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Entangled by Design: A structured Overview of Management Challenges concerning AI Adoption in Organizations

Tim Klos
0009-0003-3041-8432
University of Applied Sciences Augsburg
An d. Hochschule 1
86161 Augsburg, Germany
Email: tim.klos@hs-augsburg.de
University of Applied Sciences Konstanz
Alfred-Wachtel-Str. 8
78462 Konstanz, Germany
Email: tim.klos@htwg-konstanz.de

Alessandra Zarcone
0000-0001-9380-4638
University of Applied Sciences Augsburg
An d. Hochschule 1
86161 Augsburg, Germany
Email: alessandra.zarcone@tha.de

Christopher Rentrop, Constanze Riedinger, Niculin Prinz
0000-0003-3629-3821, 0009-0003-0226-4114, 0000-0002-3656-2668
University of Applied Sciences Konstanz
Alfred-Wachtel-Str. 8
78462 Konstanz, Germany
Email: {christopher.rentrop, constanze.riedinger, niculin.prinz}@htwg-konstanz.de.

Melanie Huber
0000-0001-8020-9055
BITCO³ GmbH
78467 Konstanz, Germany
Email: melanie.huber@bitco3.com

***Abstract*—Artificial Intelligence (AI) adoption poses complex, multidimensional challenges for organizations that extend beyond technical implementation. While strategic interest in AI is rising, many initiatives struggle to scale sustainably. This paper addresses the fragmented state of AI adoption research by offering a theory-driven synthesis of the key management challenges organizations face. Based on a systematic literature review and grounded in the socio-technical systems (STS) perspective, the study identifies challenges across technological, organizational, and social domains—such as data governance, organizational inertia, skill shortages, and ethical ambiguity—as mutually reinforcing. The resulting framework highlights the systemic entanglement of these barriers, underscoring the limits of isolated interventions. This study contributes to Information Systems (IS) research by conceptualizing AI adoption as a socio-technical transformation and providing an integrative typology of adoption challenges. The findings offer a foundation for future empirical research and guide strategic decision-makers in navigating the organizational complexity of AI integration.**

***Index Terms*—AI Adoption, STS, Organizational Change, AI Challenges, Information Systems**

I. Introduction

ARTIFICIAL Intelligence (AI) has recently evolved rapidly into a strategic priority for organizations across industries. In a 2019 survey, already over 84% of 1,500 surveyed C-suite executives from high-profit international companies across various industries emphasized that AI is essential for achieving their growth targets [1]. Despite this ambition, the majority of organizations continue to face substantial barriers in scaling AI effectively to this day [1], [2], [3]. Many initiatives remain confined to isolated pilot projects, lacking cross-functional integration and strategic alignment [1], [4]. Even as AI tools become more accessible, only a minority of organizations have redesigned their core workflows accordingly, and governance responsibilities often remain unclear or underdeveloped [2]. These discrepancies reveal a deeper issue: AI adoption is not merely a matter of technology implementation but requires ongoing adaptation to complex structural, procedural, and human dynamics. This paper, therefore, aims to identify and systematize the management challenges organizations must overcome to successfully adopt AI, using a socio-technical systems (STS) lens to account for the intertwined nature of these challenges.

Although existing research has addressed various barriers to AI adoption, ranging from technical and infrastructural issues to strategic misalignments or cultural resistance, it has typically examined these challenges in isolation. Several studies investigate specific barriers through expert interviews, systematic literature reviews, or conceptual models (e.g., [5], [6], [7], [8], [9]). However, few contributions adopt an integrative, theory-driven perspective that accounts for the socio-technical entanglement of AI adoption management challenges in organizations. On the other side, scholars increasingly argue that technological, structural, and social dimensions of AI implementation are tightly coupled and mutually reinforcing [9], [10], [11]. Without a holistic understanding of these interdependencies, even advanced AI initiatives risk stagnation or failure to scale sustainably [10], [12]. This paper responds to this gap by proposing a structured, STS-based synthesis of existing knowledge on AI management challenges in an organizational context. To do so, the paper addresses the following research questions:

RQ1: *What are the management challenges of AI adoption in organizations?*

RQ2: *How does existing literature consider the socio-technical entanglement of the challenges?*

By providing a structured overview of AI adoption challenges from a socio-technical perspective, this paper contributes to Information Systems (IS) research in two ways: first, by enhancing theoretical understanding of AI adoption as an entangled socio-technical process; and second, by offering a systematic categorization of challenges that can support both academic inquiry and practical decision-making. The findings aim to support researchers, strategists, and policymakers in navigating the complex landscape of organizational AI management.

The paper is structured as follows: Section 2 provides the theoretical background on AI adoption and socio-technical systems. Section 3 outlines the methodological approach used to identify and synthesize the relevant challenges. Section 4 presents the results of the systematic analysis. Section 5 discusses the socio-technical interdependencies and implications for research and practice. Section 6 concludes with a summary and outlines directions for future research.

II. Background

AI is broadly understood as the science and engineering of developing intelligent systems capable of replicating or augmenting human cognitive functions such as reasoning, problem-solving, and decision-making [13], [14], [15]. When it comes to technology, AI comprises a diverse set of approaches including machine learning, deep learning, natural language processing, and computer vision [6], [7], [15], [16]. Functionally, AI can be defined as the capacity of systems to autonomously interpret data, learn from experience, and apply that learning to achieve goal-oriented behavior [8], [12]. Due to its general-purpose nature [17], AI is increasingly integrated into organizational routines, enabling automation, augmentation, and innovation across industries. In contrast to traditional IT systems, AI is characterized by three interrelated properties: autonomy, learning, and inscrutability [10]. Autonomy refers to AI's ability to make decisions without human intervention; learning captures the system's capacity to evolve through experience; and inscrutability addresses the opacity of AI decision-making, particularly in complex models such as deep neural networks [12], [18]. These characteristics complicate organizational control and validation practices and contribute to uncertainty in implementation outcomes[19]. As a result, AI systems often act as semi-autonomous agents, embedded in decision-making contexts with significant organizational and societal implications [20].

While the concept of technology adoption has been widely studied in the IS field (e.g., TAM, TOE, DOI), AI adoption presents a new level of complexity [9], [21]. The unique characteristics of AI challenge traditional assumptions regarding transparency, accountability, and control, rendering many existing models insufficient [21]. AI adoption refers not only to the technical integration of AI tools but also to the organizational transformation required to generate sustained business value [9], [12]. This includes the alignment of strategic priorities, development of technical and organizational capabilities, stakeholder coordination, and iterative adaptation of business processes [10], [14]. Several studies have already contributed to identifying and categorizing challenges related to AI implementation, drawing on methods such as qualitative interviews (e.g., [22]), conceptual frameworks (e.g., [14]), and systematic literature reviews (e.g., [8], [19]). These works have yielded valuable insights into key barriers, including data governance, infrastructure limitations, skill gaps, and organizational inertia. Collectively, they have helped establish a rich foundation for understanding critical factors that affect AI adoption. However, despite these advances, most studies tend to examine these challenges in isolation or emphasize predominantly technological or organizational dimensions. While a socio-technical entanglement of these challenges is often implied or acknowledged in principle [12], [18], a systematic and theory-based integration that explicitly maps their interdependencies across functional and structural boundaries remains limited. This fragmented view is problematic. Given the socio-technical nature of AI, challenges cannot be addressed in isolation. A detailed understanding of these challenges supports more effective implementation by revealing organizational gaps and enabling proactive risk mitigation. Yet, there is limited research that systematically examines how challenges from different organizational levels and functional domains interact and reinforce each other [5], [7], [8], [11], [12], including no systematic STS-classification of AI management challenges of AI adoption in organizations.

III. Method

In order to identify and synthesize current academic discourse on challenges in managing AI adoption in organizations, we conducted a concept-centric literature review following the guidelines of [23] and [24]. The objective was to provide a structured overview of the key challenges associated with organizational AI adoption and to analyze their socio-technical interdependencies using a theory-informed framework. We followed the five-stage model of [23] for literature reviews: (1) problem formulation, (2) data collection, (3) data evaluation, (4) analysis and interpretation, and (5) presentation. Stages (1) and (5) are addressed in the introduction and results sections, respectively; this section covers stages (2) through (4).

A. Data collection and evaluation

For our data collection, we use Litbaskets.io, a curated and reproducible search tool optimized for IS research, covering over 1,000 IS-relevant journals indexed in Scopus. This tool allows dynamic filtering of the "medium bucket" of 51 core IS journals and conferences, mitigating risks of over- or under-inclusiveness often associated with traditional search strategies [25], [26]. To define the search space, we applied the string ("artificial intelligence" OR "AI") AND "manag*" AND "challenge*" across abstracts, titles, and keywords, covering the period from 2000 to January 2025.

The initial result of 196 hits was filtered by applying multiple exclusion criteria. First, duplicates and non-English entries were removed. Second, only papers addressing AI management challenges within an organizational context were considered, excluding papers focused solely on technical or specific domain implementations (e.g., in healthcare, logistics, or mobility domains) without addressing overall organizational implications. Third, the search was extended via forward and backward snowballing, as suggested by [24].

By adopting the described method, a targeted yet inclusive identification of AI-related literature was achieved, ensuring that both high-impact contributions and emerging research trends were systematically captured. At the end of the entire process, 15 publications specifically included challenges of AI management on an organizational level.

B. Data analysis and interpretation

The final corpus of 15 contributions was analyzed using the six-step qualitative thematic analysis procedure from [27]. This approach is well-established in IS research and supports systematic and transparent theme identification. The goal was to extract, classify, and interpret explicit challenges regarding AI management in organizations. We employed a deductive coding strategy guided by the Socio-Technical Systems (STS) model [28], [29], which conceptualizes work systems as interactions between four components: technology, task, structure, and people (cf. Fig. 1).

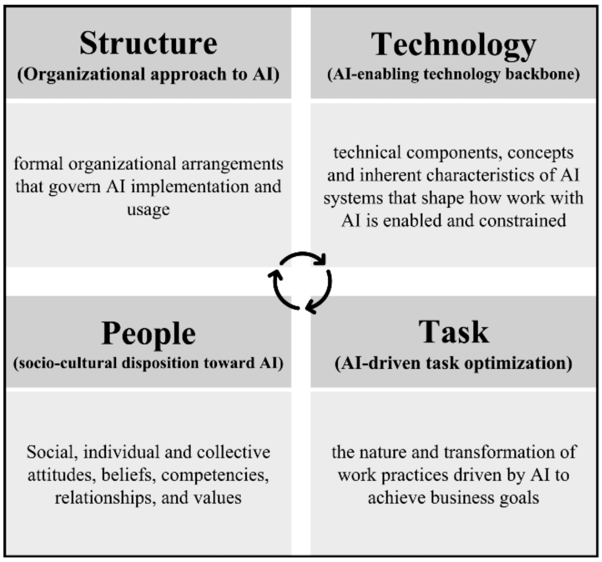

Fig 1 - STS perspectives applied on AI based on [28]

To explain the STS lens for AI adoption, we briefly outline the relevance of each of the four core perspectives. The *technology perspective* addresses the "AI-enabling technology backbone" and therefore refers to the technical components, concepts, and inherent characteristics of AI systems that shape how work is enabled and constrained. This includes, for example, physical infrastructure such as computing power and storage, as well as virtual resources such as pre-trained models, algorithms, training data, or IT-security efforts to keep the new technology safe. These elements determine not only the feasibility of AI deployment but also the system's autonomy, learning capacity, and opacity—factors which are central to how AI affects organizational routines (e.g., [8], [10]).

The *task perspective* considers the "AI-driven task optimization" and captures the nature and transformation of work practices driven by AI. It concerns the activities and processes through which organizational goals are pursued and how these are augmented, redefined, or automated by AI technologies. AI integration can shift task boundaries, introduce new dependencies, or alter performance criteria, thereby affecting both productivity and work design (e.g., [7], [19]). The *structure perspective* consolidates aspects of the "organizational approach to AI", which addresses the formal organizational arrangements that govern AI implementation and use. This includes decision rights, coordination mechanisms, and governance structures that define how responsibilities are distributed, risks are managed, strategies are defined, and AI capabilities are scaled across organizational units. As AI blurs traditional boundaries between human and machine decision-making, structural adaptation becomes a prerequisite for responsible and effective use (e.g., [22], [30]). Finally, the *people perspective* focusing on the "socio-cultural disposition toward AI" focuses on the human actors—such as employees, managers, and other stakeholders—and their perceptions, beliefs, competencies, and values. AI implementation is shaped by individual and collective attitudes, digital skills, trust in AI systems, and willingness to engage with algorithmic processes (e.g., [8], [12]).

This framework allows for theory-informed mapping of challenges and their systemic interrelations. The operationalization of the STS components was informed by prior IS research that applied similar socio-technical logics to technology and platform adoption (e.g., [26], [31]). Coding was conducted manually in Excel using a structured matrix and visualized on a collaboration board. One researcher initially coded all 15 papers, and afterwards the coding was refined across three iterative rounds in expert workshops with another 3 researchers. Disagreements in coding were resolved through discussion within the expert workshops until consensus was reached. During coding, no new categories emerged outside the STS framework, indicating thematic sufficiency. The final coding structure was thus stable and consistent with the four original dimensions. To ensure validity, definitions and representative indicators for each category were documented in a shared collaborative board and reviewed across the rounds.

IV. RESULTS

This section presents the identified management challenges in the literature that organizations face when adopting AI, answering RQ1 and visualizing the interdependencies regarding

RQ2 (cf. Table 1). It is oriented on the four STS model components and their derived categories.

A. Technology

The literature analysis resulted in 10 challenges related to the technology dimension of the STS model clustered by the categories AI security, AI infrastructure, AI characteristics, and data management.

In the context of the category **AI security**, addressing technical vulnerabilities emerged as a critical concern due to the growing deployment of AI systems in safety- and mission-critical domains. A key challenge lies in *mitigating security vulnerabilities* inherent to AI technologies, particularly those resulting from adversarial examples, data poisoning, or insufficient model robustness. These vulnerabilities present new attack vectors and expose AI systems to manipulation or malfunction, potentially leading to catastrophic outcomes in real-world applications [11], [32]. AI models, particularly those based on machine learning, are susceptible to inputs that are deliberately designed to cause misclassification while appearing benign to human observers —for example, when strategically placed stickers on a stop sign lead a vision model to interpret it as a speed limit sign [11]. This complicates the detection and mitigation of adversarial attacks. Furthermore, training data can be subtly manipulated to introduce harmful biases or reduce model performance, underscoring the urgency of robust data validation and attack-resilient learning algorithms [11].

In the category of **AI infrastructure**, *legacy integration* challenges persist as organizations attempt to embed AI within outdated or fragmented IT landscapes. Technical debt, rigid architecture, and incompatible data structures hinder seamless deployment and scalability. Consequently, AI implementation efforts are often delayed or limited in scope due to the inability of legacy systems to support dynamic and data-intensive AI functionalities [7], [9], [12], [16]. Beyond integration, infrastructure resilience has been identified as a prerequisite for the sustainable operation of AI systems [5], [7]. Ensuring resilience entails mitigating system downtimes, enabling rapid recovery, and maintaining consistent performance under stress [11], [16]. AI-specific demands, such as continuous learning and high-volume data processing, impose additional strain on traditional infrastructures [8], necessitating architectural adaptability and robust failover mechanisms [12]. Simultaneously, *ensuring infrastructure resilience* proves to be challenging, as there is a constant need to adapt to an increasingly volatile technological environment. Frequent shifts in tools, platforms, and vendor ecosystems place additional pressure on organizations to maintain flexibility without compromising reliability. A lack of strategic foresight or modularity in AI infrastructure design can result in systemic inefficiencies or incompatibilities when transitioning between rapidly evolving AI ecosystems [8], [9], [14].

The concerns within the category **characteristics of AI** stress the distinct challenges complicating its effective deployment and governance. A central issue arises from *the limited transferability of AI models*. Context-specific training and performance constraints hinder model generalization, thereby requiring resource-intensive retraining and calibration efforts when AI is applied across diverse domains or tasks [8], [10], [11], [16]. Compounding this is the difficulty of *understanding computable human cognition* within organizational settings. AI maturity is often overestimated, and the disparity between perceived and actual capabilities leads to misaligned expectations and strategic missteps in adoption efforts [7], [9], [14], [18], [19], [22]. Another key challenge lies in *handling probabilistic behavior*. AI systems frequently produce non-deterministic outcomes due to inherent stochastic modeling. This unpredictability can undermine user confidence, especially in critical applications requiring consistent and repeatable decisions [8], [11], [12]. Equally critical is the need to *address information processing bias*. Biases stemming from data selection, model assumptions, or systemic societal inequities can propagate through AI outputs, leading to skewed or unfair results that compromise ethical and operational standards [5], [8], [11], [14]. Finally, *handling the inscrutability* of advanced AI systems presents substantial governance risks. Complex architectures such as deep neural networks often lack interpretability, making it difficult to justify decisions or intervene in case of failure. This opacity impedes transparency and undermines accountability structures [8], [12], [14], [32].

Another category of **data management** addresses the management challenge of *ensuring a robust data foundation* as a critical prerequisite for the effective deployment of AI systems. Challenges arise when data is fragmented, incomplete, poorly structured, or inaccessible across organizational silos, thereby limiting model training quality and reliability. These limitations constrain the scalability and performance of AI applications and increase the risk of biased or unstable outcomes [5], [7], [8], [10], [16], [22]. Insufficient governance and weak integration between data sources further aggravate these problems. Inadequate metadata, inconsistent taxonomies, and a lack of data lifecycle management practices impede effective AI use and model interpretability. Moreover, the absence of real-time data pipelines delays responsiveness and undermines decision-making precision in dynamic environments [5], [7], [16]. As a result, building a solid data foundation not only requires a robust technical infrastructure but also strategic alignment between data stewardship, organizational objectives, and AI initiatives. Without such alignment, data management inefficiencies will propagate into model behavior, reducing trust, scalability, and business value across AI-driven systems [8], [10], [22].

B. Task

The literature analysis resulted in 4 challenges related to the task dimension of the STS model, all clustered within the category AI lifecycle management.

Within the category of **AI lifecycle management**, the *identification of valuable AI use cases* represents a persistent challenge. Strategic misalignment, lack of domain understanding, and unclear business objectives often hinder the selection of use cases with real organizational impact. Without a systematic process to prioritize AI initiatives, resources risk being diverted to projects with limited value creation [5], [7], [8], [10], [12], [14], [30]. Once use cases are identified, *the optimization of AI solution design* becomes critical. Challenges emerge when requirements are poorly captured, stakeholder needs remain unstructured, or technical feasibility is not properly assessed. This leads to mismatches between designed systems and operational realities, reducing solution effectiveness and user acceptance [5], [8], [10], [12], [19], [22]. Equally complex is the *development of AI solutions*, where iterative prototyping, model training, and validation demand high levels of coordination and technical expertise. Challenges arise from data constraints, evolving requirements, and difficulties in transferring conceptual models into deployable systems, often resulting in extended timelines and reduced reliability [10], [11], [12], [14]. The *operationalization of AI solutions* further introduces barriers related to integration, scalability, and governance. Insufficient monitoring, unclear ownership, and a lack of standardized practices for maintenance and update cycles impede sustainable AI operations, placing long-term reliability and compliance at risk [8], [10], [12], [14], [16].

C. Structure

The literature analysis resulted in 10 challenges related to the structure dimension of the STS model clustered within the categories AI strategy, AI readiness, AI risk & compliance.

Within the category of **AI strategy**, the *alignment of strategic AI initiatives across organizational levels* presents a persistent challenge. Discrepancies between top-level vision and operational execution often result in fragmented initiatives, conflicting priorities, and inefficient resource use, undermining enterprise-wide AI coherence and effectiveness [6], [7], [10], [19], [30]. Closely related is the need to *align cross-domain collaboration for AI adoption*. Functional silos and disciplinary boundaries impede the integration of technical, business, and operational expertise, thereby restricting the co-creation of viable AI solutions and slowing organizational learning [5], [7], [9], [10], [18], [30]. Compounding these challenges is the difficulty of *identifying business value from AI integration*. Without clear mechanisms to assess and translate AI capabilities into measurable outcomes, initiatives risk remaining technology-driven rather than impact-oriented, limiting stakeholder support and long-term investment [5], [7], [8], [9], [10], [14]. A further obstacle lies in *clarifying the role of AI within the broader organizational vision*. Ambiguities regarding AI's strategic purpose or future role hinder commitment and direction, leading to ad hoc experimentation rather than coordinated transformation efforts [5], [6], [8], [18], [30]. Finally, the *navigation of resource constraints* remains a cross-cutting issue. Budget limitations, talent shortages, and technical debt constrain the scope, pace, and sustainability of AI initiatives, often forcing organizations to deprioritize foundational efforts in favor of short-term experimentation [5], [7], [8], [9], [14], [16], [19].

In the category of **AI readiness**, *ensuring transparency in information processing for organizational decision-making* has emerged as a critical concern. The opacity of AI-driven analytics impedes trust and accountability, particularly when decision outcomes cannot be traced back to interpretable data logic or model behavior, thereby limiting managerial acceptance and regulatory compliance [8], [11], [12], [14]. A further barrier is the *insufficient understanding of the organizational AI status quo*. Many firms lack a clear assessment of their current AI maturity, adoption level, and capabilities, which hinders strategic planning and investment prioritization, while also impairing the identification of internal gaps and alignment needs [7], [9], [14], [18], [19], [22]. Moreover, *managing the disruption caused by AI* constitutes a central readiness challenge. The transformation of workflows, redefinition of roles, and shift in decision authority induced by AI adoption frequently trigger organizational resistance, role ambiguity, and cultural friction, thereby complicating effective change management and sustainable implementation [5], [8], [12], [14], [18], [19].

Within the category of **risk and compliance**, the *management of AI-related risks* has emerged as a core organizational concern. Especially, in high-stakes environments, the inability to anticipate or explain AI behavior under attack undermines trust and usability. Therefore, increasing emphasis is placed on developing risk-aware AI systems capable of assessing, quantifying, and managing the multifaceted security threats posed by intelligent algorithms [11], [32]. Additionally, the probabilistic nature of AI systems, combined with limited transparency and unpredictable interactions, generates uncertainties that may result in unintended consequences, undermining both operational reliability and stakeholder trust [5], [8], [11], [16]. Closely connected to risk management is the challenge of *ensuring AI compliance*. Regulatory frameworks also increasingly demand transparency, fairness, and accountability in AI systems, yet technical opacity and unclear governance structures hinder compliance with standards such as the GDPR or emerging AI-specific regulations like the European AI Act [5], [8], [11], [12].

D. People

The literature analysis resulted in 3 challenges related to the people dimension of the STS model clustered within the categories AI competence development and AI workforce transformation.

In the category of **AI competence development**, *overcoming a lack of organizational AI competence* has been identified as a fundamental barrier to successful adoption. Deficits in technical skills, strategic understanding, and interdisciplinary collaboration inhibit the effective design, implementation, and governance of AI systems, leading to misaligned initiatives and underutilized potential [8], [9], [14], [19].

Looking at the category of **workforce transformation**, *facilitating human-AI collaboration* presents a significant challenge. Unclear role definitions, insufficient interface design, and a lack of trust impede effective interaction between employees and AI systems. Without structured integration and mutual augmentation, the potential of hybrid intelligence remains largely underexploited [6], [8], [12], [19], [22]. Moreover, *overcoming cultural distance toward AI* constitutes a critical barrier to transformation. Deep-seated skepticism, fear of replacement, and resistance to change create a climate of mistrust that slows down adoption and undermines engagement. Addressing these tensions requires not only communication and training, but also a shift in organizational mindset [5], [7], [8], [9], [18], [22].

TABLE II.
CHALLENGES OF MANAGING AI ADOPTION IN ORGANIZATIONS FROM A TECHNOLOGY SYSTEM PERSPECTIVE

STS Perspective	Category	Challenges	15 contributions resulting from the literature review														
			Alsheibani et al. (2020) – [Ref. 9]	**Asatiani et al. (2021) – [Ref. 12]**	**Benbya et al. (2020) – [Ref. 14]**	**Borges et al. (2021) – [Ref. 6]**	**Dwivedi et al. (2021) – [Ref. 8]**	**Enholm et al. (2022) – [Ref. 5]**	**Hansen et al. (2024) – [Ref. 7]**	**Holmström (2022) – [Ref. 18]**	**Jan et al. (2023) – [Ref. 16]**	**Jöhnk et al. (2021) – [Ref. 22]**	**Kučevič and Brandes (2025) – [Ref. 30]**	**Lee et al. (2023) – [Ref. 19]**	**Wang and Siau (2019) – [Ref. 32]**	**Weber et al. (2023) – [Ref. 10]**	**Zhang et al. (2022) – [Ref. 11]**
TECHNOLOGY	**AI Security**	*Mitigate AI Security Vulnerabilities*													X		X
	AI Infrastructure	*Overcome Legacy Integration*	X	X					X		X						
		Ensure Infrastructure Resilience		X				X	X		X						X
		Manage rapid AI Evolution	X		X		X										
	AI Characteristics	*Manage limited AI Model Transferability*					X				X					X	X
		Understand computable Human Cognition			X	X	X	X									
		Handle Information Processing Bias			X		X	X									X
		Handle Probabilistic Behavior		X			X										X
		Handle Inscrutability		X	X		X								X	X	
	Data Management	*Ensure robust Data Foundation*					X	X	X		X	X				X	
TASK	**AI Lifecycle Management**	*Align AI Use Case Derivation*		X	X		X	X	X				X			X	
		Handle AI Solution Design		X			X	X				X		X		X	
		Handle AI Development Phase		X	X											X	X
		Handle AI Operations Phase		X	X		X				X					X	
STRUCTURE	**AI Strategy**	*Align AI Strategy across organizational Levels*				X			X				X	X		X	
		Align cross-domain collaboration for AI Adoption	X					X	X	X			X			X	
		Identify Business Value from AI Integration	X		X		X	X	X							X	
		Clarify Role of AI (Vision)				X	X	X		X			X				
		Navigate Resource Constraints	X		X		X	X	X		X			X			
	AI Readiness	*Ensure transparency in AI-driven decision-making*	X		X		X										X
		Understand organizational AI Status Quo	X		X				X	X		X		X			
		Manage Disruption caused by AI		X	X		X	X		X				X			
	AI Risk & Compliance	*Manage AI Risks*					X	X			X						X
		Manage AI Compliance		X			X	X									X
PEOPLE	**AI Competence Development**	*Overcome lacking AI Competence*	X		X		X							X			
	AI Workforce Transformation	*Facilitate Human-AI Collaboration*		X		X	X					X		X			
		Overcome Cultural Distance toward AI	X				X	X	X	X		X					

V. Discussion

This section reflects on the findings, considering the two guiding research questions. First, we revisit RQ1 and summarize the identified barriers. Second, we address RQ2 by evaluating the extent and limitations of current research through the lens of the STS framework.

While the challenges identified—such as data bias [11], legacy infrastructure limitations [10], unclear strategic anchoring [30], or persistent skill gaps [7]— on their own are well-documented in the literature, their significance shifts when examined through a structured sociotechnical (STS) lens. The findings support and extend prior research by demonstrating that these issues do not merely coexist but are systematically interlinked across organizational levels. This multi-level mapping reveals not just the breadth but the vertical distribution of management challenges in the context of AI adoption. For instance, earlier studies have pointed to a misalignment between strategic intent and operational realization [7], whereas now results show how such misalignment frequently stems from disconnects between abstract ambitions and the concrete readiness of middle and technical layers. Moreover, it also becomes visible that, for example, technical-level data issues—such as infrastructure bottlenecks or lack of clean training data—can reverberate upward, fostering cultural skepticism toward AI and weakening governance capacity [12]. Although certain challenge areas are known previously from other contexts, our observations align with the broader literature, which increasingly acknowledges the systemic nature of AI adoption challenges. For example, [18] emphasizes that organizational readiness must be understood as a socio-technical configuration, not a purely technological state. Similarly, [19] stresses the need for integrated frameworks that bridge organizational, technical, and human dimensions. Our findings offer empirical reinforcement of these positions by illustrating how misalignments are often not incidental but structurally embedded, emerging from insufficiently coordinated transformation efforts across different layers of abstraction.

The second RQ examined how literature addresses the socio-technical entanglement of AI management challenges. Our analysis shows that while many studies acknowledge interdependencies between technological, organizational, and human factors, few analyze them through a theory-informed lens. The application of the STS framework has demonstrated value not as a descriptive taxonomy but as a diagnostic tool. By revealing how challenges in one dimension—e.g., *inscrutability* (Technology)—can constrain *transparency* (Structure) and foster *mistrust* (People), the analysis substantiates the STS proposition that AI adoption is inherently a system-wide transformation rather than a technical integration exercise. The study confirms through the STS view that managing one subsystem effectively requires anticipating feedback from others. This insight also resonates with current literature from a perspective of organizational change management [33], which also posits that the four STS core components must be kept in dynamic balance for change efforts to succeed. Imbalances or unilateral interventions in one domain are likely to trigger unintended effects in others. Thus, managing AI requires more than technical readiness—it demands systemic alignment [34]. Nonetheless, the review also reveals blind spots. Some entanglements are better theorized than others. Vertical interconnections (e.g., from vision to implementation) are rarely articulated, pointing to a need for longitudinal research. Horizontally, identical challenges—such as AI governance—are framed differently depending on disciplinary or epistemic perspectives. While this study offers a structured and timely synthesis of AI adoption challenges, it has certain limitations. The final analysis draws on a relatively small set of 15 peer-reviewed papers, which—despite a broad search window (2000–2025)—mostly stem from recent years. This likely reflects the evolving discourse, shaped by the rise of generative AI and increasing accessibility. Still, the limited sample and primarily descriptive approach call for further empirical validation and broader literature inclusion. Future research should explore to what extent challenges are recognized across domains (e.g., medicine, agriculture) and functions (e.g., supply chain, finance), and how IS research can address such pluralism without fragmenting. Several implications emerge from this analysis:

Theoretical integration: To validate this work's diagnostic potential, future research should examine cross-dimensional dependencies in organizational contexts. This aligns with recent calls for theoretically grounded and empirically tested models of AI readiness and maturity (e.g., [7], [18])

Methodological pluralism: To address the complexity and context-specific nature of sociotechnical entanglements, we advocate mixed-method designs—e.g., comparative case studies combined with systems modeling. This reflects broader demands in AI research to integrate qualitative depth with quantitative generalizability (e.g., [8], [19]).

Constructive interdisciplinarity: Management challenges in AI adoption often reflect the disciplinary lens through which they are viewed. Future work should distinguish between "perspective-conditioned" and universally critical challenges. This supports calls for integrative frameworks bridging technological, organizational, and societal viewpoints (e.g., [6]).

Governance-focused modeling: Our results suggest that STS-informed maturity or capability models can help assess AI readiness systemically, beyond narrow metrics of technology or compliance. The need for such governance-oriented frameworks has also been underscored in recent work on sociotechnical envelopment [12], organizational AI capabilities [10], and risk-aware AI systems [11].

In summary, the recent literature increasingly acknowledges AI as a socio-technical transformation but stops short of treating it as such in analytical practice. Our study bridges that gap and opens a trajectory for more systematic analyses and empirical verifications.

VI. Conclusion

This study examined AI adoption challenges in organizations through the socio-technical systems (STS) lens. Addressing two core research questions, it synthesized fragmented literature and revealed interrelations across the STS dimensions of Technology, Task, Structure, and People.

To advance AI operationalization amid rising regulatory and strategic demands, this study is both timely and necessary. It shows that AI adoption is not merely technical, but a socio-organizational transformation. Key challenges do not occur in isolation—they reinforce each other. The study's novelty lies in its theory-driven, cross-dimensional mapping of entangled AI challenges. Unlike prior work treating obstacles as standalone, this paper highlights how misalignments across layers can hinder adoption. It thus extends the IS discourse beyond techno-centric models. The findings address multiple audiences: researchers gain a conceptual framework for empirical validation, practitioners a diagnostic lens for identifying coordination gaps, and policymakers criteria to expand governance beyond technical performance toward structural and cultural readiness.

Future research should empirically validate the proposed framework across sectors through case studies, develop STS-based maturity models for AI readiness, and explore governance mechanisms that account for cross-dimensional dependencies. These steps are critical for ensuring that AI is not just implemented—but implemented responsibly, strategically, and sustainably.

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