information systems evolved over the years, new types of systems emerged, the most recent of which have the adjective Intelligent in them. Intelligent Decision Support System (IDSS) is a relatively new term that refers to information technology applications that support decision making processes and problem solving activities, which have been recognized to encompass an intelligence element. In its broadest sense, IDSS includes Decision Support Systems and Expert Systems at a minimum; moreover, Knowledge-Based Systems, Neural Networks, Fuzzy Systems, Intelligent Agents, etc., can also be considered as IDSS. Solution concepts emerging from or trended by these AI tools have all been integrated into the IDSS family.

2.2. Components of Decision Support Systems

Decision Support Systems (DSS) are information technology applications that assist decision-making processes and problem-solving activities. They evolved from simple spreadsheet-based systems to complex and intelligent systems, enabling effective and efficient decision-making. DSS can take full advantage of cutting-edge technologies, such as Advanced Data Mining, Data Visualization, Predictive Modeling, On-line Analytical Processing (OLAP), Artificial Intelligence (AI), and the Internet & Web-based technology. However, users will have less understanding of core technologies of DSS, especially in Intelligent Decision Support Systems (IDSS). It is critical to provide a high-level view of IDSS, including the definitions, frameworks, key components, and emerging intelligent tools. Artificial intelligence (AI) is technology that simulates human intelligence for performing a task. AI has made DSS a new breed of systems called Intelligent Decision Support Systems (IDSS). IDSS actively incorporates reasoning or self-learning capability into traditional DSS in exploring and analyzing the domain data to provide intelligent and user-friendly assistance to decision making. IDSS includes domain knowledge, modeling, and analysis systems to provide users the capability of intelligent assistance which significantly improves the quality of decision making. In addition, it includes a knowledge management component, which stores and manages a new class of emerging AI tools such as machine learning and case-based reasoning and learning. These tools can extract knowledge from previous data and decisions which give DSS capability to support repetitive, complex real-time decision making. There has been considerable research on understanding how the DSS works, what are the effective DSS, and what are the components of DSS in the past few decades. The Decision Support System (DSS) is an area of the information systems (IS) discipline that is focused on supporting and improving managerial decision-making. It helps the decision makers in enhancing the efficiency, speed, and quality of decision making. As this area is growing vastly, especially in the past few decades, many companies are investing resources in knowledge acquisition, knowledge representation, and knowledge processing for making intelligent decisions. An important application area is to use a DSS for auditing systems in the financial and budget sectors for the government. An effective DSS is primarily meant to aid the decision makers and ensure that important details are not overlooked. Systems do not supervise the decision and never replace human decision makers. Rather, they support them and help them to make better and consistent decisions. An effective DSS should: 1) Assist decision makers for availability of new and verified data of relevance; 2) Provide access to a knowledge repository; 3) Provide an infrastructure for interpretation and classification for new knowledge; and 4) Be able to discriminate between verified and unverified data. Various factors induce organizations to implement DSS. A computer based system allows a decision maker to perform a large number of computations very quickly and at a very low cost.

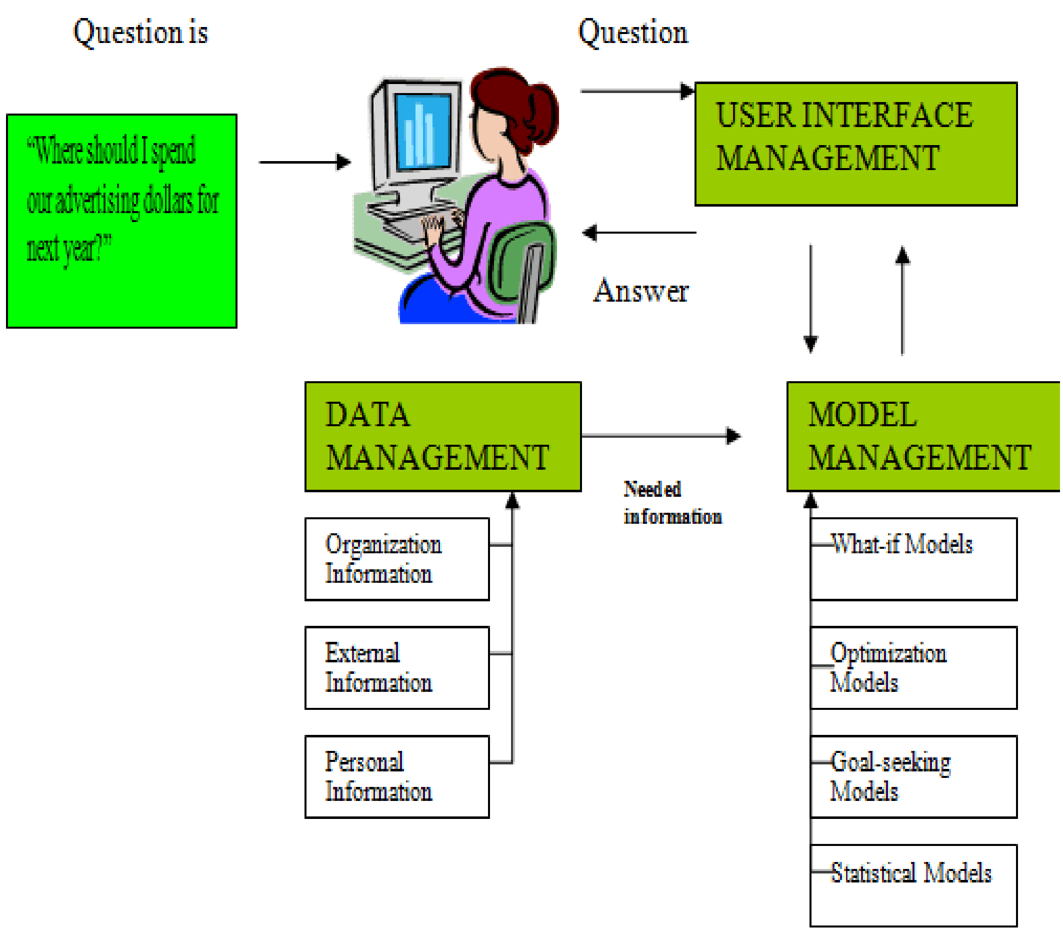

Fig 2: Components of Decision Support Systems

2.3. Types of Decision Support Systems

As the Digital Age accelerates, the expansion of information technology applications has evolved into various forms of Decision Support System (DSS) including DSS oriented to intelligence. Information technology applications that assist or provide support in decision-making processes in organizations or businesses are commonly referred to as Decision Support Systems (DSS). As a continuous development of DSS, Intelligent Decision Support Systems (IDSS) are also included within the information systems that are oriented to assist decision-support systems in organizations or businesses.

An Intelligent Decision Support System (IDSS) is a system that consists of a knowledge base containing domain knowledge and a modeling infrastructure that allows for the development and execution of reasoning processes and a graphical interface allowing the user to construct and edit decision-panels, execute decision processes, and visualize results. Users can share their experiences in a form of a decision panel using XML and later they can send the decision panel to the IDSS engine for execution.

IDSS includes domain knowledge, modeling scenario, and analysis systems that allow for the intelligent assistance of the participant in decision-making processes across various domains with the goal of improving the decision-making quality. Users of IDSS will utilize the tool by accessing the knowledge that is represented in various forms including model, and case libraries. A knowledge management component accompanies the system which can augment the web-based product with a knowledge management component that can store, manage, and update the AI tools as they emerge.

3. The Importance of Auditing in Government

The significant increase in fraud and corruption cases in almost every country has led governments to investigate the circumstances and tighten controls on the conduct of audits. Transparency and accountability are key features of good governance, in which public funds entrusted to governments to provide services and the wellbeing of people are handled with care. Government auditing is one of the five key elements for unbiased, credible, fair and effective government across the world in the 21st century. A major factor contributing to good governance is an accountability framework, of which auditing plays a vital role. Audit is an investigation into financial activities, generating information about their legality, probity, and propriety. This information needs to be reported to the public and interested bodies in an understandable way. Auditing activities deter the unethical and out of the ordinary conduct of businesses and individuals.

Audit, as an element of a government economy, acts as an essential check and balance on the activities of government. Auditing is also part of good governance, as it attempts to make the conduct of government spending and other activities accountable. In societies where democratic values are emerging, implementation, legislation, and administrative matters require checks and balances. Probably in these societies audit is more important than in established democracies. This has intensified efforts to disseminate the concept and conduct of audit, as well as the auditing profession itself. New forms of audit have appeared which underscore professionalism and independence. These audits may be performed totally under privately or community control. Audit services bidding to the lowest price appear in all markets. Mired in a search for legitimacy, independence, and professionalism, auditors have heightened their marketing efforts. They have presented auditors as credibility providers to stakeholders. It is nevertheless evident that unqualified audit opinion is not an ultimate guarantee against frauds and corruption, and in many circumstances has been compounded in malfeasance. The possibility of conflict of interest is also inherent in the bid-sending wards competition, in which the client is also in charge of setting the ‘rules of the game’. On the other hand, expectations towards auditors have been unrealistic. Baronial expectations about audit have led to criticism and frustration and sullied the value of audit opinion and accountants’ reputation.

3.1. Objectives of Government Auditing

External audits of the government are ideally conducted by independent audit institutions, which, in turn, are supervised by independent audit committees. This is also known as “audit of the auditors”. As one of the highest open-access repositories in the world, government audits that comply with agreed-upon auditing standards are made publicly available. The independent audit institutions generally cannot redeploy auditors to different auditing departments to avoid concerns over long tenured auditor engagement. In addition to indifference, the government auditing comprises too many factors influencing the audit process, and chaotic and unpredictable processes make it infeasible in a traditional sense. The design, management, and execution of government audits, especially performance audits, must consider many factors: auditing several entities, extensive audits for a couple of years, lack of quantitative data input, etc. This renders the adoption of traditional DSS technologies infeasible. To tackle the challenges, it is proposed to apply AI technologies to improve efficiency, reduce reliance on institutional knowledge, encourage the establishment of new rules and structures, and provide a basis for exploratory analysis. recognizes performance audits as desirable as the emergence of regulations governing the conduct of audits.

3.2. Challenges in Government Auditing:

Auditing the actions of the State and Municipal Public Administrations (APs) in Mexico, which spend money from the Federal Public Budget, is a challenge for the Federal Superior Audit Office (ASF). In this sense, there are many techniques and tools available to government auditing entities worldwide. These tools and techniques vary according to the legislation, regulations, and infrastructure of each agency that composes their corresponding governments. However, the existence of information in one of the sectors makes it obsolete in another. This fact, although it motivates agencies to update their infrastructure and audit techniques, also implies the existence of a large number of responsible parties (referring to individuals and roles, or a combination of both). Detecting the various uses (legitimate and illegitimate) and/or compliance or non-compliance with regulations is a challenge for these organizations. In this scenario, Decision Support Systems (DSS) represent a space for the exploration and integration of domain knowledge and specific techniques, along with necessary data (design) for the identification of legality compliance (structure) of actions through the developed rules and queries (function) in the governance auditing process (task). A relevant contribution of the current work is the formulation and development of a public tool based on DSS for exploring its use in the area of government auditing. This tool integrates domain knowledge and techniques for checking how, to what extent, and under what conditions the behaviors of agents and practices in the administration of the Public Budgets of the agencies and entities of the APs are governed by laws, regulations, covenants, contracts, and documents. This tool has been developed and is available for use around the world.

Equ 2: AI Model Accuracy for Fraud Detection

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

- TP: true positives
- TN: true negatives
- FP: false positives
- FN: false negatives

4. Artificial Intelligence in Auditing

Artificial Intelligence (AI) is an umbrella term encompassing a range of technologies and systems designed to mimic human thought and action processes, as well as a broader set of theories, paradigms, and encouraging visions. Its usage in government auditing is on the rise, albeit at a slower pace than expected. AI systems in government auditing play an essential role in filtering huge amounts of data, automating launder detection and social media analysis, and assisting IT professionals in conducting more substantial IT audits using AI systems. Most audit agencies had some level of AI understanding, education in nearest concern, and knowledge of prescriptive AI and ethical training.

In addition to the teleological view of AI, public sector audit agencies also must try to assure AI algorithm trustworthiness across bias, safety, effectiveness, interpretability, and legal issues . Releasing large datasets without a proper data governance framework and rules can ease AI algorithm training, but willingly or unwillingly brings moralization risks of hack data misuse and generated data privacy infringement. A lack of stop-correction mechanism in AI system release can jeopardize inclusiveness and safety. The evolving technology of AI can disseminate and deepen the pervasive issue of trust on both a social and a technical level. All institutions and citizens can be engulfed by AI-generated misinformation, disinformation, and hate speech, undermining social cohesiveness. Moreover, AI algorithms with heavy usage of data and security cases may lead to massive losses. Last but not least, AI deals with a vast number of variables that interact with unforeseen patterns, decreasing the chance of finding a rational reconstruction from a user perspective. As ChatGPT captivates the public's attention, published generative AIs also bring ethical concerns with social, economic, and political ramifications.

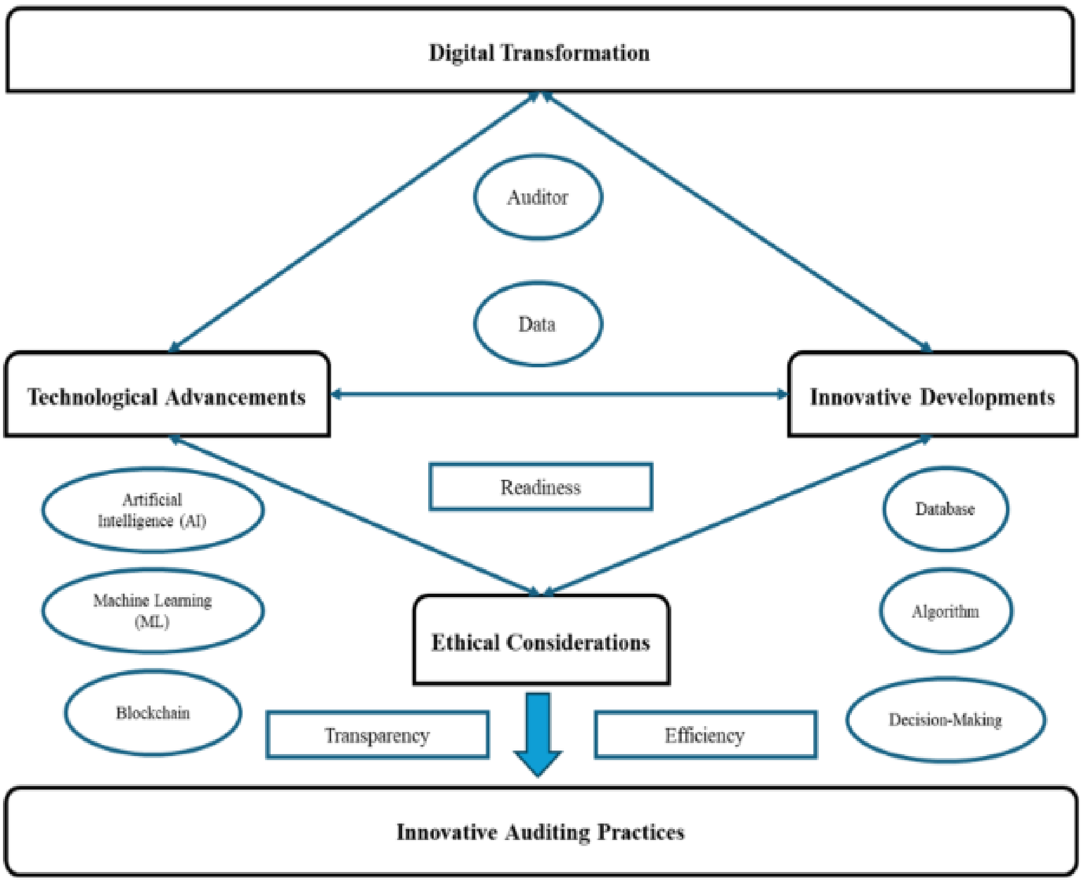

Fig 3: Artificial Intelligence in Auditing

4.1. AI Technologies in Auditing

AI systems are being explored to mitigate risks associated with government processes and offer possibilities of effective safety solutions. The goal of this research is to provide timely and relevant audit alerts for data-driven tracking of risks associated with the implementation of key automated decision-making systems. It focuses on financial bidding processes for large public contracts, a sensitive area in the domain of public procurement that merits particularly high importance in compliance auditing efforts. This research centres on the exploratory development of dedicated AI explainable decision rules for establishing elucidated audit trails of the automated compliance checks applied in procurement agencies. Phased machine learning, natural language processing, and knowledge-based deep learning methods are combined in a hybrid AI system to obtain a comprehensive process understanding of public procurements and prepare dense data records for a graphical audit trail generation. These proactive compliance audits, embedded with an engaging user interface, would help auditors unaffiliated with the production processes to understand the application of cross-process compliance checks as well as segregated sensitive information effectively. As test implementations showed, the approach strengthens the prospects for a more efficient auditing process and quicker and timely audit alerts in compliance auditing. The public sector should regulate the use of AI algorithms, particularly in biodemographic surveillance, CV-ANT, potential AI whitewashing, ethnic and regional biases in ML-backed algorithms, and proactive measures for mitigation. Policy measures by government directors, in collaboration with privacy regulators, should include implementing a Code of Conduct for surveillance purposes of AI vis-à-vis the provision of safeguards, information claim, weighted fairness, and an AI ethics commission. There is an urgent need for screening the general characteristics of the public sector and, in particular, the ML-based systems in various related contexts via a good-sense checklist balancing the potential benefits and harms across possible direct, societal, and governance dimensions.

4.2. Benefits of AI in Auditing Processes

The initial 3 case studies illustrate how AI can affect the auditing process from a functional perspective. The statements on the second sheet present some keywords that the AI-model has picked up from the large trove of evidence, whilst simultaneously producing a narrative to summarize the same evidence, suggesting a remarkable opportunity for analysts instead of clerks within the analysis sub-process of the auditing process. Most large-scale audits today are likely to rely extensively on computer programs that independently analyze records and report on exceptions on the basis of certain criteria. Similarly, AI could significantly assist analysts in deciding which narratives should be reviewed and what other further evidence should be collected to enhance a review. The direct assurance audit task could involve the review of several continuous audiotapes, telephone conversations, and customer complaint logs relating to numerous transactions. The completion of this process implies that no evidence supporting the initial suspicions was found over the duration under consideration. Such and similar auditing tasks are probably better suited for neural networks (NN-based) audio-to-text algorithms; they not only red-flag transactions continuously but could also incidentally establish a (virtual) timeline of reviews, along the lines of replaying footage from an automatically generated movie.

The two last case studies from the audit perspectives illustrate how AI-based tools can affect or complement the auditing process. As said on the first sheet of the downloaded presentation from the task execution, in recent decades, significant sums of money have been lost by public auditors as well as private auditors throughout the world. Most notably, a significant part of the property of the municipalities of Amsterdam, Rotterdam, and The Hague, listed on the stock exchange was declared worthless after auditing. This could be a pointer to unintended extra reputational risk exposure for public auditing organizations when coalesced together with the finding that a major failure to comply with the applicable regulations often becomes public knowledge. A major part of the auditing working papers tend to end up in the public domain, e.g., due to film producers overlooking a six-year term on confidential evidence and actively seeking ‘scoops’ for documentaries. Actors such as public auditing organizations should therefore seek to try to render the governance of the design, development, deployment, and execution of AI-based systems like any new transformational technology adequately transparent to facilitate independent oversight and assurance.

5. Integration of AI in Decision Support Systems

DSS are information technology applications that support decision-making members by translating data into information. The effective operation of DSS depends on the quality of input information. Errors in raw data can mislead managers. Automated processes eliminate human interaction which may lead to automation bias. Knowledge management tools are needed to improve the relevance and quality of information delivered to DSS. Knowledge management identifies critical knowledge as useful information. IDSS includes domain knowledge, modeling, and analysis systems to provide users with intelligent assistance that significantly improves decision making. The IDSS knowledge management component is a repository that stores and manages emerging AI tools. DSS systems range from very simple management information systems to complex systems that can evaluate alternatives for financial and capital investments and forecast their organizational implications. IDSS is one of the particular types of DSS. The IDSS categorization was based on the components and capabilities of specific DSS setups. Those capabilities include intelligent assistance during sensitive periods, support for complex real-time decision making, and reasoning over an explicit body of domain knowledge. IDSS stores not only application-independent but also domain-specific knowledge. By combining knowledge management and advanced modeling, modeling techniques from various disciplines can be merged into an IDSS. Combining different modeling techniques offers the potential to create more accurate and comprehensive models. Formulating models in the context of a specific application allows non-experts to understand those models and reuse them afterwards. Using higher-level languages with domain knowledge enables a model-building capability. IDSS allows for transparent and understandable assessments of a certain situation. IDSS is augmented by a knowledge management component which stores templates for reasoning tasks and emerging AI tools. With respect to knowledge management, there can be different kinds of advanced reasoning capabilities. One group of AI techniques is capable of automating certain kinds of reasoning tasks or supporting them in the context of DSS with agent technologies. Another group of tools focuses on the representation and visualization of large knowledge bases. IDSS can be complemented with several other emerging AI tools from a variety of domains used in various types of DSS for knowledge management.

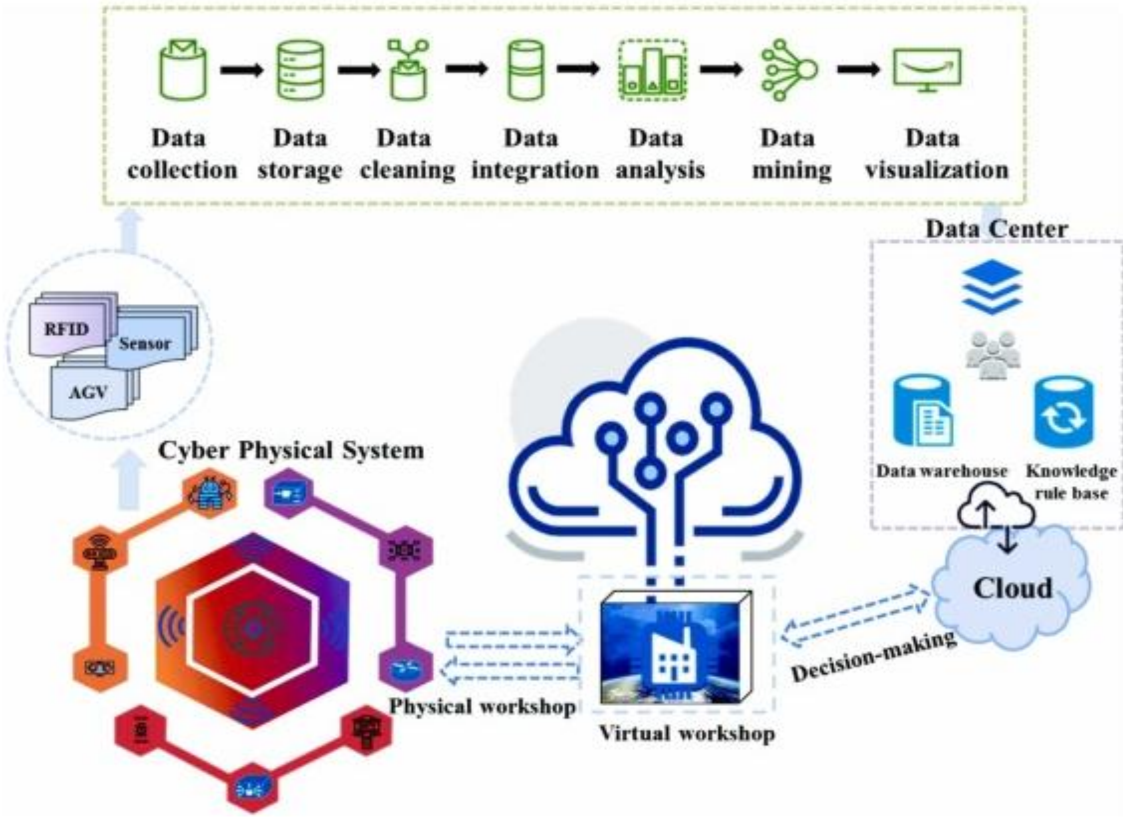

Fig 4: AI-Based Decision Support Systems

5.1. Framework for Integration

To ensure thorough and ongoing assurance of this architecture, only high veracity supply chain actors should be engaged to deliver or modify the core systems, and to integrate and build applications. The origin, nature, integrity, security and performance of every artefact in the value chain should be determined at the outset, with high veracity assurance a continuous obligation through the lifetime of each system. This assurance needs to be determined by independent third parties with appropriate qualifications, and with the power to impel remediation and sanction breaches. The assurance portfolio should be determined by the risks of harm, and updated when warranted by new risk situation reports. In addition, as relevant, formal assurance should be complemented with a regulatory regime which includes some or all other mandated assurance processes such as code review, independent audits, governance protocols, regulatory responses to breaches of requirements, and licensing and other legal obligations.

High veracity supply chains for government decision systems need high veracity assurance with appropriate obligations and monitoring of the performance of all actors in the value chain. The standards, evidence requirements, compliance mechanisms and regulators for compliance with all assurance regimes must be determined and established. Independent third parties with powers to impel compliance and remediation of breaches should undertake ongoing consideration and auditing of the performance of governments and their agents against these standards. A separate authority or agency should oversee this body and have powers to intervene where warranted. Governments should provide funding and similar authorities to this body in order to be able to resource this as needed, including through the use of high veracity procurement processes to ensure continual best practice. Assurance, standards, evidence formats and processes should be open standards that facilitate reviews and assurance by as many different parties as feasible.

5.2. Case Studies of AI Integration

The Institute of Internal Auditors Austin (IIAA) enables voting members to both create and access documents. Upon entering a new revision of a document, voting members may choose whether or not to send an email alerting all voting members of the new document's existence. The new document is assigned a version number and is visible on a wiki-like website and a corresponding mobile app. A voting member may find, download, and examine any document created on the system. This document summarizes the objectionable features of the current system and proposes a potential modification.

Voting members wish to approve documents. Presently, they must check every so often for new documents, which they may miss if they are busy. They may urgently wish that the group of voting members approve a particular document but cannot force the issue by sending an email or representationally trigger a group notification. If a proxy is not accepted, they can only be notified of the document's approval if the group's schedule happens to coincide with their own. Decision processes of a few seconds can thus take far longer and necessitate more comprehensive group involvement.

If the “Send Notification” checkbox is checked, an email alerting all voting members of the new document's existence is automatically generated and is locally stored on the server. An email header is generated using the subject line from the document’s entry in the database, prefaced with “(Voting Member Documentation Notification: New Document)”. The body of the email briefly describes the document concerning other documents and the role of voting members in its approval. Voting members are assigned unique IDs, which may be automatically extracted from the database, and their email addresses, which must be manually entered. A crudely formatted email string is generated and sent. This is requested overhead to accessing documents and is hopefully limited by email header filtering.

The changing stakes posed by AI and new regulations on public engagement in government have led some to seek to widen mechanisms for public oversight. This has resulted in a variety of means to notify the public what AI entails in terms of use case, methodology, agency, and potential impact on errors and discrimination. Some agencies are exploring excluding additional considerations by automatically tagging potentially anomalous outputs with alert levels to route to auditor personnel by severity score via manual intervention. This could be further broadened, including user-initiated inquiries about robustness monitoring metrics. Expanded engagement beyond technical documentation release and crowd-sourced question appeal to expert users could engage varied members of the public and greatly enrich the discourse around potential impacts.

Equ 3: Transparency Index Function (Weighted)

$$\text{Transparency Index} = \sum_{j=1}^{m} \alpha_j \cdot T_j$$

- T_j: score for a transparency criterion
- α_j: importance weight for criterion j

6. Ensuring Transparency through Decision Support Systems

Public administrations, policy-makers, and the public want to keep track of what other actors do and how they act. Auditing provides formal mechanisms for ensuring this issue. The limitations of prior agreement include how to assess what and how much auditing is needed and how to operationalize auditing. Hence, the counter-argument regarding the veracity of audits. Earlier systems' inherent opacity and a system's inability or unwillingness to be transparent about its explanation become counter-arguments for assuring its MH. Thus, this section proposes automatically generated neutral ex-ante reasoning chains from the original data, metadata, and derived value alignments to traditional human-readable audit trails. This reasoning chain is highly transparent in explaining how AI decisions are based on data and metadata transformations over time in a neutral manner (meaning it does not select which aspects of the whole chain to provide as explanations). This addresses the most restrictive auditing by demonstrating systems' operations without disclosing potentially HC knowledge.

Despite the feasibility limitations of keeping prior agreements in fully automated systems, auditing has thus far still relied on humans. Their reasoning will need to be automated because of massive data and real-time processing demands. One innovation could be to have automated auditors relying on prior agreements and goals and acting in a fully automated manner (potentially disputing against human auditors). This means experts may need to ensure enough common understanding between systems. In recent years, research on argumentative structure has focused on the representation and construction of arguments in artificial agents when dealing with norms and the capacity to interact with non-agent systems or humans. This is hoped to assure the details of the employed reasoning and available data cannot contradict more general principles or boundaries.

Fig 5: Transparent Decision-Making Process

6.1. Transparency Mechanisms

Government action is most powerful and intimate in relation to one's home, assets, privacy rights, and family, wealth and health. Tech companies designing, implementing and operating AI systems on behalf of the government have a confounding mixture of power and influence over rights and outcomes. Most citizens do not believe that they are surveyed and evaluated by 40 plus social credit/blacklist-style systems working on their behalf. Citizens not aware of, observing, sounds in, or actioning these systems cannot navigate consequences or limits. AI systems often stop individuals escaping adverse consequences or fighting back. There is a continuous audit trail of observable, recordable, and distributable actions, policies, and information.

Government systems operate in the public sphere, are often publicly funded, and are socialized to feed information through direct observation, witness, and participation. Information and processes should be open by default. Informed consent should be sought for the use of personal data; assumptions about consent should not be made. Actions should disclose history, telemetry, and outcome information. Citizens should know ticker-tape information on how and when their information was accessed and decisions were made. Systems should produce detailed and easily understood versioned policy information auditable by any person. Outcomes should be publishable into the public domain via citizen-soundable public sphere, reporting aggregates of all kinds. Auditability enables the assessment of algorithms, data and design processes which play a centerpiece role in critical applications. All systems and services should have escalation mechanisms that are responsive to change, unexpected trends/patterns, or negative human or environmental impacts. Audit mechanisms are necessary in cases of 'risky outputs or unexpected outcomes, particularly those with social, jurisdictional or economic impact'.

There should be a mechanism for alerting AI systems designers/operators to malfunction, dangerous behavior prospects, censurable or unanticipated effects and who is responsible. It should be possible to assess tools, systems, and operators. Attribution across steps should be available. Robustness testing and stress-testing processes should be undertaken and procedures for confidentiality breach detection, redress, compensation and recourse available. The scale of judgment can be especially problematic and the price of failure massive. AI systems should have a predetermined cause of responsibility in any context of negative outcome. Auditable models and visible evidence should be produced to highlight and track the process of determining attribution timeline. Where required, application registration mechanisms should be employed. Government should prioritize implementation and mainstreaming of incorporated human review policies and procedures.

6.2. Impact on Public Trust

Trust is an important enabler of the authenticity and fairness of public sector auditable system design. Public institutions need a highly skilled workforce who can effectively deliver core functions with integrity, including the design, control, and review of AI/ADM systems, as well as monitoring/measurement and auditing functions. Skills must be able to evolve to deal with the prospective enhanced scaling and impacts of AI/ADM systems. The skills of public officials must include explanation/accountability design, control, and knowledge of what is being referred to in the systems they are using. There is a need for long-term skills and workforce planning, and the development of a capable workforce to manage the potentials of AI/ADM systems for the community. AI/ML and other big data applications become too critical to leave to private sector control. Public institutions need to either develop their own or ensure open access to public good versions/models of such products, including foundations of trustworthiness, ethics, accountability, and DSD design specifications and oversight tools.

Measuring the trustiness of evidence drawn from these systems and the subsequent trustworthiness of any resulting actions or decisions is similarly important. “Trustiness” relates to the quality and veracity of data, information, analyses produced, records about such and the auditing of such capture/production and storage/archiving. A trustiness audit process must be developed and implemented for the supply chain leading to inputs for modelling and prediction and for the derivation of outputs and their post-processing. Establishing and managing a high veracity supply chain for service delivery or decision making is also important. For nearly all large decisions made by AI or ADM systems the raw data, likely candidates for what reliable source a piece of information has come from and any post-analysis transformation of that record together with the metadata associated with this need to be recorded in an immutable, minimal-possibility-for-manipulation format. It is vital that the human or other agent/agency that established or processed that data is clearly identified (ideally with a referring verifiable “public key”).

7. Compliance and Regulatory Considerations

With soaring hype around AI, government officials face unprecedented pressures to implement systems. At the same time, their use raises important legal questions as ever more domains are governed by a patchwork of state legislatures, executive orders, and broad structural guidelines. Complexity and opaqueness are exacerbated by convergence of tensions: no approved baseline exists, regulatory bodies are scrambling to catch up, and experimentation spaces are grey and wide open. In this complex and rapidly changing landscape, officials need to meaningfully engage external concerns. Since procurement checklists don’t just gauge purchasing agency capacity and knowledge, governments should be able to scrutinize ongoing external concerns about civil rights, flexibility, and confidentiality.

A challenge for auditing AI systems is containing risk from crosscutting conversation – details that could be informed easily prove hard to contain, difficult to mitigate, and impossible to consider fully. Throughout the government, individuals are searching for places to “hide” in writing, for information, and for scrutiny that sufficiently fit these systems [8]. This is especially poignant in the context of the National Defense Authorization Act (NDAA): rather than passively watching in the face of all-too-frequent and grave misconduct, individuals can actively piece together how inappropriate AI system use is possible. As contracts, regulations, and checklists proliferate, new dynamics of awareness shape scrutability. Awareness flows both broad and deep, like water finding cracks at risk of leaks, with large flows on both sides attempting to peer inside black boxes.

Simultaneously, external demand for information is being affected by a stark knowledge gap at the intersection of procurement, regulation, and government AI audit. Despite rising awareness of how these systems can fail government, scrutiny ideas put forward thus far have also largely been overlooked. This sits oddly against a narrative of AI expertise growing in circles well-informed enough to know that being meaningful, it must go sufficiently much deeper than previously proposed approaches, hemisphere in its initial state (similar to a layer of varnish). Frustrated demands for audits of processes passed down from officials sit alongside incomplete understanding of how such scrutiny ought to occur and what it ought to entail.

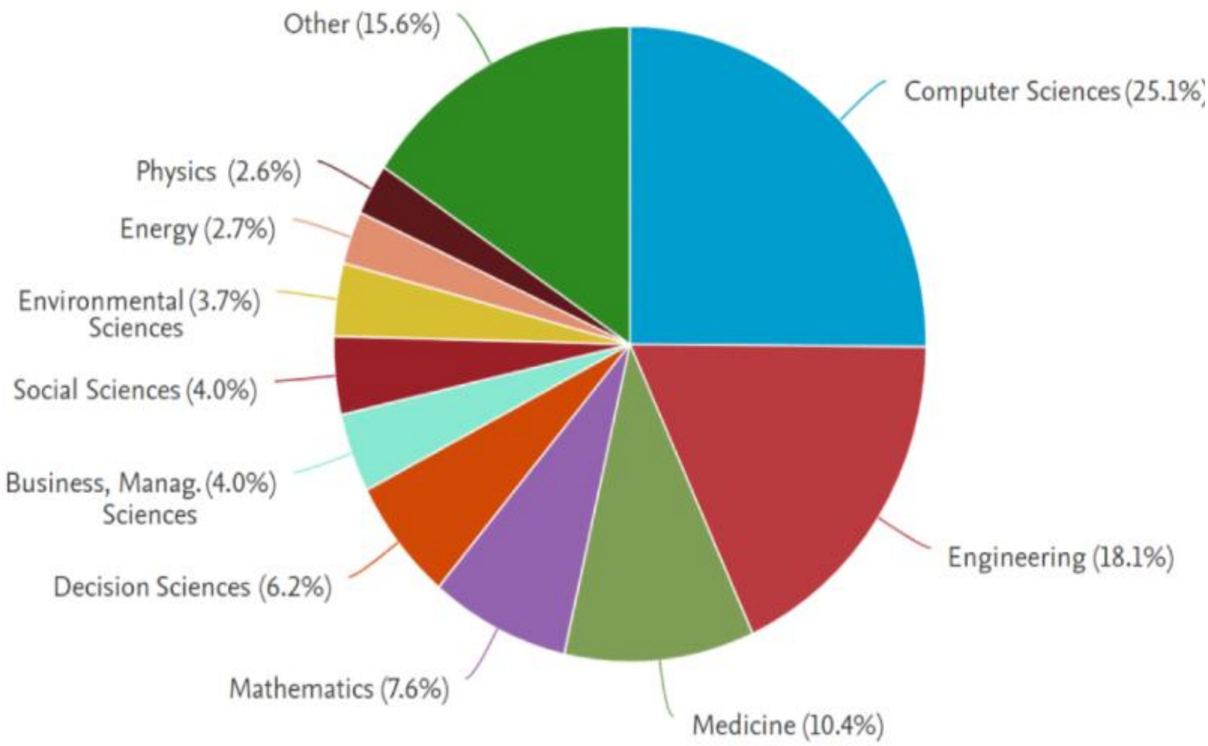

Fig 6: AI for Decision Support: Balancing Accuracy, Transparency, and Trust Across Sectors

7.1. Legal Frameworks Governing Auditing

In terms of legal frameworks concerning auditing, there are three main sources of regulation for various levels of government in Australia: Acts, Standards and Guidance. Auditing is an essential component of assessment, accountability and assurance within public institutions. The purpose of auditing within public institutions is to independently scrutinise the way a public institution is discharging its public function in order to provide the public with objective evidence about the validity and reliability of relevant claims.

A number of legal documents articulate a role for external auditing of specific public institutions. The Auditors-General Act establishes the statutory authority of the Commonwealth and each State and Territory auditor-general to undertake audits of the performance and operations of relevant public institutions and prepare reports to Parliament in order to inform assessment of public expenditure and the discharge of public function relevant to the public institution. The Act provides for auditor-general's to employ their discretion in determining the focus and breadth of individual audits, reporting provisions and, optional, follow-up audits.

Legal powers of access and information go both ways. Just as service delivery agencies are required to share information with audit offices, audit offices can be queried in order to clarify understandings of audit evidence, expectations and intention regarding the purpose, scope and methods of an audit. External auditing is undertaken within a set of agreed principles as well as specific audit mandates. A right to audit does not indemnify auditors from having to be accountable for the manner in which the statutory right is exercised. Relevant statutes, external and internal review processes and standards regulate actions that are considered outside the terms or spirit of the law.

7.2. AI Compliance Challenges

Regulations to ensure AI compliance are nascent and, as such, provide a range of strategic options for governments wishing to adopt them. For AI systems already in government agencies, the first priority is likely to pass any new legislative test of compliance. If they don’t, governments may need to consider pausing by ceasing the use of the AI system in question, acquiring an assessment for an existing one, or internally monitoring post hoc for wrongdoing as a stopgap for compliance. Compliance measures may be difficult and expensive to implement, so governments are directed to consider regulatory advice and examples when grappling with implementation (or non-implementation) for the relevant systems. A wealth of assistance with compliance governance is being built by a local community of advocacy organizations, deliberating on and collaborating toward purposeful internal operation and external oversight of AI systems. Such actions should benefit from transparency-enhancing legislation and be influenced by principles and examples from this work. A related task is to seek help with AI systems being procured by government agencies in the coming months. The requested reports, checklists, and frameworks to assess transparency and compliance in the procurement of AI systems will assist decision-makers to adequately assess and vet AI system designs from vendors.

With regards to ongoing oversight, governments are directed to consider establishing a science-advisement committee, since new knowledge, questions, and guidance about AI systems must inevitably arise. It should be cautioned that many firms developing and deploying AI systems have a commercial interest in misrepresenting those systems. Scrutiny of an AI system's use in governmental processes considered to have human rights implications is perhaps invaluable to guard against misuse. Internally auditing government departments, agencies, and firms developing or deploying AI systems not subject to public scrutiny is also prudent. If misalignment is detected, governments should consider exposing any uses of AI systems that do not align with regulations, standards of care, or political expectations, as well as considering measures with respect to misaligned institutions and individuals.

8. Data Privacy and Security in Auditing

Daily, organizations, both public and private, use billions of personal records. AI systems are integrated into government bodies and administration systems in many areas, including job recruitment and allocating access to public services. AI is being studied by diverse sectors and academia for its innovation and efficiency, and academic research is working intensively on machine learning (ML), NLP, and reinforcement learning to develop AI systems to be used in Public Organization Operations. However, several doubts arise over AI systems, and their algorithms cannot be fully assessed, forcing organizations to trust the companies creating and maintaining them.

Several technologies are developed to make sure the data cannot be exploited or presented to any unauthorized entity. There are many public campaigns leveraging these technologies to ensure votes are safe and prevent tampering from different entities. Homomorphic encryption aims to determine the output of a computation, encrypting the input. It allows for addition and multiplication directly in the encrypted space, responding through ciphertexts only. It can first filter incoming data and encode it, passing datasets to the secret key while producing secret outputs for other parties. The total sum remains hidden if aggregation occurs after the teams send their encodings.

Differential privacy assures that any query from a database does not identify any one individual among a large group of data. Individual privacy cannot be guaranteed, but this methodology protects sensitive data in databases. The output of a query from a data set does not change significantly as one record is added or removed from the schema. For instance, the US census data can statistically reveal the number of citizens living in a neighborhood without compromising the individual's address. The probability of being selected is roughly equal between the real dataset and one with fewer citizens. In such cases, the norms should be changed to comply with privacy. SMPC is a privacy-preserving technique that allows data operations to be done on datasets without revealing them. The data input from entities/sciences is separated via basic mathematical operations, and inputs are recreated.

8.1. Data Protection Regulations

The European Union (EU) is committed to ensuring the protection of personal data. The general data protection regulation (GDPR) is the primary regulation governing the collection and processing of personal data. Accordingly, it applies to any organization that processes personal data of EU residents, regardless of the organization's location. Compliance with the GDPR is a legal obligation for any entity that falls under its jurisdiction. Organizations using software systems that collect, process, or share personal data are subject to compliance with such regulations. However, developing compliant software depends heavily on addressing legal requirements stipulated in applicable regulations.

Requirements engineering (RE) is concerned with specifying and maintaining requirements of a system-to-be, including legal requirements. Legal agreements which describe the policies organizations implement for processing personal data can provide an additional source to regulations for eliciting legal requirements. Consequently, it is crucial to analyze the extent to which organizations' legal agreements reflect the requirements prescribed by regulations. The GDPR introduces a large number of requirements that organizations must comply with. Although implementing all requirements is cumbersome, this is mainly due to the inherently vague nature of the regulation. To solve this challenge, the semi-automatic legal requirement extraction method is proposed, which extracts legal requirements by reasoning on legal agreements and regulations. This addresses the following research questions: How to semi automatically extract legal requirements from legal agreements to capture regulations? and How well does this approach match the requirements prescribed by regulations?.

8.2. Security Measures for AI Systems

AI-managed security provisions are at the forefront of contemporary business technologies. Such systems can also sometimes overshare or work in unintended ways. Moreover, AI systems may fall short of minimum expectations for accuracy and fairness but simultaneously pass other checks. Security measures help to prevent problems in two areas: assessing AI-enabled government systems prior to use, and continuous monitoring of those systems as they operate.

When governments consider the procurement of a new AI system, an assessment is generally undertaken to evaluate characteristics of the system, such as its accuracy and fairness. In addition to examining the system itself, security measures may also assess the organization that will implement the system for capacity and commitment to operating the system safely. Continuous monitoring concerns the actions and processes needed to ensure that systems remain compliant after deployment, helping to keep tabs on performance and mitigating risks as they arise.

As with other safety measures, the impactful implementation of security provisions requires serious attention to detail and a commitment to sustained effort. The implementation of such systems is complex, resource-intensive, and often mathematically sophisticated, and security systems at peer organizations could be inadequate or even non-existent. Moreover, information asymmetries can constrict accountability, with model developers often publicly touting their systems' strengths while concealing weaknesses. Further, a reliance on highly specialized understanding of model behavior can make controlling AI systems similar to a kind of "technocracy." All of these difficulties mirror challenges seen across risk, audit, and regulatory systems more broadly. ai_advisors can also prove helpful in clarifying compliance issues and potential concerns.

9. Conclusion

In recent years, the government sector's use of AI and automated decision-making has increased, often with a lack of awareness about the trust design requirements or pitfalls of automation. There is a clear business case for better AI. Personalisation, experience automation and process optimisation provide the basis for more unified data systems and much improved decision-making at all levels. However, to fully realise this potential, trust must be built into the AI systems considered. An imagined failure, costing millions of dollars, can be an instructive thought experiment in working backwards toward trust requirements. The level of design work needed to ensure the proposed AI systems could operate in a way that avoided this imagined failure is extensive. A set of new questions, decisions and responsibilities emerges that the user and vendor must share. Testing and auditing requirements must also be understood, along with implications for the skill sets needed within those organisations.

Many of the issues that are generally considered problematic with AI in government services are design requirements which can be solved with effort and insight. Many of the choices needed to assign responsibility are very uncomfortable, but they remain choices. In working through the implications of the imagined failure, it became clear that many avoidable pitfalls were under the control of government agencies. Nevertheless, the quality of design and audit will likely govern the level of desirable automated decision-making in the later-deployed services and models. Agencies can choose to use AI well, not just because it is demanded, but also to provide significant new opportunities for better services, decisions and experience.

AI and advanced analytics have the potential to improve social outcomes and, as such, they offer unique decision-making capabilities. When thoughtfully deployed in a transparent, auditable framework, they can also promote compliance with rules, policies and regulations. However, AI or other advanced technologies alone cannot resolve the myriad issues of accountability, compliance, transparency, ethics and fairness that bedevil modern society. AI is, after all, just a tool for implementing decisions. Policy and regulatory frameworks, regulatory bodies and standards setting bodies, organisational structures and auditing practices, accountability frameworks and ethical considerations all shape how AI can be applied. Many such bodies exist today and their capabilities will need to be considered and addressed over time as AI becomes more ubiquitous across the government sector.

9.1. Future Trends

Advancements in information technology capable of monitoring a wide variety of activities in real time will create unprecedented opportunities for cross-reference data, for assessing the performance of individual public administrators, and consequently for auditing public governance. Of course, such algorithms may also be used to monitor citizen's activities and threaten their privacy or limit their freedoms, should the balance of power between the public sector and its citizens tilt in that direction. It is thus democratization in auditing, or monitoring government governance, to which this essay hopes to contribute. Such democratization would entail the creation of platforms that allow any citizen to hold any given public prosecutor accountable for their actions. Think of the possibilities freed by refreshing audit data such as tender award data, amended procurement contracts, or updated expenditure accounts, all linked to a sonar-and-visualization engine running as software-as-a-service. A democracy's collective consciousness can be located where the risk of government misconduct flourishes, such as shadowy public affairs, or procurement deals between public and privately-owned firms. These scars of contemporary governance can be discovered through constantly searching for unexpected bursts of activity in a state's economic, social and environmental variables and their rapid dispersions, through repeating or overlapping identical signatures found in compliance-relevant data, such as public procurement. A vision of the role of AI in bipartite auditing in a digitalized society is also presented. While technology inquiring into the possibility of automated controls for performing audits on public governance through an algorithmic decision support system is still lacking, current capabilities are discussed. Algorithms that can conduct qualitative checks such as matching and searching equality, validating completeness, estimating expected market price, or extracting simple coercive evidence are available, as are stylometrical measures that can indicate whether the output of a text writing engine may be composed by a human being. It is contended that realistically these measures can provide the first line of defense into semi-automated audit procedures such as those proposed. They can immensely assist in the quality assessment of mass-produced compliant texts and certified accounts, and curtail the human effort in audits of public governance applications while offering a transparent, explicit compensative control over any automation in the predicted step. The democratization of auditing is presented in terms of enabling non-experts to conduct audits on the basis of information primarily liberated for public scrutiny. In a digitalized democracy, however, reporting on anticipated conduct is only half of the story. A deeper scrutiny into the effectiveness of the auditing appears then imperative.

That audit outcome data itself should be made available for scrutiny in order to enable a collective consciousness of a democracy is argued. Following the arguments presented above, this essay will conclude with a hope to have narrowed the digitalization divide when approaching untapped opportunities for auditing public governance in democracy.

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