Review of Governance, Risk Management and Compliance of Artificial Intelligence Adoption for An Organization

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Abstract
While ethical discourses are useful for specifying the principles required for the adoption of trustworthy artificial intelligence, these principles need to be translated into best practices by organizations. In this regard, governance activities are known to support the core businesses of organizations and optimize risks and resources while promoting transparency for shareholders. In addition, risk management is an integral part of governance measures, as it affords organizations the justification to implement controls in managing the identified risks of artificial intelligence adoption. While regulations are beginning to take shape, this study performs a systematic review of articles on the associated governance, risk management and compliance approaches. A framework is synthesized from the literature to illustrate the dependencies between the various components and to facilitate practice by an organization. Finally, the study suggests ways in which external parties can support the efforts of organizations in this respect as well as future research directions.

Keywords: *Governance, risk management, compliance, artificial intelligence*

1. Introduction

Prior to the proliferation of Artificial Intelligence (AI), organizations adopted best practices in organizational and IT governance through the use of industry standards such as ISO 38500 (Calder, 2008) and The Control Objectives for Information and Related Technology version 5 (COBIT-5) (Khanyile & Abdullah, 2013). Taking a leaf from COBIT-5, the governance objectives of IT include benefiting the core business of an organization and optimizing risks and resources while promoting transparency to stakeholders. While the COBIT-5 differentiates between governance and management tasks, risk management remains one of the main considerations in the investment of resources to ensure that risks are managed transparently and accountably in an organization (ISO, 2018). In line with the development and implementation of AI, the International Organization for Standardization (ISO), in collaboration with the International Electrotechnical Commission (IEC), recently published the ISO/IEC 23894:2023-Information Technology-Artificial Intelligence-Guidance on Risk Management and ISO/IEC 42001:2023-Information Technology-Artificial Intelligence-Management System as guidance for the adoption of AI by organizations. Interested researchers can refer to the AI Standards Hub, which lists more than 200 AI-specific standards curated by the Alan Turing Institute (Institute, 2022).

While organizations that develop or implement AI have their own objectives in doing so, they need to manage the risks associated with AI adoption, as these risks are uncertainties in the attainment of objectives. In this regard, the risks of undesirable outcomes from the use of AI include hallucinations from chatbots and the inaccuracy of AI-generated results (BBC, 2020; Kaddour et al., 2023; NTSB, 2020). Given that AI models are data dependent, bias may occur when the underlying data used to train the models are inherently biased (Jeff Larson, 2016). In addition, it is important to ensure that personally identifiable information is not reproduced by the system such that it could cause information leakage or harm to individuals (Azam et al., 2023). Also, AI system is subject to adversarial attacks from malicious actors (Chakraborty et al., 2021). Figure 1 shows that there is an increasing trend for AI incidence and controversies worldwide, as reported by the Organization for AI, Algorithmic, and Automation Incidents and Controversies (AIAAIC).

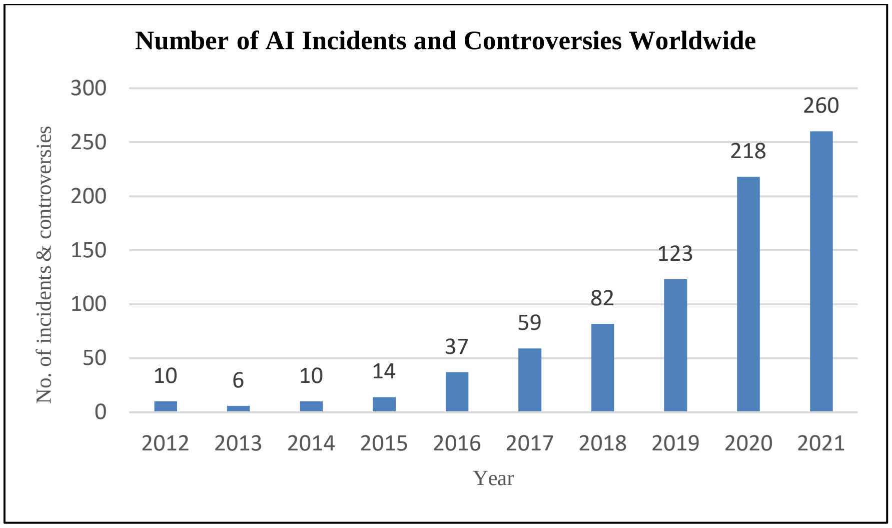

Figure 1: AI Incidents and Controversies from 2012 to 2021 (AIAAIC, 2023)

In the absence of accountability mechanisms, the Governance, Risk Management and Compliance (GRC) standards established for the corporate, IT and data domains can guide organizations in promoting best practices with endorsement from management in the form of policies, rules, and regulations. The term "GRC" was conceived by PricewaterhouseCoopers in 2004 to encapsulate the different areas of activities within an organization (Gill & Purushottam, 2008). A frame of reference for the GRC was introduced by (Racz et al., 2010) in 2010, as reproduced in Figure 2. Against this backdrop of development, this study proposes the following research questions (RQs):

RQ1: What are the governance, risk management and compliance approaches to AI adoption for an organization according to the academic literature?

RQ2: What are the research gaps in governance, risk management and compliance approaches to AI adoption for an organization?

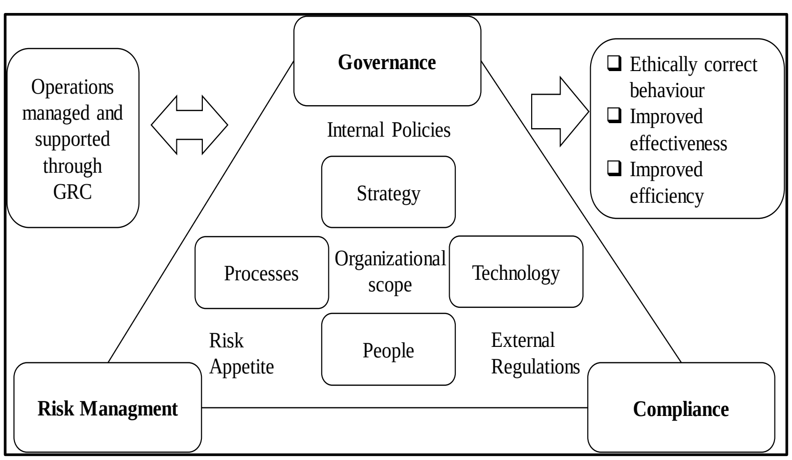

Figure 2: Frame of Reference for GRC (Racz et al., 2010)

2. Related Work

As early as the 1940s, when AI technology was merely an imagination conceived of autonomous robots, Asimov proposed 3 mandatory laws to be followed by a fictitious robot which necessitate the establishment of laws in the use of this technology (Penman, 2021). Subsequently, AI risks were articulated as ethical, technological, data and analytical risks; informational and communicational risks; economic and social risks; and legal and regulatory risks (Wirtz et al., 2022). Acknowledging the impact of drivers and barriers, Lee et al. (2023) formulated a conceptual framework underpinned by the theory of input-process-output (IPO). The framework included motivation, challenges and guidelines as inputs and consequences as outputs for AI implementation. The challenges were divided into organizational, information system (IS), technological and people dimensions. From a narrower perspective, (Camilleri, 2023) highlighted 10 ethical aspects of responsible AI that served as the basis for governance. The author explored the regulatory principles and guidelines available for AI adoption by organizations formulated by governments, non-governmental organizations (NGOs) and businesses. Similarly, Birkstedt et al. (2023) synthesized the themes of organizational AI governance as follows: technology, stakeholder and context, regulation, and processes. While the proposals by Camilleri (2023) and Birkstedt et al. (2023) were typologically grounded, the relationships among governance, risk management and compliance approaches were not clearly demonstrated, as illustrated in the framework by Lee et al. (2023). In an effort to clarify the activities involved in the governance of AI by businesses, Schneider et al. (2023) constructed a framework similar to that of Lee et al. (2023), which replaced the input with antecedents. The authors considered the ‘how’ and ‘what’ of governance activities where ‘how’ involves organizational, structural, and relational scope and ‘what’ includes the components of data, model and system. In a nutshell, the adoption of these frameworks and guidelines remains to be validated by empirical data due to the complexity of the technology and evolving risks, let alone the required reconciliation between business and governance objectives.

3. Methodology

This review was performed in accordance with the steps outlined in the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) guidelines (Petticrew & Roberts, 2008). This method was originally used for comprehensiveness, objectivity and reproducibility of systematic reviews in the medical field and subsequently by researchers from other disciplines (Moher et al., 2009). The search strategy stipulated by this approach is explicit, transparent and reproducible and involves examining preceding theoretical and empirical substantiation derived from articles disseminated in reputable peer-review journals (Durach et al., 2017). In addition, it presents evidence on a phenomenon across a diverse range of contexts and empirical approaches, thus mitigating potential biases in the literature (Denyer & Tranfield, 2009). First, the purpose and preparation of protocols were identified during the planning stage. The selection phase involved practical screening and searching for relevant literature. This step was followed by the extraction phase, which involves extracting the data and appraising its quality. Finally, the execution phase consisted of synthesizing the study and writing the review. Figure 3 shows the phases involved in the review process (Okoli, 2015).

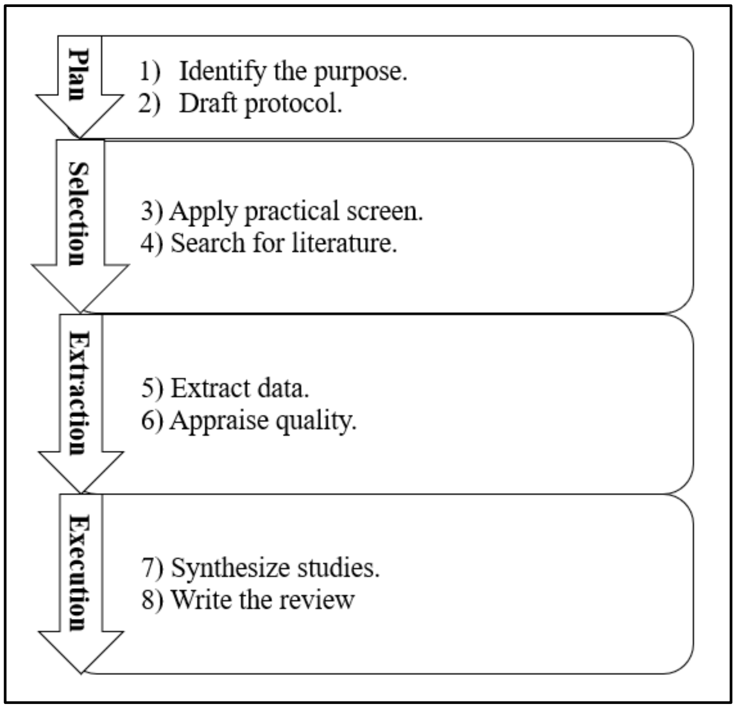

Figure 3: Systematic Literature Review Process (adapted from (Okoli, 2015))

Since the research topic is “Governance, Risk Management and Compliance of Artificial Intelligence for AI Adoption in an Organization”, the keywords and search tags are constructed with a combination of keywords inclusive of organizational, corporate, enterprise, governance, risk, compliance, and artificial intelligence. The databases used for the searches included major databases accessible from Universiti Teknologi Malaysia inclusive of ACM Digital Library, IEEE Xplore, ScienceDirect, Scopus, SpringerLink and Web of Science. The search strings applied to the abstracts of the articles is given in Table 1.

Table 1: Search criteria and sources

(organizational OR corporate OR enterprise) AND (governance AND "artificial intelligence") OR ("risk management" AND "artificial intelligence") OR (compliance AND "artificial intelligence") NOT ("COVID-19" OR "coronavirus") NOT ("electronic government" OR "e-government")

The selection stage started with practical screening, during which the inclusion and exclusion criteria were formulated. If duplicate documents were obtained, the most recent document was considered for analysis. Table 2 lists the inclusion and exclusion criteria.

Table 2: Inclusion criteria for research articles

Attribute	Inclusion Criteria	Rationale
Language	English	Ensure researcher’s understanding (Linares-Espinós et al., 2018)
Content	Studies that consist of GRC components and approaches	In line with research scope
Distinctiveness	Complete and distinct article	Elimination of duplicate articles
Accessibility	Full text accessible by UTM researcher	Full text is required
Published Period	1 January 2019 until 27 October 2023	Ethical concerns and requirements were established by European AI HLEG (AI, 2019) and Montréal Declaration for a Responsible Development of Artificial Intelligence in 2019 (Declaration, 2019) followed by OECD in 2020 (Yeung, 2020).

Attribute	Inclusion Criteria	Rationale
Document Type	Peer-reviewed articles which are not classified as books, review articles or conference papers.	In accordance with PRISMA requirement

Prior to the extraction of data, the snowballing method was applied when references to previous studies, as cited by the articles already found, were necessary (Wohlin, 2014). In applying quality assessment for the articles, five quality criteria were chosen from the checklist developed by Larsson and Patriksson (2016); these criteria were originally conceived for mathematical optimization or operations research. The checklist for quality assessment uses three coded scales, which are given a score of Yes=1, Partially=0.5, or No=0. A summation of each of the items from the item checklist is performed for each article, where possible scores range from 0 to 5. This score was used to determine if an article was considered for further analysis. Table 3 shows the checklist for quality assessment of the articles. The entire process of identification, screening, eligibility, and inclusion resulted in the shortlisting of 51 articles. The quality assessment criteria outlined in Table 3 were applied at the inclusion stage; 3 of the studies obtained were rated poor (scores of 2 and 2.5); 9 of the studies were graded as fair (scores of 3 and 3.5); 17 of the studies were classified as good (scores of 4 and 4.5); and 33 of the articles were given a perfect score of 5. Since this study emphasizes relevance, originality, consistency, integration and consequences as the quality criteria, only articles with scores of good or very good were considered. Hence, 51 articles were selected for further analysis.

Table 3: Criteria for Quality Assessment (adapted from Larsson and Patriksson (2016))

Criteria	Question	Answer
Relevance	Is the research question (RQ) motivated by any needs, or potential benefits of any results obtained?	Yes/No
Originality	Are the RQ or methodology unique, creative, or innovative, or of the established kind?	Yes/No/Partially
Consistency	Are the results and conclusions match the study objectives?	Yes/No/Partially
Integration	Can the work connect several scientific fields—in the paper or in possible future research?	Yes/No/Partially
Consequences	Is the result significant in terms of contribution to relevant components in for AI adoption?	Yes/No/Partially

From the synthesis of concepts after a review of the literature, we may identify topics that are under-researched and contradictory theories (Post et al., 2020). To characterize these research gaps, one can refer to the l7 types of gaps differentiated by (Miles, 2017). While the localization of the research gap is a creative process, one can elucidate the gaps by generating a chart or table that combines the concepts outlined in the literature (Webster & Watson, 2002). Figure 4 depicts the framework used for identifying research gaps (Müller-Bloch & Kranz, 2015).

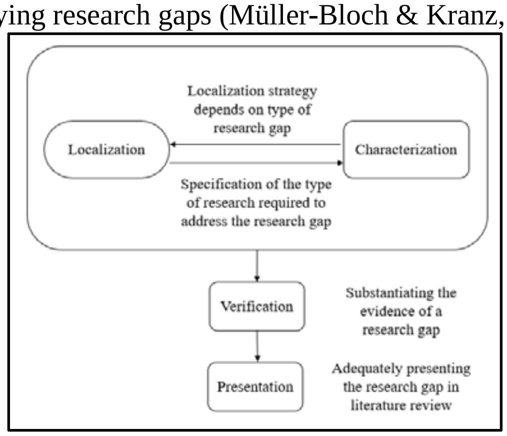

Figure 4: Framework for Identification of Research Gaps (adapted from (Müller-Bloch & Kranz, 2015))

4. Result

4.1 Conceptual Framework for GRC of AI Adoption

The GRC components are arranged by considering the relationships espoused in the literature. The scope of GRC implementation needs to be demarcated between the organization level (internal) and the external party. Figure 5 shows the proposed GRC framework for AI adoption in an organization.

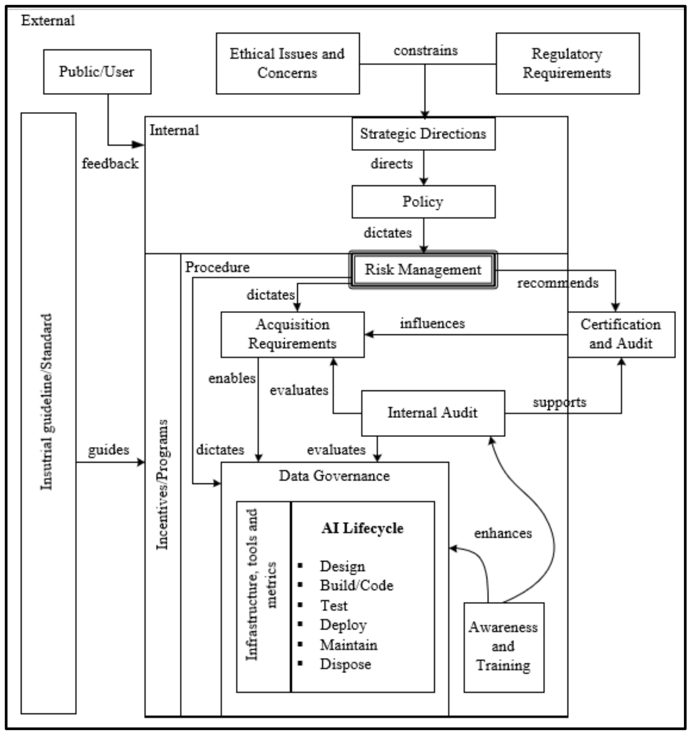

Figure 5: GRC Framework for AI Adoption in an Organization

The input or antecedents for the framework consist of ethical issues and concerns as well as the regulatory requirements for the use case proposed. Following this, the organization sets the strategic directions of the organization and formulates policies in line with the directions envisioned. Policies that may include aspects such as human resources, acquisition, third-party relations, cybersecurity, and safety specify the responsibilities and lawful conduct of members of an organization pertaining to a specific area. After the policies are established, procedures for the performance of various ensuing activities need to be established for the organization. Primarily, risk management is a composite process, which is highlighted with triple-rectangular lines in Figure 5.

In this regard, acquisition requirements are affected by decisions made during risk management. For example, instead of using an online LLM, an organization might choose to deploy its own open source LLM, which may be installed on the organization's own premise or on a cloud provider's infrastructure. Incidentally, awareness and training are vital to ensure that the various stakeholders involved are equipped to carry out their duties pertaining to trustworthy AI. This includes training for data engineers, AI scientists, developers, and evaluators. Similarly, the Internal Audit team should be trained on where and how to perform proper inspection to ensure that the system is performing as expected. Their role is crucial because confidential information or trade secrets such as the parameters and weights of an AI model should not be disclosed to an external party. Such information is proprietary and affects the competitive advantage of a business entity.

Generally, an AI life-cycle stage can be divided into data, modelling and deployment pipelines. Additionally, IT infrastructure, data and models are assets that need to be governed in contrast to the method of governance. In this regard, the data that are used for the modelling pipeline need to be processed accordingly to prevent poisoning or corruption. In addition, testing should be carried out using software tools with industry-accepted metrics. For example, there are tools that can measure accuracy, fairness and transparency. In addition, the ability to scale the infrastructure according to usage increases to ensure business continuity and customer satisfaction. Hence, various controls and safeguards implemented for each stage of the life cycle depend on the decision made during risk management.

4.2. Research Gaps

This section intends to provide answers to RQ2. In this regard, localization and characterization are carried out based on the framework in Figure 4. From the review conducted, four types of gaps are identified.

(A) Practical-knowledge Gap

Only a few studies have mentioned the adoption or adaptation of published standards in an organization's approach to GRC (Cihon et al., 2021; Felländer et al., 2022; Haakman et al., 2021; Shahriar et al., 2023; Tidjon & Khomh, 2023). This begs questions about the relevance of standards and the mechanism through which standards are promoted for AI-adopting organizations.

(B) Methodology Gap

From the 51 articles selected for review, 29 performed a conceptual review, 4 performed SLR, and 1 performed a scoping review. These studies collectively formed more than half (66.67%) of the articles. Although valuable insights are derived from these articles, empirical evidence that verifies actual GRC practices in an organization cannot be obtained from these articles. Additionally, several authors have highlighted the need to perform field studies to obtain contextual data (de Almeida et al., 2021; Mun et al., 2020; Papagiannidis et al., 2023). Figure 6 illustrates the methodology used by the selected studies. The total number of selected studies exceeded 51 because one article used a combination of conceptual review, qualitative and quantitative approaches (Coates & Martin, 2019).

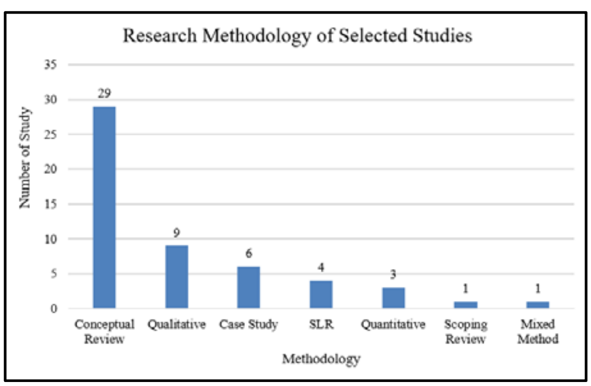

Figure 6: Methodology of the Selected Studies

(C) Empirical Gap

This gap arises because of the methodology gap highlighted. There is a lack of numerical evidence on the applicability of GRC approaches for evaluating AI adoption by organizations. Sufficient numerical data are required to claim the generalizability of any framework related to GRC approaches (Coates & Martin, 2019). Recent proposals, such as a risk and guideline-based integrative framework for AI governance (Wirtz et al., 2022) and a multistakeholder value-based assessment framework (Yurrita et al., 2022), while providing extensive guidelines for practices, are needed to identify the challenges, if any, in the application of these frameworks.

(D) Population Gap

Previous studies on this topic have been conducted in the finance (Fritz-Morgenthal et al., 2022), banking (Ratzan & Rahman, 2023), energy (Alsaigh et al., 2023; Su et al., 2022), healthcare (Chamola et al., 2023), pharmaceutical (Mokander et al., 2022) and automotive (Chamola et al., 2023) industries as well as the public sector (Gonzalez Torres & Sawhney, 2023; Hickok, 2022). The cross-boundary and cross-industry nature of AI technology requires examining GRC approaches in other under-researched sector, such as education, leisure and entertainment, farming, public safety, and supply-chain management. Hence, Table 4 summarizes the gaps identified.

Table 4: Verification of Research Gaps

Gap		Verification
(A)	Practical-knowledge gap	The application of framework or published standards is low at best and non-existent at worst. This is illustrated in the statement by (Tidjon & Khomh, 2023): *"The principle-to-practice gaps identified include a lack of effective practical guidance tools, and weakness of the practical guidance of AI ethics principles in corporate governance."*
(B)	Methodology gap	As exerted by (Wirtz et al., 2022): *"As a first step for conceptually complementing the framework and testing its empirical validity, future studies could conduct expert interviews with public managers."*
(C)	Empirical Gap	Most of the tools, models and framework proposed are conceptual in nature without validation of actual application. The importance of closing this gap is also echoed by (Birkstedt et al., 2023) as follows: *"Our understanding of AI governance mechanisms' characteristics, effectiveness and determinants should be more detailed, calling for in-depth empirical research."*
(D)	Population Gap	Currently, only European Union proposed a comprehensive AI legislation to date while the UK is expected to have connected and automated mobility on the roads by the year 2025 through the ratification of related laws (Government, 2023). The absence of accountability mechanism for high-risk use cases prompted the following conclusion by (Papagiannidis et al., 2023): *"..all cases are from the same sector. Hence, generalizability could be an issue that should be taken into consideration. As future research, it would be interesting to gather more empirical data through interviews, from firms that belong to different sectors…"*

5. DISCUSSION

A GRC framework is proposed that resembles an actionable process so that organizations can operationalize it to minimize drawbacks in their AI adoption. Although the GRC components can be arranged in the framework proposed by (Schneider et al., 2023), the arrangement proposed in this study demonstrates the dependencies between components and provides stakeholders with a processual mechanism for implementation in their organization. This approach can be validated empirically via qualitative research to gauge acceptance by organizations, such as through case studies conducted for pharmaceutical companies (Mökander et al., 2022). As the structure of the framework resembles a process, it may also be validated through the interpretive structural modelling method (Attri et al., 2013). In support of GRC efforts, external parties have important roles to play as elaborated in the following subsections.

5.1 Specification of Procurement Requirements

This action by the government is a signal to the industry concerning the minimum expectation or standards needed. Since procurement is performed by government offices, officials need to be aware of the standards and the risks of non-compliance with AI technology.

5.2 Law and Legislation

Although it may be regarded as a form of restriction to innovation, legislation is a double-edged sword in which it promotes the responsible use of AI and hence increases trust in the widespread usage of AI technology by the public. Laws are also enforceable; hence, the assignment of responsibilities ensures that high-risk applications of AI are closely monitored by all relevant stakeholders. Additionally, laws and legislations are necessary to deter malicious actors from misusing AI or illicit purposes.

5.3 Audit and Certification

Like in the case of the Information Security Management System (ISMS), audit exercise can be carried out by government-appointed certification bodies for certain use cases or industries (Asosheh et al., 2013). Furthermore, industry-wide recognition can also be established for certification requirements, which are a form of soft law that could incentivize the adoption of best practices.

5.4 Research and Development

Researchers from academic institutions and businesses should collaborate and share information on techniques and tools to promote the development of trustworthy AI.

5.5 Mandatory Approval for High-Risk Use Cases

Proof-of-concept should be mandated prior to the issuance of permits for the deployment of AI technology in high-risk environments, such as medical diagnostic devices, self-driving vehicles or identifying unlawful activities. Approval criteria should be defined, and pilot tests can be conducted before such solutions are deployed. This role can be played by the relevant government authorities in collaboration with industry experts.

6. CONCLUSION

In this study, a GRC framework for AI adoption in an organization is conceived to facilitate AI adoption by the organization. This framework is synthesized from SLR and indicates the dependencies between the related GRC components. Additionally, the framework illustrates the mechanisms through which external stakeholders can support organizations in their adoption of AI, which is trustworthy and fulfils organizational objectives. In conclusion, this study is limited by the selection of databases and future research may apply the framework to specific use cases or organization for validation.

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