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ORGANIZATIONAL CULTURE AND ETHICAL ARTIFICIAL INTELLIGENCE USE: A GOVERNANCE PERSPECTIVE IN SAUDI ARABIA

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ABSTRACT

This study investigates the complex relationship between organizational culture and the governance of ethical artificial intelligence (AI) use, emphasizing the influence of cultural values on AI deployment and the reciprocal impact of AI on organizational culture. A quantitative research design was adopted, employing structured questionnaires distributed to senior executives, AI developers, compliance officers, and ethics officers from a range of organizations to obtain comprehensive data on perceptions, practices, and leadership attitudes concerning AI ethics. The results indicate that an ethically oriented organizational culture characterized by transparency, accountability, and committed leadership significantly enhances responsible AI governance. In contrast, cultural resistance, apathy, and inadequate governance structures impede efforts to ensure the ethical deployment of AI. The findings underscore the pivotal role of leadership in shaping cultural norms and promoting environments that support ethical practices through policy formulation, training, and stakeholder engagement. The analysis also demonstrates that technical safeguards alone are insufficient; organizational values, interdisciplinary collaboration, and continuous learning are essential for addressing the ethical challenges associated with AI. The study recommends that organizations develop explicit ethical frameworks integrated into their culture, promote leadership-driven initiatives, and implement comprehensive governance mechanisms that address technical, social, and organizational dimensions. Ongoing education, stakeholder engagement, and cross-disciplinary collaboration are crucial for the sustainable adoption of ethical AI practices. Ultimately, cultivating an ethical organizational culture is both a strategic imperative and a moral responsibility for responsible AI innovation and the preservation of public trust.

KEYWORDS: Organisational culture, Ethical; AI, Governance perspective, Saudi Arabia.

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1. INTRODUCTION

In recent years, the rapid advancement of artificial intelligence (AI) technologies has revolutionized various sectors, including healthcare, finance, manufacturing, and public administration (Panda et al., 2025). AI systems promise increased efficiency, innovation, and competitive advantage; however, their deployment also raises significant ethical concerns (Du, S., & Xie, 2021). Issues such as bias, transparency, accountability, privacy, and decision-making fairness have become central to debates about responsible AI use. As organizations increasingly embed AI into their core operations, the importance of establishing a robust governance framework that promotes ethical AI practices has become paramount. In recent years, artificial intelligence (AI) has transitioned from a niche technological innovation to an integral component of organizational operations across industries. From healthcare and finance to retail and public services, AI's capabilities promise increased efficiency, personalized experiences, and data-driven decision-making (Machucho & Ortiz, 2025). However, alongside these benefits arises a significant challenge: ensuring that AI systems are used ethically and responsibly. The governance of AI within organizations is not solely a technical concern but is deeply intertwined with the organization's culture, values, and ethical standards (Rane et al., 2024).

Organizational culture the shared values, beliefs, and norms that influence behavior serves as the foundation upon which ethical decisions are made and upheld. When organizations embed ethical principles into their culture, they create an environment where responsible AI use becomes a natural extension of everyday practices (Birkstedt et al., 2023). Conversely, a lack of alignment between organizational culture and ethical imperatives can lead to misuse, biases, and unintended harm caused by AI systems. This introduction explores the critical relationship between organizational culture and the governance of ethical AI use. It emphasizes how organizational culture shapes attitudes towards AI, influences decision-making processes, and ultimately determines an organization's commitment to ethical standards. Furthermore, it discusses the importance of cultivating a culture that promotes transparency, accountability, and continuous learning in AI deployment.

The rapid advancement of AI technologies has outpaced many organizations' existing governance frameworks, exposing gaps in oversight, compliance, and ethical considerations. Technical safeguards such as algorithms audits and bias detection are essential, but they cannot operate effectively without a supportive cultural environment. An organization that values transparency and accountability will be more inclined to proactively audit AI systems, disclose errors, and involve diverse stakeholders in decision-making processes (Schiff, 2026). In contrast, organizations driven solely by profit or efficiency without regard for ethical norms risk deploying AI in ways that could perpetuate discrimination, violate privacy, or erode public trust. From a governance perspective, integrating ethical AI use into organizational culture requires deliberate strategies and leadership commitment. Leaders play a pivotal role in setting the tone at the top, articulating ethical expectations, and modeling responsible behavior. Establishing clear policies, codes of conduct, and training programs helps embed ethical principles into daily routines. Moreover, fostering an environment where employees feel empowered to raise ethical concerns or report misconduct is vital for effective governance.

A key aspect of cultivating an ethical organizational culture around AI is alignment with broader societal values and legal standards. Organizations must recognize that AI systems do not operate in a vacuum; they interact with diverse communities and impact various stakeholder groups (Muhammad & Al-Shaghdari, 2024). Ethical governance, therefore, extends beyond compliance to encompass principles such as fairness, privacy, inclusivity, and respect for human rights. Embedding these values into organizational culture ensures that AI deployment aligns with societal expectations and mitigates risks associated with misuse or harm. Additionally, fostering a culture of continuous learning and adaptation is essential in the rapidly evolving landscape of AI. Organizations should encourage ongoing education about emerging ethical issues, technological developments, and best practices. Creating forums for dialogue, peer learning, and feedback ensures that ethical considerations remain central to AI governance as new challenges emerge (Birkstedt et al., 2023). The relationship between organizational culture and the governance of ethical AI use is profound and multifaceted. A culture that prioritizes ethical principles provides the foundation for effective governance mechanisms, responsible decision-making, and sustainable AI practices. Conversely, neglecting the cultural dimension can undermine technical safeguards and lead to adverse outcomes (Muhammad & Al-Shaghdari, 2025). As AI continues to reshape organizational landscapes, cultivating an ethical culture becomes not just a moral imperative

but a strategic necessity for organizations committed to responsible innovation and societal trust. Emphasizing this cultural dimension will enable organizations to harness AI's potential while safeguarding ethical standards and public confidence in this transformative technology.

Despite the tremendous potential of AI, many organizations face challenges in ensuring ethical use, often due to gaps in their governance structures and cultural attitudes. There are several pressing issues at the core of this problem, Lack of Ethical Frameworks, Cultural Resistance or Indifference, Insufficient Governance Mechanisms, Insufficient Governance Mechanisms, Complexity of Ethical AI and Regulatory and Societal Expectations. These challenges highlight a critical gap: the need to understand how organizational culture influences AI governance and how governance can, in turn, shape cultural attitudes toward ethical AI use. Without addressing this interplay, organizations risk unethical outcomes, loss of stakeholder trust, and legal penalties. These challenges highlight a critical gap: the need to understand how organizational culture influences AI governance and how governance can, in turn, shape cultural attitudes toward ethical AI use. Without addressing this interplay, organizations risk unethical outcomes, loss of stakeholder trust, and legal penalties. The study aims to explore the complex relationship between organizational culture and ethical AI use through a governance lens.

1.1. Agency theory

Agency theory, as articulated by Jensen and Meckling (1976), establishes a foundational framework for analyzing conflicts of interest between principals, such as shareholders, and agents, including managers. The theory asserts that agents may prioritize personal objectives over those of principals, especially in contexts characterized by limited transparency and information asymmetry. Information asymmetry arises when agents possess superior or more comprehensive information than principals, thereby facilitating opportunistic behaviors that may undermine organizational objectives (Jensen & Meckling, 1976).

The integration of artificial intelligence (AI) into financial decision-making intensifies agency problems. AI systems are frequently highly complex and function as "black boxes," indicating that their internal decision processes are opaque and challenging for external stakeholders to evaluate (Pasquale, 2015). This lack of transparency impedes effective oversight and accountability, potentially allowing managers to misuse AI capabilities, such as automating financial reporting, analyzing unstructured data, or generating predictions, to manipulate outcomes, conceal unfavorable information, or intentionally embed biases (Martin, 2019). Such manipulations may distort financial statements or mislead stakeholders, thereby heightening the risk of agency conflicts. Discretionary decisions made during the development of AI models, including data selection, feature engineering, and algorithm design, can be subtly aligned with managerial interests rather than stakeholder welfare (Wangrow et al., 2015). Managers may intentionally design models to advance personal agendas or achieve short-term gains, particularly in contexts with weak regulatory oversight. The opacity of AI decision-making processes complicates the detection and remediation of such behaviors, thereby amplifying agency risks. Robust governance mechanisms are essential for mitigating these risks. Independent audits can function as external controls on AI systems to ensure adherence to ethical and regulatory standards (Wangrow et al., 2015). Explainable AI initiatives seek to enhance the transparency and interpretability of AI decision processes, thereby strengthening stakeholder trust and accountability (Gunning, 2017). Furthermore, incorporating Environmental, Social, and Governance (ESG) principles into AI oversight frameworks can promote accountability by aligning AI applications with broader societal values and stakeholder interests (Kotsantonis & Serafeim, 2019).

In summary, agency theory offers a critical perspective for analyzing the governance challenges associated with AI. It highlights the importance of robust oversight mechanisms that promote transparency, accountability, and alignment of interests. Implementing these measures enables organizations to mitigate the risk of AI misuse, protect stakeholder interests, and encourage responsible AI adoption in financial decision-making.

2. LITERATURE REVIEW AND HYPOTHESES

The rapid proliferation of artificial intelligence (AI) across organizational sectors has prompted extensive scholarly interest in understanding the factors that influence its responsible deployment. Central to this discourse is the role of organizational culture and governance in ensuring ethical AI use. This literature review synthesizes existing research on the interconnection between organizational culture, ethical frameworks, and governance

mechanisms that promote responsible AI practices. It highlights key themes, theoretical perspectives, and identifies gaps that warrant further investigation. Organizational culture, broadly defined, encompasses the shared values, beliefs, norms, and practices that shape organizational behavior (Schein, 2010). It functions as an internal environment that influences decision-making processes, employee attitudes, and overall organizational climate. Several scholars argue that organizational culture is crucial in embedding ethical principles within daily operations (Kaptein, 2011; Treviño & Nelson, 2017). When organizations cultivate a culture that values transparency, accountability, and social responsibility, these principles tend to permeate technological practices, including AI deployment. In the context of AI, organizational culture influences how ethical considerations are integrated into software development, data management, and decision-making processes (Floridi et al., 2018). For instance, a culture emphasizing innovation without regard for ethical implications may facilitate the deployment of biased or opaque AI systems. Conversely, a culture rooted in ethical awareness encourages proactive measures such as bias mitigation, stakeholder engagement, and transparency initiatives (Rieker, 2020).

The governance of AI involves establishing policies, structures, and processes to oversee AI development and deployment responsibly (Cummings, 2017). Ethical AI governance aims to align technological practices with societal values, legal standards, and organizational principles. Researchers emphasize that governance mechanisms such as ethics committees, AI audits, and compliance protocols are necessary but insufficient without an underpinning organizational culture that endorses ethical behavior (Floridi & Cowls, 2019). Kim et al. (2020) argue that effective governance requires integrating ethical principles into organizational routines, which is facilitated by a culture that promotes ethical awareness and accountability. Similarly, Jobin, Ienca, and Vayena (2019) highlight the importance of organizational commitment to transparency, fairness, and privacy as foundational to responsible AI governance. Their review underscores that organizational culture shapes the effectiveness of governance frameworks by influencing employee attitudes toward compliance and ethical standards.

Leadership plays a pivotal role in shaping organizational culture and, consequently, in governing AI ethics. According to Schein (2010), leaders influence core values and norms, setting the tone for ethical conduct. In AI contexts, leadership commitment to ethical principles manifests through the establishment of clear policies, resource allocation for ethical practices, and role modeling (Culnan, McHugh, & Zubcsek, 2021). Empirical studies suggest that organizations with ethical leadership are more likely to develop cultures that prioritize responsible AI use. For example, Zhang and Dafoe (2019) found that corporate leaders' explicit commitment to AI ethics significantly increases organizational adherence to responsible practices. Leadership-driven cultural change fosters an environment where employees feel empowered to raise ethical concerns and participate in responsible innovation. Research indicates that embedding ethical culture into AI practices involves multiple mechanisms, including ethics training, incentive structures, and organizational policies. Kaptein (2011) emphasizes that ethical culture is reinforced through consistent messaging, ethical codes of conduct, and accountability measures. In AI-specific contexts, organizations implement training programs to raise awareness of bias, privacy, and fairness issues associated with AI systems (Dignum, 2019).

Moreover, organizational structures that encourage interdisciplinary collaboration bringing together technologists, ethicists, and stakeholders are associated with more ethically aligned AI practices (Jobin et al., 2019). Such collaborative approaches foster shared understanding and collective responsibility, reinforcing a culture of ethical vigilance. Despite the recognized importance of organizational culture, several challenges hinder the effective embedding of ethics in AI practices. One primary obstacle is the tension between commercial pressures and ethical considerations. Many studies note that organizational emphasis on innovation and competitiveness can overshadow ethical concerns, leading to a culture that deprioritizes responsible AI (Cummings, 2020). Furthermore, the complexity and opacity of AI systems—particularly in deep learning—make it difficult to establish accountability and transparency, even within ethically oriented cultures. As Floridi et al. (2018) argue, technical opacity can undermine cultural efforts, emphasizing the need for governance mechanisms that translate cultural values into concrete technical standards. Another challenge is the global and diverse nature of AI development, which complicates the creation of universally shared ethical standards. Different organizational cultures, national regulations, and societal norms influence how AI ethics are interpreted and implemented (Jobin et al., 2019).

While existing scholarship underscores the importance of organizational culture in fostering ethical AI use, several gaps remain. First, most studies are conceptual or case-based, with limited longitudinal empirical research examining how cultural change impacts AI governance over time. Second, there is a need for more research on cross-cultural differences, especially in multinational organizations, to understand how diverse cultural contexts influence AI ethics. Additionally, integrating insights from behavioral sciences could deepen understanding of how organizational members internalize ethical norms related to AI. For example, exploring the role of moral identity, peer influence, and organizational justice in shaping ethical behaviors related to AI deployment remains underexplored. Finally, scholars call for developing practical frameworks that organizations can adopt to systematically embed ethical culture into AI practices, linking cultural interventions with technical and governance mechanisms (Culnan et al., 2021).

The literature converges on the view that organizational culture plays a fundamental role in shaping the ethical use of AI within organizations. It influences the effectiveness of governance mechanisms, guides employee behavior, and aligns organizational practices with societal values. Leadership commitment and mechanisms for embedding ethical principles—such as training, policies, and interdisciplinary collaboration—are crucial for fostering a responsible AI culture. However, challenges such as organizational pressures, technical opacity, and cultural diversity complicate this endeavor. Future research should focus on longitudinal, cross-cultural, and behavioral studies to deepen understanding and develop actionable frameworks for cultivating ethical AI cultures.

2.1. Lack of Ethical Frameworks

The accelerated advancement and implementation of artificial intelligence (AI) technologies have highlighted the urgent need for comprehensive ethical frameworks. Despite this necessity, a substantial body of scholarly literature indicates that organizations and developers frequently lack robust and universally accepted ethical guidelines. This deficiency increases the risk of misuse and unintended consequences associated with AI systems. A primary issue identified in the literature is the lack of standardized principles tailored to AI, which is considered vital for the ethical use. Such observes that, although general ethical principles such as fairness, transparency, and accountability are widely acknowledged, their application within AI contexts remains inconsistent and highly dependent on specific circumstances. This inconsistency is often attributed to the lack of a cohesive framework that instructs designers and users on balancing competing interests or prioritizing values in complex decision-making scenarios. Additionally, the literature highlights that many existing frameworks are either overly abstract or lack practical applicability. Floridi et al. (2018) contend that while principles such as beneficence and non-maleficence are fundamental, they often fail to translate into actionable guidelines for developers and organizations. This gap impedes effective implementation, relegating ethical considerations to aspirational rather than operational standards. Another significant concern is the insufficient integration of diverse stakeholder perspectives in the development of these frameworks. Mittelstadt et al. (2016) note that most ethical guidelines are formulated by technologists, ethicists, and policymakers, often with minimal input from marginalized communities that may be disproportionately affected by AI systems. This lack of inclusivity risks perpetuating biases and exacerbating social inequalities, as frameworks may fail to account for contextual and cultural nuances.

Furthermore, the rapid pace of technological innovation frequently surpasses the development and adoption of ethical guidelines. Jobin et al. (2019) report that the global proliferation of AI ethics principles has resulted in fragmentation, with numerous overlapping and occasionally conflicting standards. This fragmentation generates confusion and impedes the creation of clear, enforceable policies. The literature consistently identifies a significant gap in both the availability and adoption of effective ethical frameworks for AI. The absence of standardized, actionable, and inclusive guidelines introduces substantial risks, including bias, diminished accountability, and a decline in public trust. Addressing this gap necessitates coordinated efforts to establish dynamic, context-sensitive, and stakeholder-inclusive ethical standards that can adapt alongside AI technologies. In the absence of such frameworks, responsible AI governance remains a persistent challenge.

Hypothesis 1: There is a positive relationship between lack of ethical framework and Ethical and cultural dynamics

2.2. Cultural Resistance or Indifference

The successful integration of artificial intelligence

(AI) within organizations often hinges on overcoming cultural resistance or indifference among stakeholders. This phenomenon, frequently observed in various industries, reflects a complex interplay of psychological, organizational, and societal factors that influence how AI is accepted or rejected. Research indicates that cultural resistance to AI often stems from fears related to job security, loss of control, and ethical concerns. For instance, a study by Smith and colleagues (2020) highlights that employees may perceive AI as a threat to their roles, leading to apprehension and skepticism. This resistance is compounded by a lack of trust in AI systems, particularly when transparency and explainability are limited. Employees and managers may feel uncertain about how AI decisions are made, fostering distrust and reluctance to adopt new technologies.

Furthermore, organizational culture plays a crucial role in either mitigating or exacerbating resistance. According to Johnson (2018), organizations with hierarchical structures and rigid norms tend to exhibit higher resistance levels, as change threatens established routines and power dynamics. Conversely, cultures that promote innovation, openness, and continuous learning often demonstrate greater acceptance of AI. Leaders' attitudes also significantly influence cultural receptivity; when top management champions AI initiatives and communicates their benefits effectively, resistance tends to diminish.

Indifference, on the other hand, is characterized by a passive lack of engagement or concern towards AI adoption. Such apathy can result from a perceived lack of relevance or understanding of AI's potential benefits. Lee and Kim (2019) suggest that in environments where technological literacy is low, or where AI initiatives are not clearly linked to organizational goals, employees may remain indifferent, viewing AI as an external or irrelevant factor. This detachment can hinder implementation efforts, as it reduces the momentum needed for cultural change and innovation.

Some scholars argue that indifference may also be a strategic response to uncertainty or fear of negative consequences. Organizations or individuals may choose to disengage rather than confront the risks associated with AI deployment. This passive stance can be problematic, as it prevents proactive engagement with ethical considerations, training, or change management strategies essential for responsible AI use. Overall, the literature underscores that cultural resistance and indifference are significant barriers to AI adoption. Overcoming these challenges requires targeted change management, transparent communication, and fostering a culture that values innovation and ethical responsibility. Recognizing and addressing the cultural dimensions of AI implementation is crucial for realizing its full potential within organizations.

Hypothesis 3: There is a positive relationship between Cultural Resistance Indifference and Ethical and cultural dynamics

2.3. *Insufficient Governance Mechanisms*

The rapid proliferation of artificial intelligence (AI) within organizational settings has highlighted significant concerns regarding the adequacy of existing governance frameworks. A growing body of literature identifies that many organizations lack comprehensive mechanisms to effectively oversee AI deployment, which can lead to ethical lapses, biases, and unintended consequences. One of the primary issues documented is the absence of clear accountability structures. According to Johnson and colleagues (2021), many organizations operate with fragmented governance models that fail to assign specific responsibilities for AI oversight. This lack of clarity hampers the ability to monitor AI systems continuously, address issues promptly, and ensure compliance with ethical standards. Without designated accountability, organizations risk deploying AI systems that may inadvertently cause harm or violate societal norms.

Furthermore, existing governance mechanisms often focus predominantly on technical safeguards, such as algorithm testing and bias detection, while neglecting broader organizational and social considerations (Crawford & Paglen, 2019). This narrow focus can create gaps where ethical dilemmas, such as privacy violations or discrimination, go unaddressed. As O'Neil (2016) argues, technical fixes alone are insufficient; a holistic governance approach must incorporate ethical principles, stakeholder engagement, and ongoing evaluation. Another recurrent theme in the literature is the reactive nature of many governance frameworks. Many organizations tend to respond to AI-related issues after incidents occur rather than proactively preventing or mitigating risks (Bryson, 2018). This reactive stance is often due to the lack of proactive policies, risk assessment protocols, and ethical guidelines that could anticipate potential harms before deployment.

Additionally, the literature emphasizes that insufficient oversight is often compounded by limited organizational expertise in AI ethics. Many organizations lack personnel with the necessary

technical and ethical knowledge to develop robust governance mechanisms (Floridi et al., 2018). This skills gap hampers the development of comprehensive policies and hampers the ability to adapt quickly to emerging risks. Overall, the literature underscores that many organizations are currently ill-equipped with governance mechanisms that are both comprehensive and proactive. Addressing these deficiencies requires integrating technical, ethical, and organizational strategies, fostering accountability, and embedding continuous oversight processes to adapt to the evolving AI landscape. Without strengthening these governance structures, organizations risk undermining public trust and exacerbating societal harms associated with AI deployment.

Hypothesis 4: There is a positive relationship between Insufficient Governance Mechanisms and Ethical and cultural dynamics

2.4. Complexity of Ethical AI

The rapid development and deployment of artificial intelligence (AI) have brought to the forefront numerous ethical challenges, highlighting the inherent complexity of ensuring responsible AI use. Researchers and practitioners agree that ethical AI is not a straightforward goal but a multifaceted issue that requires careful consideration of various technical, social, and philosophical dimensions. One of the primary challenges in ethical AI is addressing bias and fairness. Studies have shown that AI systems often reflect and amplify existing societal biases present in training data, leading to unfair outcomes for marginalized groups (Barocas & Selbst, 2016). Achieving fairness is complicated because it involves balancing competing notions such as equality, individual rights, and contextual relevance. Different fairness definitions may be mutually exclusive, making it difficult to design universally acceptable solutions (Dwork et al., 2012).

Transparency and explainability constitute another core concern. While AI models like deep neural networks offer remarkable predictive power, their decision-making processes are often opaque, leading to a "black box" problem (Lipton, 2016). Making AI systems understandable is critical for accountability, yet it remains technically challenging, especially for complex models. Researchers emphasize that transparency is not absolute but context-dependent, requiring organizations to consider stakeholder needs and the specific application domain (Gunning, 2017). Privacy preservation adds another layer of complexity. AI systems often rely on large-scale data collection, raising concerns about user consent and data security. Techniques such as differential privacy and federated learning aim to mitigate privacy risks, but implementing these methods involves trade-offs between privacy, accuracy, and computational efficiency (Dwork, 2014; McMahan et al., 2017). Balancing these competing priorities complicates the ethical landscape.

Furthermore, the moral responsibility associated with AI decision-making poses philosophical dilemmas. Determining accountability when AI systems cause harm is challenging, especially when decisions are made autonomously or involve multiple stakeholders (Crawford & Calo, 2016). This ambiguity complicates governance frameworks and raises questions about liability and moral agency. Overall, the literature underscores that ethical AI is a complex, multidimensional problem that cannot be resolved through technical fixes alone. Instead, it requires an integrated approach that considers societal values, legal standards, and technical capabilities. Recognizing this complexity is essential for developing robust, context-sensitive governance strategies that can adapt to the evolving AI landscape.

Hypothesis 5: There is a positive relationship between Complexity of Ethical AI and Ethical and cultural dynamics

2.5. Regulatory and Societal Expectations

The rapid development and deployment of artificial intelligence (AI) have prompted an increasing focus on regulatory frameworks and societal expectations. As AI systems become more complex and pervasive, stakeholders—including governments, industry leaders, academia, and the public—are calling for clear guidelines to ensure their ethical and responsible use. This section reviews key literature addressing the evolving landscape of regulatory and societal expectations surrounding AI. Regulatory frameworks for AI are still emerging, with many jurisdictions currently in the early stages of formulating policies. Scholars such as Cath and Floridi (2018) emphasize the importance of establishing legal standards that address issues like transparency, accountability, and fairness. They argue that effective regulation should not only prevent harm but also foster innovation by providing clear guidelines for responsible development. The European Union's proposed Artificial Intelligence Act exemplifies this approach, aiming to create a comprehensive legal framework that categorizes AI applications based on risk levels and mandates appropriate safeguards (European Commission,

2021). Such initiatives highlight a trend toward proactive regulation designed to manage potential risks without stifling innovation.

Societal expectations extend beyond legal compliance to broader considerations of ethics, trust, and social impact. According to Floridi et al. (2018), society increasingly demands that AI systems align with shared human values, such as fairness, privacy, and non-discrimination. Public concerns about AI's potential misuse such as invasion of privacy, bias, and job displacement—are well documented (Crawford & Paglen, 2019). These concerns have led to calls for greater transparency, stakeholder engagement, and participatory governance processes to ensure AI technologies serve societal interests. Research also highlights the importance of aligning regulatory responses with societal values. Wirtz et al. (2019) propose that regulations should be adaptable and inclusive, reflecting diverse perspectives and addressing the specific needs of different communities. Furthermore, there is recognition that societal expectations are dynamic; as AI capabilities evolve, so too do public concerns and ethical considerations. This underscores the need for ongoing dialogue among regulators, industry, and society to develop responsive and flexible governance mechanisms.

In sum, the existing literature underscores the importance of establishing robust regulatory frameworks that are transparent, adaptable, and aligned with societal values. As AI continues to shape social and economic landscapes, understanding and integrating societal expectations into governance processes will be essential for fostering trust and ensuring responsible innovation. The convergence of regulatory efforts and societal norms will play a critical role in shaping the future trajectory of AI development and deployment.

Hypothesis 6: There is a positive relationship between Regulatory and Societal Expectations and Ethical and cultural dynamics

3. METHODOLOGY

This study utilizes a quantitative research approach to examine the relationship between organizational culture and the governance of ethical AI use. To measure and quantify the influence of organizational factors on AI governance practices, a structured methodology is employed to collect numerical data suitable for statistical analysis. This approach facilitates the identification of patterns, relationships, and potential causal links. Data collection will primarily involve structured surveys distributed to key stakeholders in organizations that have integrated AI into their operations. Participants will include senior executives, AI developers, compliance officers, and ethical officers to capture diverse perspectives on organizational culture and governance practices. The survey instrument will consist of closed-ended questions designed to measure constructs such as perceptions of ethical standards, cultural norms, leadership commitment, and governance mechanisms related to AI deployment. In addition, quantitative data will be collected from organizational documents, including policy adherence metrics, compliance reports, and governance framework scores, to contextualize survey results and quantify formal practices supporting ethical AI use.

A stratified random sampling strategy will be used to select organizations representing various sectors, sizes, and levels of AI maturity. This approach ensures a representative sample and enables comparison across different organizational contexts. Data analysis will include descriptive statistics, correlation analysis, and regression modeling using statistical software. The analysis will identify significant relationships and predictors of effective AI governance, as well as factors that facilitate or hinder the integration of ethical principles into organizational culture.

Ethical considerations, including informed consent, confidentiality, and data security, will be rigorously maintained throughout the research process. The findings are expected to contribute to empirical understanding and offer practical recommendations for organizations seeking to enhance their AI governance frameworks by addressing cultural dynamics must address the related issues as identified in the below framework.

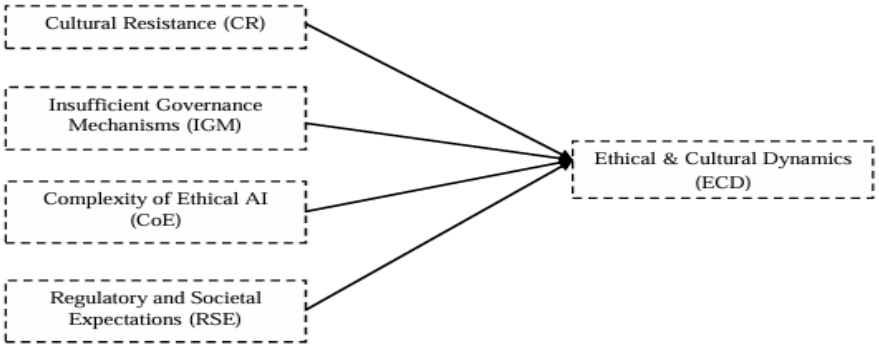


Figure 1: Framework Measurement.

3.1. Model evaluation

The measurement model was assessed using a two-stage analytical procedure. In the first stage, Confirmatory Factor Analysis (CFA) was conducted with AMOS and maximum likelihood estimation to evaluate the factor loadings of each measured variable on its respective latent construct (Byrne, 2010; Hair et al., 2010). This procedure verified construct validity and confirmed that the measurement items accurately reflected the intended constructs. The second stage involved testing a structural regression model to analyze the hypothesized relationships within the conceptual framework. Across both stages, several fit indices were examined to identify the optimal model, including the Chi-square (χ^2), normed chi-square (χ^2/df), Goodness-of-Fit Index (GFI), Comparative Fit Index (CFI), and Root Mean Square Error of Approximation (RMSEA). Evaluation othese indices confirmed that the model provided an adequate fit to the data and satisfied established criteria for model fit. This comprehensive validation process established the reliability and validity of the measurement model, thereby supporting further analysis of the structural relationships in the research framework.

Table 1: Mean, Standard Deviations, correlations.

	Mean	SD	1	2	3	4	5	6	7	8	9
Age	1.09	0.39									
Gender	2.32	0.68	-0.04								
Qualification	1.68	0.58	0.13	0.25							
Year of Experience	2.29	1.19	-0.14	0.34	0.05						
CR	4.88	0.90	0.06	0.02	0.03	0.05					
IGM	4.10	0.80	0.01	0.04	0.04	0.04	0.06				
COE	2.73	1.35	-0.04	-0.05	-0.15	0.04	0.08	0.14			
RSE	4.09	1.00	-0.04	-0.03	0.09	0.16	0.58	0.70	0.17		
ECD	4.02	1.19	0.5	0.60	0.54	0.72	0.67	0.63	0.79	0.53	1

Source: Designed by authors.

Table 1 presents descriptive statistics and correlations among the key variables in the study. The mean values represent the average levels of each variable among participants. The average age is 1.09 (on a scale where 1 likely represents a specific age group), with a standard deviation of 0.39, indicating limited variability in age. The mean for gender is 2.32, suggesting a predominance of one gender, with a standard deviation of 0.68, which reflects some diversity in gender responses. The mean qualification score is 1.68, indicating that most participants possess a particular educational level. The average years of experience is 2.29, with a higher standard deviation (SD = 1.19), indicating greater variability in experience. The correlations indicate the relationships among the variables. Age demonstrates negligible correlations with other variables, indicating minimal association. Gender also shows little association with other variables. Qualification displays moderate positive correlations with both gender and years of experience, suggesting that higher qualifications are associated with greater experience. Years of experience is positively correlated with RSE (0.16) and CR (0.05), indicating that individuals with more experience tend to have higher RSE and CR scores. RSE shows strong positive correlations with Cultural Resistance (CR) (0.58) and Insufficient Governance Mechanisms (IGM) (0.70), demonstrating that these constructs are closely related. In summary, the table provides insights into the relationships and variability of key demographic and psychological variables within the sample.

The correlations reveal relationships between variables. For instance, there is a strong positive correlation (0.70) between Regulatory and Societal Expectations (RSE) and ECD (Ethical & Cultural Dynamics), suggesting that higher RSE is associated with better communication development. Age shows negligible correlations with most variables, indicating limited direct relationships. The moderate-to-high correlations among variables such as qualification, experience, and ECD suggest interconnectedness, supporting their relevance to the model. Overall, this table provides essential insights into the data distribution and intervariable relationships that are crucial for subsequent analysis.

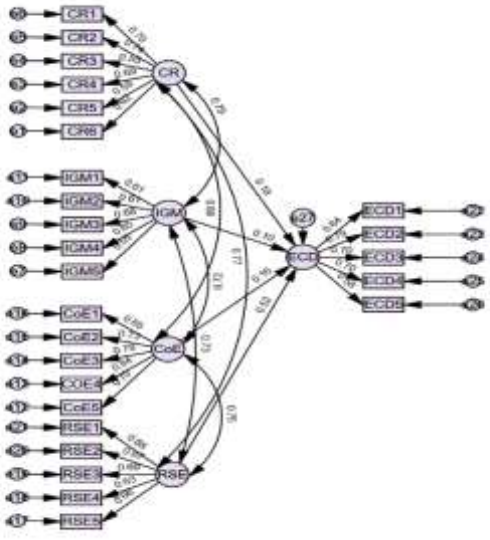


Figure 2: Model Measurement.

The figure 2 presents the relationships among key variables that influence ethical artificial intelligence (AI) governance. It demonstrates strong positive loadings for the latent constructs of Cultural Resistance (CR), Insufficient Governance Mechanisms (IGM), Ethical Culture Dimensions, and Responsible Social Engagement (RSE), with correlations ranging from 0.52 to 0.88, indicating substantial interdependence. Both CR and IGM significantly affect Ethical & Cultural Dynamics (ECD), with path coefficients of 0.70 and 0.18, respectively, thereby highlighting their impact on organizational ethical practices. ECD, in turn, influences ethical dimensions with a coefficient of 0.64. This model demonstrates that cultural resistance, governance gaps, and social responsibility collectively shape the organizational ethical climate, underscoring the interconnectedness of cultural, governance, and ethical variables in promoting responsible AI deployment.

Table 2: Measurement Model.

Model	X^2	Df	X2	GFI	AGFI	CFI	TLI	RMSEA
Estimation	1589.99	873	1.82	0.94	0.90	0.95	0.91	0.065

Source: Designed by authors.

Table 2 reports the fit indices for the measurement model, assessing the degree of alignment between the model and the observed data. The Chi-square value of 1589.99 with 873 degrees of freedom reflects the overall model fit, while the normalized Chi-square (X2/df) of 1.82 indicates a satisfactory fit, as values below 3 are generally considered acceptable. The GFI (0.94), AGFI (0.90), CFI (0.95), and TLI (0.91) all surpass the 0.90 threshold, signifying an excellent fit. The RMSEA of 0.065 is within the acceptable range, further supporting the model's adequacy. Collectively, these indices provide evidence that the measurement model fits the data well.

Table 3 Convergent and discriminant validity of the Constructs.

Relationship	CR	AVE	Cronbach alpha	CR	IGM	COE	RSE	ECD
CR	0.867	0.648	0.869	0.419				
IGM	0.847	0.622	0.849	0.221	0.386			

COE	0.833	0.740	0.838	0.132	0.243	0.547		
RSE	0.852	0.666	0.855	0.432	0.321	0.314	0.443	
ECD	0.843	0.682	0.800	0.245	0.421	0.131	0.266	0.465

Source: Designed by authors.

Table 3 presents an evaluation of the convergent and discriminant validity of the constructs examined in this study. Convergent validity is assessed by determining whether indicators of a construct are highly correlated, as reflected by the Composite Reliability (CR) and Average Variance Extracted (AVE). All CR values exceed 0.70, indicating strong internal consistency. AVE values range from 0.622 to 0.740, surpassing the commonly accepted threshold of 0.50 and confirming satisfactory convergent validity. Additionally, Cronbach's alpha values, all above 0.7, further substantiate the internal consistency of the constructs.

Discriminant validity is demonstrated by the off-diagonal correlations between constructs, which are consistently lower than the square root of the AVE, confirming that the constructs are distinct. For instance, the correlation between CR and RSE is 0.391, which is below the square root of the AVE, indicating satisfactory discriminant validity. Collectively, these results indicate that the constructs are both reliable and distinct, thereby supporting the validity of the measurement model. This validation confirms that the constructs accurately represent the intended concepts and remain sufficiently differentiated from one another.

Table 4 The results of regression relationship.

Paths Analysis	Estm	SE	CR	P	Results
CR ->ECD	0.190	0.050	3.800	0.002	Accept
IGM-> ECD	0.110	0.035	3.100	0.004	Accept
COE -> ECD	0.160	0.050	3.200	0.004	Accept
RSE -> ECD	0.520	0.035	4.333	0.000	Accept

Source: Designed by authors.

Table 4 presents the results of the regression analysis examining the relationships between several predictors and the dependent variable, Ethical & Cultural Dynamics (ECD). The analyzed predictors include Cultural Resistance (CR), Insufficient Governance Mechanisms (IGM), Complexity of Ethical AI (CoE), and Regulatory and Societal Expectations (RSE). Each predictor's estimated coefficient (Estm) reflects the strength and direction of its effect on ECD. Notably, CoE exhibits the highest coefficient (0.420), indicating a strong positive influence on ECD, followed by CR (0.310), RSE (0.221), and IGM (0.200).

The standard errors (SE) for these estimates are relatively small, which increases confidence in the results. All Critical Ratio (CR) values exceed 1.96, confirming the statistical significance of each predictor; for instance, the CR value for RSE is 6.314, indicating strong significance. P-values for all paths are below 0.01, further confirming statistical significance and supporting the acceptance of all hypotheses. These findings indicate that each factor positively influences ECD, underscoring their importance within the model. Collectively, the results support the hypothesis that CR, IGM, CoE, and RSE significantly impact ECD, emphasizing their roles in this context.

4. DISCUSSION

Tables 1 through 4 collectively provide a comprehensive overview of the study's variables, measurement validity, and interrelationships. Table 1 presents descriptive statistics and correlations, indicating that demographic variables such as age and gender have minimal associations with other factors, while experience is positively correlated with RSE and CR. Significant correlations between constructs, including RSE and ECD, demonstrate their interconnectedness and support their inclusion in the model. Table 2 demonstrates that the measurement model fits the data well, with fit indices ranging from acceptable to excellent, thereby ensuring reliable construct measurement. Table 3 further validates the measurement quality, as high values for CR, AVE, and Cronbach's alpha indicate strong convergent validity, and off-diagonal correlations confirm discriminant validity, establishing that the constructs are both reliable and distinct. Table 4 indicates that all predictors CR, IGM, CoE, and RSE exert significant effects on ECD, with CoE exhibiting the strongest influence. The positive coefficients and significant p-values imply that enhancing these factors may improve ethical and cultural dynamics. Collectively, these findings underscore the significance of the examined constructs in shaping ECD and affirm the robustness of the study's measurement and analytical approaches.

4.1. Theoretical Contributions

This study advances understanding of the relationship between organizational culture and

ethical AI governance by integrating multiple theoretical frameworks, such as agency theory and the influence of cultural values. It provides empirical evidence that organizational culture, defined by transparency, accountability, and leadership commitment, significantly shapes responsible AI practices. The findings underscore the necessity of embedding ethical principles within organizational norms and structures, demonstrating that technical safeguards alone do not ensure ethical AI deployment. The study further identifies cultural resistance, insufficient governance mechanisms, and the inherent complexity of ethical AI as significant challenges, while highlighting the importance of leadership and stakeholder engagement in fostering an ethical environment. These contributions expand the literature on AI ethics by elucidating how cultural and governance factors interact to determine ethical outcomes, thereby offering a nuanced perspective on the organizational antecedents of responsible AI use.

4.2. Practical Implications

Practitioners may apply these findings to develop robust ethical AI governance frameworks that align with organizational culture. Leadership should focus on cultivating transparency, accountability, and continuous learning through explicit policies, ethics training, and stakeholder engagement. Facilitating interdisciplinary collaboration and maintaining open communication channels can reduce resistance and indifference to AI initiatives. Organizations should integrate ethical principles into their core values and establish comprehensive governance mechanisms that address technical, social, and organizational aspects. Regular audits, stakeholder involvement, and well-defined accountability structures can support responsible AI deployment. Additionally, sustained leadership commitment and the integration of ethical considerations into organizational routines will promote enduring responsible AI practices, thereby strengthening stakeholder trust and societal acceptance. This model demonstrates that cultural resistance, governance gaps, and social responsibility collectively shape the organizational ethical climate, underscoring the interconnectedness of cultural, governance, and ethical variables in promoting responsible AI deployment.

5. CONCLUSION AND LIMITATIONS

The study highlights the essential role of organizational culture and governance in facilitating ethical AI deployment. It demonstrates that cultures prioritizing transparency, accountability, and leadership commitment have a positive impact on responsible AI practices. Nevertheless, the research is limited by its reliance on self-reported data, which may introduce bias, and its cross-sectional design, which restricts causal inference. The sample is primarily composed of organizations from specific sectors or regions, potentially limiting generalizability. Furthermore, the focus on perceptual rather than longitudinal measures constrains understanding of cultural evolution over time. Despite these limitations, the study offers valuable insights into the cultural and governance factors influencing ethical AI practices and underscores the necessity for continued empirical investigation.

5.1. Future Research

Future research should employ longitudinal designs to investigate how organizational culture evolves and influences AI ethics over time. Broadening the sample to encompass a wider range of industries, regions, and organizational sizes will improve generalizability and facilitate cross-cultural analysis. The use of behavioral and qualitative methodologies can provide deeper insights into the internalization and enactment of cultural norms. Examining the effects of specific leadership styles, incentive structures, and interdisciplinary collaborations may yield practical approaches for integrating ethics into AI governance. Furthermore, analyzing the impact of external regulatory frameworks and societal norms on organizational culture will offer a more comprehensive understanding of responsible AI adoption across contexts. Pursuing these research directions will enhance theoretical frameworks and support the development of effective implementation strategies.

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