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# Artificial Intelligence as a Distributed Actor: Rethinking Organizational Theory Through Sociotechnical Networks

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**Abstract:** The rapid integration of Artificial Intelligence (AI) into organizational contexts is profoundly changing the fundamental assumptions in contemporary management and organizational theory. In response to these changes, this article introduces the Distributed Sociotechnical Agency Model (DSAM), a novel conceptual framework that synthesizes insights from Actor-Network Theory (ANT), sociomateriality, and principles of ethical governance. The DSAM framework conceptualizes AI as a distributed actor operating within complex networks and highlights three core dimensions: distributed agency, relational dynamics between human and non-human actors, and the imperative of ethical accountability. By using an integrated approach combining extensive literature review and analysis of real-life case studies, including a practical example involving an AI-driven university monitoring system, this study demonstrates how DSAM can facilitate more inclusive, user-friendly, flexible, responsive, and ethically aligned approaches to AI integration in organizations. To provide clarity and practical understanding, this article includes a detailed flowchart and a comparative table as well. Furthermore, recent academic studies and evolving policy developments are included in the discussion to strengthen the global relevance of the model. The article concludes by offering strategic recommendations for organizational governance and identifying promising directions for future empirical research.

**Keywords:** distributed agency, Actor-Network Theory, sociomateriality, AI governance, organizational dynamics

## 1. Introduction

The rapid spread of Artificial Intelligence (AI) technologies is reshaping the structure of contemporary organizations and forcing scholars and practitioners to reconsider fundamental concepts in organizational theory. As AI systems become increasingly involved in production, marketing, resource allocation, and strategic planning, they are moving beyond the role of mere tools or facilitators into the lens of decision-making as distributed actors within complex sociotechnical networks. These developments require a new theoretical understanding of organizational structures to understand how AI interacts with human agents, technological infrastructures, and institutional practices. While existing studies explore AI governance and algorithmic management, few have systematically examined the role of AI as an active agent within organizational theory, particularly from a sociotechnical perspective. This article aims to bridge this gap by introducing the Distributed Sociotechnical Agency Model (DSAM), which aims to conceptualize AI as a distributed actor that influences organizational structures and decision-making processes.

Actor-Network Theory (ANT) and Sociomateriality are examples of some frameworks that offer valuable insights, but they fall far short of fully explaining the changing role of AI in decision-making, power relations, and management in organizational settings. ANT argues that both human and non-human actors and entities can act as agents within a network. In this way, they can collectively shape results through relational interactions. Similarly, sociomateriality emphasizes the indivisibility of the social and material, highlighting how technology can actively play a role in the formation of organizational phenomena. These perspectives challenge traditional divisions in organizational settings that can separate human beings from technology. In this way, they can pave the way for a richer understanding of AI as an organizational actor. Thus, recognizing AI as a distributed actor requires acknowledging its capacity to generate diverse effects, such as learning from large data streams and adapting to different emerging conditions. For example, AI-powered recommendation systems can effectively influence consumer preferences. Similarly algorithmic management platforms can regulate employee behavior and productivity. These examples demonstrate that AI not only supports human decision-making but also creates impact through continuous feedback loops and iteratively shapes organizational realities.

This paradigm shift raises critical questions about organizational structure, practices, and governance mechanisms: For example, how should organizations adjust managerial practices to adapt on AI's distributed agency? What new forms of accountability and responsibility may emerge when AI systems participate in decision-making processes in organizational settings? To find answers to these questions, revisions need to be made in organizational structures, control systems, and feedback materials to accommodate the impact of the distributed nature of AI. Moreover, the integration of AI into organizational networks brings with it complex ethical and justice dimensions. For example, algorithmic biases, data privacy concerns, the uncertainty of machine learning models, and the lack of any authority in these areas can pose significant risks to institutional legitimacy and stakeholder trust. Therefore, defining AI as a distributed actor requires scholars and practitioners to examine the ethical foundations of AI platforms and their diffusion.

Ultimately, this article aims to explore future research directions by proposing a novel conceptual framework that can bring together the aspect of distributed agency in AI with evolving organizational

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dynamics. By synthesizing insights from ANT , sociomateriality, and contemporary AI research, this framework aims to provide researchers and practitioners with analytical tools to identify the complexities of organizational contexts impacted by AI. To support the applicability of the proposed framework, this study includes a case example based on secondary data from a university-based AI implementation in online exam supervision and evaluation. In this way, it aims to contribute to an ongoing dialogue about the future of organizational theory in an era where human and artificial actors are inextricably linked. Therefore, this study differs from prior research by proposing a new theoretical model (DSAM) that integrates distributed agency, relational processes, and governance mechanisms in organizational settings. By focusing on these dimensions, this article aims to contribute to a deeper understanding of AI-infused organizational transformations and provide new actionable perspectives for researchers and practitioners alike.

AI technologies are now integrated into production, human resource (HR), marketing, and decision-making processes. This article frames AI as a distributed actor that shapes outcomes through interaction with human agents, infrastructures, and algorithms. Current theoretical tools help conceptualize this complexity but lack emphasis on management and justice. The DSAM framework proposed here addresses this gap and aims to offer practical tools for analyzing the role of AI in organizational change.

This study aims to contribute to organizational theory and AI research in four key ways. First of all, as a result of this article, the authors have created a conceptual innovation by proposing the DSAM, a novel framework candidate that integrates ANT and sociomateriality with ethical governance. By bridging the gaps in current models by incorporating ethical and governance dimensions into AI's distributed agency, this study achieves theoretical integration. In terms of practical relevance, the study aims to demonstrate the applicability of the proposed framework (DSAM) through multi-sectoral use cases (e.g., healthcare, supply chain, digital platforms). Finally, insights are presented on several policy and governance concerns , such as strategic recommendations for organizations to align their use of AI with human-centered and fairness-focused practices.

## 2. Actor-Network and Sociomaterial Perspectives

The widespread growth of AI technologies has triggered important theoretical discussions about agency, autonomy, and interaction within modern organizations. Drawing on ANT [1] and sociomaterial perspectives [2], this section examines the role of AI as a distributed actor that participates in and transforms organizational dynamics. Unlike traditional human-centered understanding of agency, AI systems function through hybrid sociotechnical entities in which human and non-human parts can combine to create complex adaptive systems.

The activity of AI is inherently relational and emerges through constant interaction with humans, digital infrastructures, and algorithmic logics. For example, decision support systems mediate organizational systems not as passive tools but as active participants, influencing outcomes through learning processes, probabilistic reasoning, and feedback loops [3]. This distributed nature of AI will challenge classical organizational structures and blur the distinction between decision-makers and decision enablers. Rethinking hierarchy and power relations in organizations will be inevitable.

Furthermore, digital platforms and Application Programming Interface ecosystems facilitate the distributed presence of AI across multiple organizational layers, enabling dynamic knowledge distribution and real-time adaptability [4]. These enhance the effects of AI , embedding it deeply into organizational practices (and structures) and ensuring that naïve activities are combined as much as possible. By reframing AI as an actor within evolving sociotechnical networks, we can gain a more diverse understanding of how technological activity emerges and raise important questions about responsibility, control, transparency, and ethical accountability.

The concept of distributed agency, although relatively underexplored in institutional theory, has significant potential for understanding complex, multi-actor systems. Quack [5] shows how legal professionals contribute to transnational lawmaking through distributed representation, emphasizing the dynamic interplay of human actors, institutions, and evolving norms. Building on this foundation, AI systems can be conceptualized as systems that extend and transform distributed representation in organizational contexts. By interacting with human agents, algorithmic systems, and digital infrastructures, AI can contribute to the iterative shaping of organizational practices and decision-making processes [1]. This perspective is consistent with ANT, which argues that both human and non-human entities actively shape networks through relational relationships. Integrating these insights, this study aims to explore how AI-embedded agency can not only support but also extend distributed organizational dynamics. ANT conceptualizes both human and non-human entities as agents that shape outcomes through relationships. Sociomateriality, on the other hand, highlights the inseparability of the social and the technological. In this respect, they can provide a basis for recognizing the agency of AI within dynamic, networked organizational systems, which is what we intend to achieve in this study.

In the following sections, we will examine the configurations of human-AI networks, the dynamics of the evolving infrastructure, and the governance models required to navigate this distributed landscape. From this perspective, we aim to create a comprehensive framework for analyzing AI as a distributed actor, combining organizational theory with contemporary technological realities.

## 3. Artificial Intelligence as Distributed Actor

Considering AI as a distributed actor within organizations requires examining its activity and impact throughout decision-making processes. Zuboff's [6] study on surveillance capitalism is an important work that provides us with a critical lens through to examine the role of AI in data-driven corporate practices. Zuboff [6] argues that digital technologies can not only extract behavioral data but also shape human behavior through predictive analytics and algorithmic processes. This perspective is crucial for understanding how AI systems can powerfully drive corporate strategies and employee actions.

Approaching AI from the perspective of distributed agency can explain how it plays a role in repetitive decision-making. For example, algorithmic systems used in HR for hiring or performance evaluation can reinforce power structures or imbalances if not controlled by governance mechanisms such as trade union audits. In another example, in platform economies, AI-powered tools such as chatbots present risks by highlighting centers of power concentration and the need for transparency. Another important example is the recognition of the legitimacy of independent worker representation through unions, which would provide workers with access to countervailing power sources to protect them from exploitation and discrimination, thus embedding pluralism in HR practices [7]. When organizations implement algorithmic management systems for workforce planning, performance evaluation, or recruitment, trade unions can serve as fundamental counterbalances by advocating for transparency into how these systems operate and how they use data. Charlwood and Guenole [8] argue that union representation can negotiate collective agreements that establish clear boundaries on AI-assisted surveillance, ensure algorithmic accountability, and secure employees' rights to disclosures when AI systems make considerable decisions affecting their terms of employment. Furthermore, independent employee representation can help establish shared governance mechanisms where employees participate in the design, implementation, and audit of AI systems. Therefore, they can ensure that these technologies enhance , rather than diminish, employee independence and dignity in the changing digital workplace.

Furthermore, the evolution of digital platforms, as explored by van Dijck [9], highlights the information ecosystems as hierarchical and interdependent structures through the tree metaphor. The platform approach can indicate the layered shape of the tree, drawing attention to the dynamics of power concentration in organizational structures. Structural dimensions such as vertical integration, infrastructuralization, and cross-sectorization focus on fairness for the entire society and the common good of all.

Digital platforms that constitute the environments for observing the AI interface in power relations in organizations can be observed in chatbot platforms, among others. In a recent study, the authors argue that chatbot development has accelerated rapidly since November 2022, creating an "AI arms race" with significant implications for higher education as an organizational context. They conducted a systematic comparison of various English and Chinese chatbots across multidisciplinary tests relevant to higher education. Their findings reveal that, despite the hype and sensationalist claims, none of the chatbots tested performed at A or B grade levels in academic contexts. GPT-4 and its predecessor performed best, while Bing Chat and Bard performed poorly (equivalent to "F grade averages") [10]. In the extreme, some scholars argue that some platforms can become monopolies in organizational environments [11]. This can be accepted as a phenomenon observed in the hegemony of bitcoin in the cryptocurrency market, or OpenAI in chatbots, albeit Deep Seek appears to be rapidly gaining dominance.

## 4. Organizational Structure and Management Mechanisms

The integration of AI into organizational structures disrupts traditional management paradigms and demands new approaches to coordination and governance. Brynjolfsson and McAfee's [3] work on the digital economy illustrates how algorithmic coordination can redefine human-AI collaboration. As AI systems take on tasks such as scheduling, performance monitoring, and workflow optimization, they reshape management roles and redistribute agency between human and non-human actors. With the help of AI systems, we expect new forms of departmentalization, task specialization, and role definition. In other words, all other industries should transform their core processes and business models to take advantage of learning AI applications. Thus, as some other authors have pointed out, the bottleneck now lies in management, implementation, and business imagination [5].

The growing reliance on AI is likely to transform organizational structures by reducing the need for traditional manual operations while increasing technology-focused positions. This shift will likely require employees to develop new competencies to effectively collaborate with AI systems, and organizational cultures may also need to evolve to accommodate automation and AI-driven decision-making processes [12]. Essentially, such transformation in organizational environments requires employees to acquire additional skills and organizations to invest in those skills. Therefore, the training programs and demand for this field need be shaped accordingly.

At the same time, the theory of the network society provides a useful framework for understanding distributed governance in large-scale AI systems [13]. In decentralized networks, decision-making is often emergent and shaped by complex interactions between various stakeholders and autonomous technologies. This perspective encourages scholars to investigate how distributed forms of control, collective intelligence, and algorithmic feedback loops influence organizational adaptation and resilience.

In their review study, Rudko et al. [14] show how the basic concepts and mechanisms of organizational structure, such as job richness, span of control, standardization, or chain of command, respond to AI-based demands. They propose hypotheses on optimal organizational adaptations to AI at both macro and meso levels. To assess possible employee resistance or inaction, the authors conducted an online survey that was analyzed using multiple correspondence analysis (MCA). This analysis identified four distinct groups of employees' attitudes toward AI-induced organizational changes: skeptics, doubtful skeptics, optimists, and doubtful optimists. These types of empirical evidence suggest that there is diversity in the approaches and tendencies among individuals when adapting to AI-based structural changes in their organizations.

AI transforms coordination and hierarchy by automating tasks such as workflow design and performance tracking. This calls for a rethinking of departmentalization, job roles, and management competencies. Networked organizational forms with distributed control mechanisms are more suitable for AI-enabled environments. Quantitative research supports this view and identifies clusters of employees based on AI readiness. By bringing these insights together, it becomes more possible to theorize how AI reconfigures organizational structures, both enabling new forms of efficiency and posing challenges to accountability, transparency, and human agency. This research is essential for developing management strategies that harness the potential of AI while also mitigating its unintended consequences.

## 5. Ethical and Justice Dimensions

The proliferation of AI in organizational contexts brings pressing questions about ethics, justice, and accountability to the forefront. Floridi's [15] work on information ethics provides a valuable foundation for examining how AI transforms human autonomy and collective agency. Because AI systems influence decision-making and shape work environments, they can either enhance or diminish human autonomy, depending on how they are designed and deployed.

Saurabh et al. [16] describe four main pillars for ethical use and implementation of AI in organizational settings, namely, ethical intensity and individual and organizational factors and opportunities. Similar to many other works [1, 17], these pillars reflect the importance of procedural fairness, system accountability, and transparency of mechanisms. Identifying these pillars and similar ones is clear at the theoretical level, albeit difficult to realize empirically. Therefore, ethics must be the foundation of any organizational strategy that aims to integrate AI, creating a robust framework that ensures technology development and application upholds and advances human values [16].

Some studies explore fairness in machine learning through the lens of political philosophy [18]. In this way, they offer critical insights into justice and accountability in AI-driven decision-making processes [18]. Some studies highlight how algorithmic systems can reinforce biases and systemic inequalities, if left unchecked [19]. Distributive justice, or algorithmic justice [19], is a concept related to fairness in the integration of AI into organizations and involves systematic coding into computational systems through transparent, measurable evaluation criteria and verification protocols. Those protocols either detect and mitigate bias across protected attributes and ensure equitable outcomes across demographic groups [20]. Ethical AI implementation hinges on fairness, accountability, and transparency. Fairness cannot be based solely on mathematical criteria. It should also reflect human values. The article also incorporates current ethical frameworks such as reports from the United Nations Educational, Scientific and Cultural

Organization and the Organisation for Economic Co-operation and Development [21]. In this way it aims to identify how organizations can embed fairness in AI design through bias audits, stakeholder inclusion, and transparency protocols.

Despite all the practical opportunities AI platforms provide organizations, the issues of justice and fairness remain controversial. Considerations about the differences between human perception and machines lies in the heart of this duality [22]. This article by Srivastava et al. [22] explores the gap between mathematical definitions of fairness in machine learning and how fairness is perceived by humans. The key idea here is that although fairness in machine learning is often defined using strict mathematical criteria (such as equalized odds, demographic parity, or individual fairness), these definitions may not align with human intuitions or societal expectations of fairness. By weaving together these ethical and justice-oriented perspectives, we can develop a more nuanced understanding of how organizations can balance innovation with responsibility, ensuring that AI technologies serve broader societal goals while safeguarding human dignity and equity.

## 6. Methodology

This study aims to explore AI's distributed agency within organizations through a systematic literature review. The primary research questions: (1) How can AI function as a distributed actor in organizational settings? (2) What governance and ethical mechanisms are necessary for responsible AI adoption in organizations? These questions address gaps in the existing literature, particularly the limited empirical exploration of the recursive influence of AI on organizational dynamics and justice considerations.

To achieve these goals, we adopted a systematic literature review approac h to examine the role of AI as a distributed actor in organizational structures. The study covers peer-reviewed journal articles, conference proceedings, and academic books published between 2000 and 2024. Data were retrieved from Google Scholar, Scopus, and Web of Science. Databases were searched for relevant articles. Search terms included combinations of keywords such as "AI in organizations", "distributed agency", "actor-network theory", "sociomateriality", "AI ethics", and "algorithmic fairness", and Boolean operators (e.g., AND, OR) to refine the results [23]. The search covered articles published between 2000 and 2024, focusing on peer-reviewed journals and conference proceedings. Studies were included if they addressed the impact of AI on decision-making, governance, or ethics within organizations. Non-peer-reviewed literature, studies lacking empirical or theoretical rigor, and papers outside the organizational context were excluded to ensure relevance and reliability. Articles were screened by title, abstract, and full-text reviews. Studies that met the inclusion criteria were charted for analysis. The inclusion and exclusion criteria of the searched articles can be summarized as follows:

Inclusion Criteria: Studies, research, or publications which

1) Examined the impact of AI on organizational structures, practices, settings, and decision-making processes.
2) Incorporated ANT and sociomateriality perspectives.
3) Discussed AI ethics and governance.

Exclusion Criteria: Studies, research, or publications which

1) Gave technical AI research unrelated to organizational settings.
2) Lack a strong theoretical framework or empirical validation.
3) Focused solely on AI development from an engineering perspective.

In summary, this study uses a systematic literature review guided by PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses). Data sources included Scopus, Web of Science, and Google Scholar between 2000 and 2024. The inclusion criteria targeted peer-reviewed studies on the organizational impact and ethical governance of AI. A PRISMA flow diagram outlines the selection process. Future research may include ethnography, stakeholder surveys, and AI audits to empirically test the DSAM.

## 7. Findings: Proposed Conceptual Framework as the DSAM

As we look to the future, the changing complexity of AI and organizational dynamics presents a unique foundation and opportunity for developing new conceptual frameworks. Barad's [2] theory of agential realism provides a powerful perspective for understanding the distributed agency of AI in sociotechnical systems. By viewing AI not merely as a tool but as a phenomenon that emerges through relations with human and non-human agents, researchers can explore how organizations continuously redefine themselves in response to technological advances. By building on Barad's [2] insights and designing integrative models that incorporate the co-constitutive nature of AI-human interactions, future research can push the boundaries of organizational theory. Such models will not only deepen our understanding of AI-driven organizational change but will also inform more adaptive, reflexive, and ethically coherent management practices. Such perspectives invite scholars to theorize beyond traditional models of organizational structure, embracing dynamic, intertwined, and iterative processes. For instance, new frameworks could examine how AI changes over time, influencing and being influenced by organizational culture, knowledge practices, and stakeholder ecosystems.

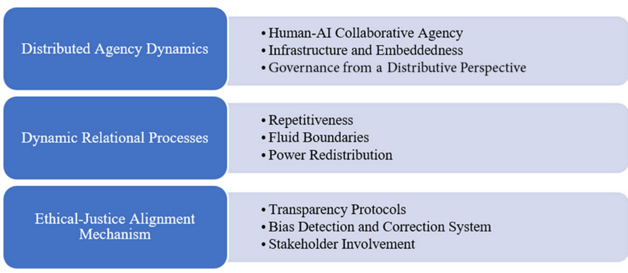
Drawing inspiration from all literature described above and the theory of agential realism, we developed a framework that aims to conceptualize AI as a distributed agent/actor in organizational settings. This framework synthesizes insights from ANT, sociomateriality, and AI research to conceptualize how AI functions as a distributed actor in organizational settings. The DSAM, described in Figure 1, builds on key insights from ANT and sociomateriality to provide a structured understanding of the role of AI within organizations. This model consists of three interconnected dimensions:

1) Distributed Agency: AI interacts with human actors and digital infrastructures, shaping decision-making processes.
2) Relational Processes: The integration of AI blurs traditional organizational boundaries, requiring new governance structures.
3) Ethical and Justice Considerations: Ensuring transparency, bias mitigation, and stakeholder inclusion in AI governance.

### 7.1. Distributed agency

According to the DSAM framework, as explained in the various sections of this article, organizations are at the edge of different organizational forms and business practices. As distributed actors, AI platforms can provide many enrichments, but they can also create

**Figure 1**
**The DSAM**



challenges if not used properly. The first dimension in this framework describes distributed agency dynamics, which has three main pillars:

1) Human-AI Collaboration: Co-construction of decisions.
2) Infrastructure and Embeddedness: Integration of AI across functions.
3) Governance Distribution: Shared accountability across actors.

Human-AI collaboration as the first distributive agency, involves how humans and AI systems co-construct decisions and actions in the organizations. We prefer to put this pillar in the first rank since it may provide infrastructure for all the others in the framework such as, decision-making in employee evaluation or fairness in employee selection processes. The second pillar of agency dimension is infrastructure and embeddedness, which involves how AI is integrated into existing organizational systems. This creates a potential point of challenge as change in organizations can sometimes face some resistance. The last pillar of agency comes into play at the point where resistance to AI adaptation arises in the organizations, that is, the distribution of governance. According to this aspect of the framework, control mechanisms and accountability are distributed among actors in the organizational setting.

### 7.2. Relational dynamics

The second dimension of this framework concerns the relational processes and relationships that emerge during the implementation of AI platforms in organizations. There are three main pillars in this dimension as follows:

1) Repetition and Mutuality: Iterative practices reshape boundaries.
2) Ambiguity in Boundaries: Shifting roles and departmental blur.
3) Power Redistribution: Changing authority structures.

Organizational practices can mutually transform each other, which we call repetition in this framework, as the first pillar of the second dimension. The mutuality in organizational practices can also cause oscillations, which can lead to ambiguity in boundaries. Traditional definitions of organizational boundaries and structural and departmental relationships can blur because of the adaptation of AI. Therefore, boundaries, power relations, and authority requirements may be redefined in organizational settings. The third pillar, power redistribution, includes how AI shifts the points of influence and authority within organizational networks.

### 7.3. Ethical and justice considerations

In the proposed conceptual framework, the third and last dimension constitutes the mechanisms of alignment of ethics and justice, which have the following pillars:

1) Transparency Protocols: Explainability mechanisms.
2) Bias Mitigation: Fairness audits.
3) Stakeholder Inclusion: Multi-voice governance.

These mechanisms are occasionally seen as results of AI implementations in organizations, albeit these need be considered at the very beginning of the processes. For example, decisions given by AI platforms and other AI actions in organizational settings must be explainable with the help of systems which can ensure explainability. This can be acheived through transparency in protocols. Systems also need to include transparent control systems and correction in measurement and decision-making. The critical issue at this point of the conceptual framework is that such systems reduce potential biases. Therefore, the ethical and justice dimension includes procedures for identifying and correcting potential algorithmic biases that may arise from the use of AI in decision-making and other organizational practices. Lastly, all related actors of the organizations, namely, stakeholders, should be included in the alignment mechanisms. These efforts may involve methods for incorporating diverse voices in AI governance. AI adoption in organizations raises critical concerns about fairness, transparency, and accountability. While theoretical discussions on algorithmic fairness exist, organizations struggle with real-world implementations. For example, the recent controversy surrounding an AI-powered hiring algorithm highlights the challenges of bias and accountability. Some technology companies implement AI-driven recruitment tools. Results of some of these tools revealed that their algorithm sometimes disproportionately favored male applicants due to historical bias in the training data. This example highlights the importance of bias mitigation strategies and explainability mechanisms in AI governance.

## 8. Multi-sectoral Case Applications

A case study method was adopted in assessing the empirical model and application areas for the applicability of the DSAM in organizational contexts. Each case is structured with (1) Context, (2) DSAM Dimensions, (3) Opportunities and Challenges, and (4) Ethical Implications.

### 8.1. Supply chain management

In the first albeit utopic case, we can assume that the DSAM is applied to the AI-driven decision-making in supply chain management.

1) Context: Global retailer uses AI for inventory.
2) DSAM: Autonomous allocation (agency), role merging (relational), exclusion of small suppliers (ethics).
3) Ethical Issue: Stakeholder feedback loop restores equity.

In organizations where AI systems are implemented in supply chain management, dynamic relational processes can come into action. The diversity of actors involved in a regular supply chain can provide observations for relational mechanisms such as repetition in transactions. The same characteristic of applying the DSAM to this case example can create challenges and opportunities in terms of power relations among diversified actors. These findings demonstrate that AI is not just a tool but also an active decision-maker, reshaping management practices and organizational governance structures. Let us suppose a global retailer implements AI for dynamic inventory allocation. The DSAM can provide insights for collaboration where AI autonomously adjusts orders but requires human intervention during outages. As regards relational processes, boundary ambiguities need be considered and solved because of the merging of traditional procurement teams with data science units. The cost-saving trend of AI has put small suppliers at a disadvantage, which can be corrected with stakeholder feedback.

### 8.2. Healthcare systems

In another case example, we can take into account the integration of AI in healthcare systems, which is very famous and can change organizational structures.

1) Context: AI in radiology.
2) DSAM: Human-AI report hybridization, role change, privacy concern.
3) Ethical Issue: Dual reporting mitigates trust loss.

In this example, if the system is to be used in a leading hospital network, we may have the opportunity to observe almost each dimension of the DSAM. Cooperation, one of the fundamental dynamics of distributed agency, lies in the heart of the healthcare system organizational structure. A hospital network using AI for radiology analysis can serve as an example of this second case. In this context, radiologists can shift from diagnosticians to AI validators, which can lead to a redefinition of their role and also impact the redistribution of power in the organizations. There may also be transparency insights as proposed in the DSAM. For example, patients may demand explanations for AI-generated diagnoses, leading to "dual reports" (human + AI). Healthcare, by its very nature, requires consultation between different areas of expertise and embeddedness into the system. The biggest potential challenge is transparency regarding patient information.

### 8.3. Start-up culture

The last case to be exemplified in this article will be related to cultural transformation.

1) Context: Fintech using real-time AI.
2) DSAM: Agile adaptation (agency), iterative decisions (relational), co-design workshops (ethics).
3) Ethical Issue: Preparation of AI ethics guidelines.

For start-ups, with their entrepreneurial spirit, the use, adaptation, and implementation of AI may be easier than for more mature organizations. AI platforms in any form can transform organizational culture, enriching collaboration, commitment, and engagement in the organization. The transformation of start-up culture can be observed in a fintech start-up that uses AI for real-time decision-making processes. The rapid iterations of AI have necessitated agile adaptations in managerial practices that can be handled through repetition of practices. Stakeholder inclusion can be achieved through distribution of governance. For example, employees should be encouraged to participate in workshops where they can co-design AI ethics guidelines.

Other empirical platforms that can be considered when observing the effectiveness of the proposed framework are automation in start-ups or digital platform governances. Automation and consultancy industries are some other examples where AI platforms can provide scope for DSAM application. Agile environments can provide an adaptive infrastructure that can provide for DSAM to highlight how entrepreneurial culture accommodates ethical oversight. As for digital platforms, chatbot development and surveillance capitalism can be considered as an indicator of the power redistribution, despite the existence of ethical controversies. To illustrate the practical application of the DSAM, a comparative analysis with existing frameworks is presented in Table 1.

This comparison highlights that the DSAM offers a novel perspective and provides a comprehensive framework for understanding the role of AI in organizational settings.

Each case substantiates the three-dimensional structure of DSAM and supports its relevance across contexts.

The results of these findings and analyses conducted within the DSAM framework highlight that the role played by AI in organizational structures must be examined in three key dimensions:

1) Human-AI Collaboration: Integration of AI into employee decision-making processes and its impact on organizational knowledge flows.
2) Infrastructure and Embeddedness: Challenges of integrating AI systems into existing organizational structures and solutions to overcome them.
3) Governance and Accountability: Development of transparency mechanisms and institutionalization of ethical standards in AI use.

## 9. Case Reflections Using Secondary Data: AI Governance in Higher Education

### 9.1. Qualitative example exemplifying the DSAM

To strengthen the empirical foundation of the DSAM framework, this section presents an illustrative case reflection based on secondary data collected from publicly available institutional reports and platform documentation related to AI-based monitoring systems in higher education. This case is particularly inspired by the implementation of an AI-supported exam monitoring system at a university during the 2023–2024 academic year. In response to the challenges of remote learning, the university deployed an AI-integrated monitoring and control platform that detect academic misconduct by monitoring students' visuality, screen activity, and environmental sounds. The platform functioned in conjunction with the university's learning management system and was part of broader digital transformation efforts. For this specific higher education case, some data were derived from publicly available documents of the university and some from documents shared by colleagues at the same university. Table 2 below summarizes these data sources and their corresponding DSAM dimensions. In the conext of higher education, the DSAM dimensions can also be listed as follows:

1) Agency: Automated flagging of anomalies.
2) Relational: Faculty–information technology (IT) collaboration.
3) Ethics: Fairness complaints regarding glasses/headwear.

Some correspondent results emerged in the analysis performed through the proposed DSAM framework above. The AI tool autonomously flagged suspicious behavior such as multiple faces and irregular gaze movement, albeit human supervisors retained the authority to investigate and interpret the logs. This illustrates the hybrid decision-making logic central to the DSAM, which constitutes the observation of distributed agency, the first dimension of the proposed framework. The adoption of this system has led to increased collaboration among IT staff, instructors, and academic leadership. This cross-functional engagement reflects the relational entanglement of technological and organizational actors in the DSAM and also constitutes relational relationship. Contrary to initial assumptions and previous expectations, the use of AI-based monitoring system during remote education did not reduce the collaboration between users, i.e., academic staff, administrative staff, and student, but rather positively accelerated these relationships. Finally, several reports and feedback information have been analyzed regarding the last dimension of the proposed DSAM, namely the ethical and justice dimensions. Corresponding results showed that students wearing glasses or face

**Table 1**
**Comparative analysis of the DSAM**

| Model | Main Focus | Role of AI | Governance |
|---|---|---|---|
| ANT [1] | Networks of human and technological actors | Views AI as a passive intermediary | Centralized governance perspective |
| Sociomateriality [24] | Dynamic human-technology relationships | Acknowledges the impact of AI on organizational processes | Weakly defined governance mechanisms |
| Proposed DSAM | AI as a distributed actor | AI actively participates in decision-making processes | Strong ethical and governance principles |

**Table 2**
**Data sources mapped to the DSAM**

| DSAM Dimension | Empirical Evidence | Data Source |
|---|---|---|
| Distributed Agency | AI-flagged student behaviors | Logs |
| Relational Processes | Collaboration improvements | Institutional memos |
| Ethical Issues | Bias complaints, appeals | Student surveys, emails |

coverings were flagged more often, raising fairness concerns. The same thing happens for those wearing hats. In response, institutions adapted its policies to incorporate human review processes and channels for student appeals, such as declaration of accessories and clothing codes for students during exams. (Policies now also include human review, dress code disclosures, and technical-pedagogical workshops.) In addition to these, transparency protocols were also updated to address the issue of algorithmic opacity, which requires another form of cooperation between employees from diversified areas of expertise and backgrounds. Faculty members reported increased collaboration with IT departments, citing "a need to bridge pedagogical and technical fluency" to ensure fair oversight. Some students expressed discomfort with the constant surveillance, describing the system as "impersonal" and "stressful." These reflections illuminate the relational and ethical dimensions of the proposed DSAM.

Although this case is based on secondary data, it illustrates the real-world tensions and adaptations required for ethically sound and operationally effective AI governance. It highlights the practical relevance of the proposed DSAM in identifying alignment gaps between regulation, automation, accountability, reporting, and inclusion in institutional settings.

## 9.2. Expanded quantitative indicators supporting the DSAM

To further strengthen the empirical foundation of the DSAM framework, this section aims to integrate some of the open-source quantitative evidence that aligns with the three key dimensions of the proposed DSAM: distributed agency, relational processes, and ethical accountability. In fact, some of the literature reviewed and summarized above provides the quantitative support for the proposed DSA and thus used in the analysis.

The first dimension in the proposed DSAM is Distributed Agency, and its reflections in higher education has been studied by Rudolph et al. [10] as a comparative evaluation of AI chatbots. The results of this study showed that GPT-4 received a average score of "C", while Bing Chat and Bard received scores of "F". Moreover, none of the systems achieved an "A" or "B" grade in terms of simulating student responses. Thus, this reflects that the current autonomous decision-making capacity of AI in education is limited and requires human supervision. It can be assumed that these findings of Rudolph et al. [10] support the ideas implicit in the proposed DSAM, in other words, the decisions given by AI platforms should be carefully observed by human experts to provide consistency and transparency.

The second dimension of the proposed DSAM, namely, Relational Dynamics, was quantitatively observed in a study by Rudko et al. [14], which measured workers' readiness to adapt to the changes in the workplaces associated with the integration of AI into systems. Based on a survey that used MCA to analyze organizational response to AI integration among N = 1,437 employees, the results revealed four main attitudinal groups toward AI-driven change: skeptics (28%), doubtful skeptics (21%), optimists (34%), and doubtful optimists (17%). These clusters reveal divergent readiness levels, validating the relational complexity in the proposed DSAM. The categorization of employees based on their tendency to accept AI-driven change in the organizational setting can be expanded and supports the idea of diversified interests and relationships in the proposed DSAM.

Finally, potential algorithmic biases as one of the pillars of the ethical dimension of the proposed DSAM was observed in the quantitative study conducted by Charlwood and Guenole in 2022 on human resource systems and their integration of AI. Their findings reveal that organizations using AI in recruitment experienced a 40% higher screening rate, despite a 26% increase in bias complaints particularly among underrepresented demographic groups, such as minorities or single mothers. Lastly, they found that trade unions play a significant role in implementing counter-governance mechanisms, including algorithm audits and transparency mandates [8].

Quantitative supporting studies indicated that the proposed DSAM has already been observed in empirical settings and therefore can be expanded in future studies. The AI tools used in these studies together with their quantitative indicators and their corresponding dimensions in the proposed DSAM are summarized in the Table 3. In this way, Table 3 provides a cross-sectoral summary of the results from these quantitative studies across higher education, human resources management, and business in general.

## 10. Conclusion

This article aims to present a conceptual advance through the proposed DSAM, which recognizes AI as a distributed actor embedded in complex organizational networks. This study aims to provide both theoretical depth and practical relevance with case studies that attempt to validate the DSAM through multi-sectoral scenarios and literature synthesis. Future research can empirically apply the DSAM across diversified sectors and also develop operational tools for AI governance in practice. This article expands the discourse on AI by conceptualizing it as a distributed actor embedded in evolving organizational networks. Therfore, future work should ask: Are DSAM insights context-specific? How can we operationalize its dimensions across sectors? Can it inform AI policies beyond academia?

**Table 3**
**Cross-sectoral summary**

| Sector | AI Tool | Quantitative Indicator | Corresponding DSAM Dimension |
|---|---|---|---|
| Higher Education | GPT-4 / Bing Chat [10] | GPT-4 scored "C"; Bard/Bing scored "F" | Distributed Agency |
| Organizational Human Resource Management | AI recruitment tools | 40% faster filtering, 26% more bias complaints | Ethical and Justice Alignment |
| General Business | MCA from 1,437 employees | 4 clusters of AI readiness (skeptics to optimists) | Relational Processes |

Considering AI as a distributed actor can reshape organizational theory and compel a reevaluation of agency, structure, and accountability. This perspective can create both opportunities and risks. For example, while AI can enhance adaptability and efficiency, it also introduces ethical complexities and power challenges. Addressing these dynamics requires organizations to adopt flexible governance models, embrace interdisciplinary collaboration, and continuously evaluate the societal impact of AI systems. Moreover, the evolving role of AI is challenging traditional organizational hierarchies, pushing organizations to explore hybrid decision-making processes where discretionary power of human and algorithmic intuition intersect. This requires ongoing training and capacity-building efforts to increase AI literacy across all levels of the organization, empowering employees to engage critically with AI tools rather than passively accepting automated outputs.

Ethical considerations must be at the forefront of AI adoption and use, and organizations must implement robust mechanisms to audit algorithms, assess biases, and ensure alignment with societal values. Stakeholder inclusion is equally vital, thus organizations should create avenues for diverse voices to influence AI governance, foster collective accountability, and reinforce public trust. Ultimately, embracing AI's distributed agency is not just a technological challenge but a profound organizational transformation. By continuously exploring the relational dynamics between AI and human actors, organizations can harness the potential of AI to drive innovation while proactively mitigating risks and reinforcing their commitment to justice, transparency, and shared prosperity. This article aims to encourage future research to extend the proposed framework and explore new methodologies and empirical studies to refine our understanding of the evolving impact of AI on organizational ecosystems.

Through the literature review, we find that the key aspects for AI to act as distributed agency in organizational settings are fairness and human-centeredness of AI applications and platforms. The DSAM framework, validated through supply chain, healthcare, and start-up case studies, demonstrates how AI's distributed agency reshapes organizations. By adopting structured governance (e.g., oversight committees, transparency protocols), firms can balance innovation with ethical accountability. Future research should test the DSAM in other sectors (e.g., education, government). According to the study, some of the policy and governance recommendations for organizations can include the establishment of AI oversight committees within organizations that implement algorithmic audit procedures. Furthermore, transparency protocols that require AI models to provide explainable decisions to affected stakeholders can be incorporated. Finally, all efforts must be supported by dedicated and smart investments in AI literacy and critical engagement at all organizational levels.

The real-world-inspired case presented in this study demonstrated the empirical applicability of the DSAM framework in addressing practical governance challenges in AI deployment. Although the case mentioned was examined through secondary data, the model revealed how AI's distributed agency, relational dynamics, and ethical alignment manifest within organizational systems. This example paves the way for future empirical applications across different sectors such as education, logistics, healthcare, production, and public administration. Organizations can be encouraged to adopt the DSAM as both an analytical perspective and a strategic recommendation tool in designing human-centered, ethically aligned AI systems that integrate into their sociotechnical environments.

To strengthen the empirical foundation of the proposed framework, this study incorporated quantitative and qualitative insights from open-source, peer-reviewed studies. In particular, some empirical and quantitative studies [10] demonstrated the inconsistent and often underperforming outputs of AI chatbots in academic assessments, which reinforces the importance of human oversight and transparency mechanisms that are central to the proposed DSAM. Similarly, some empirical studies used employee survey data and MCA to reveal how different attitudinal profiles (skeptics, optimists, etc.) influence readiness for AI integration. These findings are consistent with the focus of the proposed DSAM on relational processes, organizational adaptation, and sociotechnical negotiation of agency. These studies therefore provide a solid empirical foundation for the relevance and applicability of the proposed DSAM framework in real-world settings, particularly in the field of education, where algorithmic tools increasingly intertwine with governance, equity, and ethics. The study also explores potential use cases in healthcare, supply chain management, and digital platforms, emphasizing how distributed agency, infrastructure embeddedness, and ethical alignment differ by sector. As AI technologies continue to evolve, the proposed DSAM framework provides an analytical tool for understanding not only how AI acts but also where, with whom, and to what effect.

Future research should aim to expand the applicability of the proposed DSAM through multi-sectoral case studies, field experiments, and interdisciplinary collaborations. Scholars and practitioners alike are encouraged to evaluate AI systems using diverse, real-world metrics, such as algorithmic accuracy, false-positive rates, stakeholder satisfaction, and ethical risk exposure. Ultimately, the DSAM equips organizations with a structured perspective to govern AI with fairness, accountability, and inclusivity. As AI reshapes work, knowledge, and authority, not only technological capacity but also organizational reflexivity and ethical foresight will determine whether AI supports or disrupts collective prosperity.

Organizational structure can play an important role in delivering AI implementation in organizations. This can be achieved, for example, by establishing a multidisciplinary AI governance council composed of representatives from different functional units, such as legal, HR, IT, to oversee algorithmic systems. This council should conduct regular algorithmic assessments and share the results across the organization. In this way it is possible to promote accountability and ensure ongoing compliance with ethical standards within the organization. The findings suggest that implementing solutions that can provide clear explanations for AI decisions using advanced interpretability models can provide some measure of transparency. A practical application of these solutions would be to provide a user-friendly interface that allows employees to understand and challenge their automated performance evaluations when necessary, thus creating a more equitable workplace environment.

Other essential actions can include performing comprehensive algorithmic impact evaluations, maintaining detailed documentation of data sources used in training and clearly defining accountability frameworks for system errors to mitigate potential legal and ethical risks.

However, AI adoption also presents some practical challenges, such as potential difficulties for organizations in developing AI governance frameworks that ensure fairness and accountability. Organizations must increase AI literacy at all levels of an organization to facilitate better human-AI collaboration albeit training programs and trainers are not yet well educated in this field. Finally, this article calls for further interdisciplinary research that combines insights from organizational theory, AI ethics, and management studies to develop more adaptive, reflexive, and responsible AI-driven organizational strategies.

The DSAM bridges organizational theory with practical governance. Its three dimensions, namely agency, relational dynamics, and ethics, provide perspectives for analysis and implementation. Case examples and supporting literature validate the applicability of the model. Organizations should establish governance councils, adopt transparency tools, and align with global policy (EU AI Act, U.S. AI Bill of Rights). As AI reshapes jobs and institutions, the real differentiator will be not only technology itself, but how it is managed ethically and inclusively.

## Conflicts of Interest

The author declares that she has no conflicts of interest to this work.

## Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

## Author Contribution Statement

**Hasibe Aysan:** Conceptualization, Methodology, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration.

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