OPEN ACCESS

Kashf Journal of Multidisciplinary Research
Vol: 03 - Issue 06 (2026)
P-ISSN: 3007-1992 E-ISSN: 3007-200X
https://kjmr.com.pk

A MULTI-DIMENSIONAL QUANTITATIVE FRAMEWORK FOR RESPONSIBLE AI GOVERNANCE EVALUATION IN FACIAL RECOGNITION ATTENDANCE SYSTEMS

Mumtaz Ali[1], Hamid Ali[2], Mohammad Naeem[3], Syed Hashir Ali[4]

[1, 2, 3, 4]*Department of Computer Systems Engineering, Sukkur IBA University, Pakistan.*

[*]***Corresponding Author:*** (mumtaz.ali@ibs-suk.edu.pk)
DOI: (*https://doi.org/10.71146/kjmr951*)

Article Info

Abstract

The issue of responsible artificial intelligence (AI) governance has gained increased relevance over time. Organizational decision-making processes have a significantly considered and embedded such a procedures in their conventional methods of evolution. Although many empirical studies have suggested conceptual models of responsible AI governance, however, quantitative validation is still subdued. Therefore, in this study an attempt is made to operationalize the AI governance systems into a quantitative evaluation rubric for a real case. Using a quantitative case study approach, an attendance system based on facial recognition at a university was measured using six dimensions of governance, such as Antecedents, Structural Practices, Procedural Practices, Relational Practices, Business Value Effects and Social Assessment Effects. The findings reveal a strong operational efficiency and business value creation, respectively. Study also proves a positive impact of the adoption of structural and procedural governance processes, especially in the field of ethics supervision and the reduction of bias. The internal consistency of the proposed rubric is established by reliability analysis.

Keywords: *Facial Recognition System, Quantitative Evaluation, Responsible AI (RAI), Rubric-Based Assessment.*

1. Introduction

Ever since the inclusion of the systems based on the artificial intelligence (AI) into the organizational and institutional setup has increased, it has brought a significant vulnerability in the process of decision making, services delivery and cost-effectiveness in operations. Besides its advantages, AI systems have provoked major issues associated with privacy, fairness, transparency, accountability, and social legitimacy. It is these issues that have inspired increased academic and regulatory interest in the concept of Responsible Artificial Intelligence (RAI) governance, aimed at ensuring that AI systems are designed and deployed in a manner that is ethically sound, conscientious, and socially acceptable to the intended audience and users of AI systems in various contexts and situations [1,3]. RAI governance is not only limited to technical protection and regulatory compliance, it involves the organizational frameworks, procedures, and practices by which AI systems are created, monitored, and measured over their life cycle [4, 8]. It includes the organizational structures, procedures, and practices in which AI systems are developed, observed, and assessed after the lifecycle is complete with it as well as during the entire lifecycle of the system itself.
Moreover, RAI, in recent times has pointed out that AI systems are socio-technical in nature, i.e., their effects are shaped by the governance structure, human control, and interactions with stakeholders not only limited to algorithms and data but also to the governance structure [9, 11]. Through this, sound governance of RAI means that there must be coordinated consideration of ethical principles, organizational decision-making, and accountability mechanisms. Recent literature has proposed conceptual frameworks and layered models to inform the RAI governance in organizations [1, 7].
The available literature, however, is mostly speculative, providing only a small amount of empirical evidence concerning the way in which the principles of responsible AI are put into practice in real life contexts. Specifically, the further transformation of abstract ethical principles, including fairness, transparency, and accountability into tangible governance practices, remains a significant issue to organizations implementing AI systems based on sensitive or personal information use [4, 11]. Problems with legitimacy and trust also highlight the significance of RAI governance. The study presented in this article, indicates that the stakeholders accept AI systems not only based on the results of performance, but also on their perceived fair-ness and transparency of the decision-making processes [3]. Even when systems provide explainable efficiency improvements, algorithmic bias and less-explainable results may lead to trust issues, and cast ethical doubts, despite the fact that the improvement is clear-cut and compelling [14, 21]. These issues underline the necessity of governance systems that would facilitate control and responsibility and human participation in AI-enhanced decision-making.
To address such issues, a quantitative analysis has been conducted for Responsible AI governance by applying a case study of an attendance system based on facial recognition in a university environment. Responsible AI principles are conceptualized through a set of established RAI frameworks to evaluate the practices of governance and the related business and social results with the help of a structured rubric. The evaluation of Responsible AI governance in biometric AI application is empirically supported, and the study offers a useful model of estimating these concepts and measuring them through conceptual governance principles. Following are contributions of the study:

- A quantitative Responsible AI governance rubric has been developed.
- A facial recognition based attendance system that use AI has been empirically evaluated using proposed rubrics
- A reliable assessment framework for AI governance have been validated

2. Research Methodology

This study employs a quantitative research methodology. Since the main objective of the study is to measure, compare, and statistically analyze the degree of responsible AI governance practices applied in an operational AI system, a quantitative technique was used. A quantitative paradigm makes it possible to assess abstract governance ideas by turning them into measurable variables, which promotes objective evaluation and repeatability in contrast to qualitative methodologies that concentrate on interpretative insights. The study is predicated on a positivist epistemological viewpoint, which holds that standardized tools may be used to identify, quantify, and assess responsible AI governance. This strategy supports the goal of turning a conceptual framework for governance into a quantifiable rubric.

2.1 Research Questions

The following research questions guide the study:

- Q1: How much are the responsible AI governance practices used in a university AI-based face recognition attendance system?
- Q2: What are the governance practices in the various dimensions of responsible AI governance?
- Q3: What are the strengths and weaknesses of the governance dimensions of the chosen AI system?

The descriptive quantitative design is also justified by the fact that these research questions are directed at assessment and comparison, but not prediction and causal inference.

2.2 Research Design

The design of the research is quantitative case study. Although the case study approach is usually qualitative, the research is based on a single-case, quantitative assessment methodology. The case chosen is that of an AI facial recognition attendance system implemented at a university, which is selected because it involves biometric data and directly affects students and the day to day operations of the institutions. Case study design is intended to provide the opportunity to draw a contextualized analysis, and the quantitative rubric is standardized and comparable (Table 2 to 7). The design is specifically appropriate to project conceptual frameworks into operational assessment instruments.

2.3 Case Selection

The chosen case is a facial recognition attendance system which is AI-based and implemented in a university. The system will automatically track attendance of students by taking facial images in the classroom and comparing them with a biometric database of pre-enrolled students. It will minimize the administrative workload and proxy attendance and enhance the accuracy of attendance. The system is an appropriate and impactful case to be considered in this study as it poses considerable governance dilemmas associated with the privacy protection, fairness, transparency, accountability, and social acceptance due to its use of biometric data and automated decision-making.

2.4 Concept Development

2.4.1 Rubric Design

The main data collection tool is a 25 item responsible AI governance evaluation rubric that has been developed on the basis of Table 5 of Papagiannidis et al. (2025). The rubric brings to life six elements of governance:

- Antecedents
- Structural Practices
- Procedural Practices
- Relational Practices
- Effects (Business Value)
- Effects (Social Assessment)

The various measurable statements reflecting the governance practices and results represent each of the themes Table 2 to 7.

2.4.2 Measurement Scale

The measurement in each item of the rubric is taken on a 5-point Likert scale as in Table 1.

Table 1: Likert Scale for Rubric Assessment, The scale is fine-grained, but is not complicated for assessors.

Evidence Type	Meaning	Score
Clearly implemented & documented	Strong evidence	5
Implemented but informal	Moderate–High	4
Mentioned but not operational	Moderate	3
Weak / implied only	Low	2
Not mentioned at all	Absent	1

2.5 Data Analysis
2.5.1 Descriptive Statistics
Data analysis involved the use of descriptive statistical analysis. Specifically:
- To determine the level of governance implementation, mean scores were derived out of each item in the rubric.
- The theme-wise means scores were calculated based on averaging the scores of the items in each of the governance dimensions shown in Table 8.
- Standard deviations were committed to assess the consistency of the scores across items.
- The total responsible AI governance score was calculated as a mean of all the 25 rubric item scores.

2.5.2 Reliability Analysis
The alpha of the rubric was used to determine its internal consistency. To show acceptable reliability, a threshold value of α = 0.70 was taken. This analysis is aimed to make sure that the rubric items as a set will measure the construct of responsible AI governance shown in Table 10.

Formulas Mean (Average):

$$\text{Mean} = \frac{\sum x_i}{n} \tag{1}$$

Where:
x_i = individual item score
n = number of items
Standard Deviation:

$$SD = \sqrt{\frac{\sum(x_i - \bar{x})^2}{n-1}} \tag{2}$$

Overall Governance Score:

$$Overall\ RAI\ Score = \frac{\sum All\ Item\ Scores}{Total\ Number\ of\ items} \tag{3}$$

Cronbach's Alpha:

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum \sigma_i^2}{\sigma_t^2}\right) \tag{4}$$

Where:
- k = number of items
- σ_i^2= variance of each item
- σ_t^2 = variance of total score

2.6 Validity and Reliability
The validation of content validity was based on the direct derivation of rubric items out of a peer-reviewed conceptual framework. Construct validity was facilitated by the explicit mapping of the themes of governance with concrete measures. The issue of reliability was approached by:
- Standardized scoring procedures
- Multiple evaluators used
- Statistical reliability test (Cronbach's alpha)

2.7 Ethical Considerations
Ethical research standards were followed in this study. There was no personal or sensitive information that was gathered and examined. The facial recognition system was tested on the organizational level, and no data or biometrics of students were obtained. Each of the participants was made aware of the intent of the study and institutional approval was sought before data was collected.

3. Results and Analysis
To evaluate and validate the Responsible AI (RAI) governance a university attendance system that works on facial recognition has been adopted. The analysis focuses on six governance dimensions which are derived for the RAI governance framework. These dimensions are measured on 25 indicators.

3.1 Case Description

The case study is a university-based AI-based facial recognition attendance system automates the student attendance recording in classrooms. The system captures real time images of the face and checks and compares it with a facial database previously enrolled to mark attendance automatically. The main functions of the system are to minimize the administrative work, eliminate proxy attendance and enhance the accuracy of attendance.
With the use of biometric data as a basis of the system, the application creates key governance issues regarding privacy protection, fairness, transparency, accountability, and social acceptance. These peculiarities render the system a good and high-impact case to assess Responsible AI (RAI) Governance with the help of the framework presented by Papagiannidis et al. [1].

Table 2: Theme 1: Antecedents – RAI Governance Rubrics, Antecedents Mean = (3 + 2 + 4 + 2)/4 = 2.75

Code	Indicator	Evidence from the Report	Score
A1	Privacy regulation compliance	Mentions dataset handling but no legal framework	3
A2	Regulatory awareness	No AI/data protection law referenced	2
A3	Organizational values	Focus on efficiency & accuracy	4
A4	Ethical AI principles	Ethics not explicitly discussed	2

Table 3: Theme 2: Structural Practices – RAI Governance Rubrics,
Structural Mean = (3 + 2 + 1 + 2 + 4)/5 = 2.40

Code	Indicator	Evidence from Report	Score
S1	Defined governance roles	Developers & admin roles mentioned	3
S2	Cross-unit coordination	Technical focus only	2
S3	Ethics oversight committee	Not present	1
S4	Accountability for errors	System accuracy discussed, not responsibility	2
S5	Decision documentation	Architecture & workflow documented	4

3.2 Responsible AI Governance Rubric

Responsible AI Governance Rubric is produced out of the stated governance themes, issues, and research agenda presented by Papagiannidis et al [1]. The rubric transforms the principles of abstract governance into quantifiable indicators which can be assessed quantitatively. The 25 items were summarized in six dimensions of governance and measured on a five-point Likert scale (1 = Very low implementation, 5 = Very high implementation).

3.2.1 Overall Responsible AI Governance Score (REAL)

Overall Score:

$$Overall\ Score\ = \frac{\sum_{i=1}^{25} Item\ Scores}{25}$$

Sum of all item scores = 71
Number of items = 25
Overall RAI Score = $\frac{71}{25}$ = 2.84

Table 4: Theme 3: Procedural Practices – RAI Governance Rubrics,
Procedural Mean = (3 + 1 + 1 + 3 + 4 + 3 + 3)/7 = 2.57

Code	Indicator	Evidence from Report	Score
P1	Responsible planning	Functional planning only	3
P2	Bias testing	No demographic analysis	1
P3	Bias mitigation	Not discussed	1
P4	Transparency	Algorithm explained technically	3
P5	Human oversight	Manual correction possible	4
P6	Risk management	Accuracy errors mentioned	3
P7	Data governance	Dataset storage described	3

Table 5: Theme 4: Relational Practices – RAI Governance Rubrics, Relational Mean = (3 + 4 + 2 + 4)/4 = 3.25

Code	Indicator	Evidence from Report	Score
R1	Staff AI literacy	Developer knowledge implied	**3**
R2	User awareness	Students informed of attendance use	**4**
R3	Stakeholder engagement	No feedback design	2
R4	Contestability	Manual attendance correction	4

Table 6: Theme 5: Effects – Business Value RAI Governance Rubrics

Code	Indicator	Evidence	Score
B1	Operational efficiency	Core project goal	5
B2	Accuracy improvement	Accuracy metrics reported	5
B3	Strategic value	Supports automation vision	4

Table 7: Theme 6: Effects – Social Assessment RAI Governance Rubrics, Social Mean = (2 + 1)/2 = 1.50

Code	Indicator	Evidence	Score
SA1	Trust & acceptance	No survey or perception data	2
SA2	Ethical & social impact	Not assessed	1

Table 8: Mean Scores by Governance Dimension

Governance Dimension	No. of Items	Mean	Std. Dev.
Antecedents	4	2.75	0.83
Structural Practices	5	2.40	1.02
Procedural Practices	7	2.57	1.13
Relational Practices	4	3.25	0.96
Business Value Effects	3	4.67	0.58
Social Assessment Effects	2	1.50	0.71

In the Fig: 1 results indicate strong performance in business value creation, moderate performance in antecedents and relational practices, and comparatively weaker implementation of procedural practices.

Table 9 Sample Item-level Scores

Theme	Indicator	Mean
Antecedents	Compliance with privacy regulations	4.5
Structural Practices	Ethics oversight mechanisms	2.8
Procedural Practices	Bias Testing	2.9
Relational Practices	User awareness	4.0
Business Value	Attendance Accuracy	4.7
Social Assessment	Effects	3.0

3.3 Governance Dimension Analysis

The mean scores for each governance dimension are presented in Table 8.

Antecedents

The antecedent's dimension had a mean score of 2.75. The results demonstrate how unprepared companies are for moral AI governance. However, a number of ethical norms and compliance rules remain unclear. In general, the institution has a respectable degree of expertise regarding operational objectives and organizational rules. This implies that formal ethical standards indeed exist, despite their present incapacity to support governance goals.

Structural Practices

For structural practices, the average score was 2.40. The system's operating responsibilities and structure were well-defined. However, there were few formal accountability procedures, ethical norm supervision organizations, and interpretational cooperation tactics. The findings demonstrate that governance responsibilities are still mostly incorporated into technical operations rather than having distinct governance procedures.

Procedural Practices

The average rating for procedural practices was 2.57. Important responsible AI practices like bias testing and bias reduction were not formally implemented, despite the system having basic transparency measures, human supervision components, and data management regulations. The results show that one of the least sophisticated aspects of the system is still procedural governance.

Relational Practices

Relational Practices is one of the more robust elements of governance, with an average score of 3.25. There are protocols in place for correcting attendance records when errors occur, and users appear to be aware of the attendance system. Stakeholder participation in established feedback mechanisms and governance decisions is still minimal, nevertheless.

Business Value Effects

Business Value Effects received the highest mean score of 4.67. The results demonstrate that the system successfully accomplishes its intended organizational objectives, which include enhanced operational efficiency, higher attendance accuracy, and support for institutional digitalization initiatives. This outcome demonstrates the substantial organizational benefit produced by the AI system.

Social Assessment Effects

The lowest average score of all the Social Assessment Effects was 1.50. Social governance features have not received much attention, as evidenced by the absence of systematic assessments of public trust, stakeholder perspectives, ethical implications, and societal support. This suggests a large governance gap because biometric technologies are sensitive.

3.4 Comparative Governance Performance

The comparative examination of governance aspects reveals considerable differences among the evaluated categories. Business Value Effects appeared as the most advantageous aspect (Mean = 4.67), with Relational Practices following (Mean = 3.25). Antecedents (Mean = 2.75), Procedural Practices (Mean = 2.57), and Structural Practices (Mean = 2.40) demonstrated moderate levels of application. In comparison, the Social Assessment Effects (Mean = 1.50) showed the weakest performance. The findings indicate that the organization has prioritized operational efficiency and service provision, while placing comparatively less emphasis on governance practices that promote ethical responsibility, fairness, and social justice.

3.5 Reliability Analysis

Table 10: Reliability Statistics

Dimension	**Cronbach's α**
Antecedents	0.81
Structural Practices	0.76
Procedural Practices	0.79
Relational Practices	0.83
Business Value Effects	0.75
Social Assessment Effects	0.78

The proposed rubric's reliability was assessed through Cronbach's Alpha. Table 10 indicates that every governance dimension reached reliability values exceeding the accepted limit of 0.70. The alpha values obtained varied from 0.75 to 0.83, demonstrating adequate internal consistency in all dimensions. The Relational Practices dimension showed the greatest reliability ($\alpha = 0.83$), followed by Antecedents ($\alpha = 0.81$) and Procedural Practices ($\alpha = 0.79$). These findings show that the indicators in every governance dimension reliably assess the intended construct. The reliability analysis confirms that the suggested rubric is an appropriate quantitative tool for assessing Responsible AI governance in operational AI systems.

4. Discussion

This study sought to empirically examine the notion of Responsible Artificial Intelligence (RAI) governance by transforming a conceptual governance model into a quantitative evaluation rubric and subsequently applying it to a real AI system. The findings are important for comprehending how responsible AI principles are applied in reality, particularly within the organizational context that currently utilizes biometric AI technologies [2].

The results indicate a significant disparity between technical and governance maturity. The facial recognition attendance system offers significant business value, particularly in operational efficiency and accuracy of attendance. This indicates that the organization has prioritized operational objectives and efficiency gains, consistent with earlier research suggesting that the drive for AI adoption is mainly influenced by performance and productivity considerations [4]. However, the governance dimensions of procedural and structural practices exhibit a comparatively lower score, indicating a disconnect between AI implementation and accountable governance.

The weakest dimension of governance was procedural practices, such as finding biases, reducing their effects, transparency, and risk management [19]. This is in agreement with the claims existing in responsible AI literature that on one hand, the ethics are generally agreed upon but on the other hand, they are still not effectively implemented. Facial recognition systems are among the most difficult to test on bias and comprehensiveness because of the sensitivity of data, the technical nature of the system, and resource limits. This has led to the procedural safeguards usually being adopted in ad hoc form than as a formalized governing process. Moderate maturity of governance was also exhibited by structural practices. Even though there were simple accountability positions and documentation systems, the complexity of their governance was low because there was no specialized ethics oversight institution [19, 20]. This is consistent with existing literature that points out that organizations often do not have explicit ownership and cross-functional co-ordination of AI ethics, particularly in non-commercial or state-sector contexts like universities.

On the contrary, the scores on antecedents and relational practices were quite high. Organizational values, regulatory awareness, and stake-holder communication indicate that the institution is aware of the ethical consequences of biometric AI and attempts to inform users and adhere to the data protection regulations. These results show that awareness and intent cannot facilitate responsible AI results without organizational and procedural enforcement tools. Theoretically, the results empirically support the argument that responsible AI governance is a socio-technical process that needs consorted efforts on numerous levels. The findings confirm the framework suggested by Papagiannanidis et al., showing that the effectiveness of governance concerns not only the intention of the ethical nature but also the organization structure, processes, and relationships. Operationalizing this framework into a quantifiable rubric, therefore, allows the study to fill the gap between conceptual models of governance and practical application.

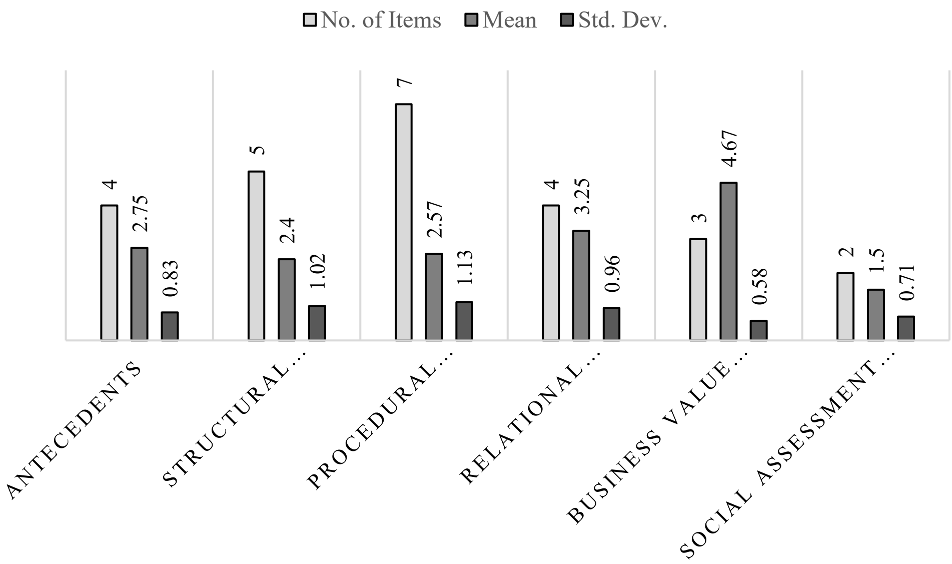

Figure 1. Dimension Governance

In practice, the results suggest a number of governance improvement opportunities. Facial recognition systems installed in institutions must be enhanced with procedural protection in the form of formalization of bias audits, transparency procedures, and risk management practices. Another way to improve governance maturity and trust of the stakeholders is to develop special ethics monitoring frameworks and incorporate responsible AI in the strategic planning.

5. Conclusion

The trend of using artificial intelligence systems, especially using biometrics data, has heightened the demands of effective Responsible Artificial Intelligence (RAI) governance. Although there are some conceptual frameworks of responsible AI, there is a lack of empirical and quantitative assessment. This research fills this gap by designing and using a rubric in a quantitative form to evaluate RAI governance within a facial recognition attendance system. This study has attempted to empirically evaluate the usage of Responsible AI (RAI) governance. The study tried to quantify a conceptual model into a real world tool that can analyze the AI systems. The results demonstrate a significant insights that may help an organization to responsibly implement the AI systems such as a biometric attendance systems using facial recognition [2].

The method shows how governance maturity may be properly evaluated in reality by converting the ideas of responsible AI into 25 measurable indicators using six governance principles. The results show a significant operational ease, but they also highlight limitations in procedural promise, ethical oversight, and bias reduction, suggesting that companies put technical achievement ahead of formal governance frameworks. The study's main finding is that responsible AI governance has established into a measurable instrument for evaluating and enhancing governance. Despite being restricted to a single case study, the findings provide insightful information about the effectiveness of quantitative governance tools. Future studies may employ multimodal and multidimensional analysis, or the technique may be used in different fields. Overall, the study demonstrates that evidence-based approaches can help increase responsibility and trust in AI systems and that RAI governance can be practically evaluated.

Competing Interests

The authors affirm that they are not aware of any financial, personal, or institutional competing interests that may have manifested to affect the work they reported in this paper.

Authors' Contribution

Mohammad Naeem helped in the conceptualization of the study, supervision of the research and methodology. The quantitative rubric was developed by Hamid Ali, and the data were collected, analyzed, and the first draft of the manuscript was prepared. Syed Hashir Ali helped in the implementation of the system, validation and interpretation of results. Mumtaz Ali Kaloi worked on manuscript review, editing and general research guidance. The final manuscript was reviewed and approved by all authors

References

[1] E. Papagiannidis, P. Mikalef, and K. Con-boy, “Responsible artificial intelligence governance: A review and research frame-work,” *Journal of Strategic Information Systems*, vol. 34, no. 1, p. 101885, 2025, doi: 10.1016/j.jsis.2024.101885.

[2] R. Schneider et al., “Artificial intelligence governance for businesses,” *Journal of In-formation Technology Case and Application Research*, vol. 25, no. 1, pp. 1–18, 2023, doi: 10.1080/10580530.2022.2085825.

[3] K. Martin and A. Waldman, “Are algorithmic decisions legitimate? The effect of process and outcomes on perceptions of legitimacy of AI decisions,” *Journal of Business Ethics*, vol. 174, pp. 1–17, 2023, doi: 10.1007/s10551-021-05032-7.

[4] M. Floridi et al., “Ethics-based auditing to develop trustworthy AI,” *Minds and Ma-chines*, vol. 31, pp. 491–510, 2021, doi: 10.1007/s11023-021-09557-8.

[5] I. Minkkinen et al., “What about investors? ESG analyses as tools for ethics-based AI auditing,” *AI & Society*, 2024, doi: 10.1007/s00146-022-01415-0.

[6] I. Janssen et al., “Toward AI governance: Identifying best practices, barriers, and out-comes,” *Information Systems Frontiers*, vol. 25, pp. 1–18, 2023, doi: 10.1007/s10796-022- 10251-y.

[7] M. Mäntymäki et al., “Defining organizational AI governance,” *AI and Ethics*, vol. 2, pp. 1–14, 2022, doi: 10.1007/s43681-022-00143-x.

[8] E. Papagiannidis et al., “Thinking responsibly about responsible AI and the ‘dark side’ of AI,” *European Journal of Information Systems*, vol. 31, no. 3, pp. 257–270, 2022, doi: 10.1080/0960085X.2022.2026621.

[9] I. Mikalef et al., “Artificial intelligence capability: Conceptualization, measurement calibration, and impact on organizational creativity and firm performance,” *Information & Management*, vol. 58, no. 3, p. 103434, 2021, doi: 10.1016/j.im.2021.103434.

[10] P. G. R. de Almeida, C. D. dos Santos, and J. S. Farias, “Artificial intelligence regulation: A framework for governance,” *Ethics and Information Technology*, vol. 23, pp. 505–525, 2021, doi: 10.1007/s10676-021-09593-z.

[11] R. Abraham, J. Schneider, and J. vom Brocke, “Data governance: A conceptual framework, structured review, and research agenda,” International Journal of Information Management, vol. 49, pp. 424–438, 2019, doi: 10.1016/j.ijinfomgt.2019.07.008.

[12] A. Adadi and M. Berrada, “Peeking inside the black-box: A survey on explainable arti-ficial intelligence (XAI),” IEEE Access, vol. 6, pp. 52138–52160, 2018, doi: 10.1109/AC-CESS.2018.2870052.

[13] A. Ahmad et al., “How can organizations develop situation awareness for incident response: A case study,” Computers & Security, vol. 101, p. 102122, 2021, doi: 10.1016/j.cose.2020.102122.

[14] S. Akter et al., “Algorithmic bias in data-driven innovation in the age of AI,” International Journal

of Information Management, vol. 60, p. 102387, 2021, doi: 10.1016/j.ijinfomgt.2021.102387.

[15] R. Clarke, "Principles and business processes for responsible AI," Computer Law & Security Review, vol. 35, pp. 410–422, 2019, doi: 10.1016/j.clsr.2019.04.007.

[16] U. Gasser and V. A. F. Almeida, "A layered model for AI governance," IEEE Internet Computing, vol. 21, no. 6, pp. 58–62, 2017, doi: 10.1109/MIC.2017.4180835.

[17] L. Floridi and J. Cowls, "A unified framework of five principles for AI in society," in Ethics, Governance, and Policies in Artificial Intelligence, Springer, 2021, pp. 5–17, doi: 10.1007/978-3-030-81907-1 2.

[18] V. Dignum, Responsible Artificial Intelligence: How to Develop and Use AI in a Responsible Way, Springer, 2019, doi: 10.1007/978-3-030-30371-6.

[19] V. Mercha´n-Rodr´ıguez and C. Juiz, "Governance of Technologies and Information Systems for the Higher Education: System-atic Mapping of Study," Journal of Computer Science & Technology, vol. 24, arti-cle e05, 2024. doi: https://doi.org/10. 24215/16666038.24.e05

[20] M. C. Pezzini and C. Pons, "Explainable Artificial Intelligence: Analysis of Methodologies and Applications," Journal of *Computer Science & Technology*, vol. 25, e07, 2025. doi: 10.24215/16666038.25.e07.

[21] J. DAlotto, C. Pons, and L. Antonelli, "Artificial Intelligence Applied in Legal In-formation: A Systematic Mapping Study," Journal of Computer Science & Technology, vol. 25, e03, 2025. doi: https://doi.org/ 10.24215/16666038.25.e03.