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Organizing at the Artificial Intelligence Frontier

Completed Research Paper

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Abstract

Researchers examined many aspects of AI. However, we still know little about how organizations can effectively allocate resources to AI. This is surprising because AI's non-deterministic nature makes it harder to fully predict resource dependencies. This raises a key question: how do organizations allocate resources to a technology when they do not always know what will be needed or when? We conducted a comparative, inductive multiple-case study of organizations that implemented AI in their customer service center to explore this puzzle. We utilize resource dependence theory to identify three responses to AI's increasingly unpredictable resource dependencies: "AI Business Unit," "AI Team," and the "AI Stream." Each reflects a different structural approach to managing AI's increasingly unpredictable resource dependencies. Our research offers insights into (1) how organizations understand AI's resource dependencies, (2) how they can structure themselves to manage these dependencies, and (3) how resource dependence theory applies to AI.

Keywords: Resource Dependencies, Artificial Intelligence Frontier, Organizational Design

Introduction

Many companies are integrating AI ever more deeply into their daily operations (Bank of America, 2023; Capital One, 2024). Hence, AI now supports a range of use cases, from voice-based customer authentication in customer service centers (Suparna et al., 2020) to fully automated self-service options (Chandra Das et al., 2023). Yet despite growing momentum in both academia (Zierau et al., 2023) and industry (McKinsey&Company, 2023), a clear gap remains between the promise of AI and the practical realities of managing it effectively.

Recent failures exemplify this challenge. For example, Argo AI, backed by \$2.6 billion from Ford and Volkswagen, set out to launch autonomous taxis by 2021. But as real-world testing progressed, the company encountered a steady stream of new edge cases, each requiring new and varied resource inputs. By 2022, both automakers shut down the initiative (SUNSET, 2025). A similar pattern unfolded with IBM's Watson for Oncology. While it was launched to revolutionize cancer care, hospitals soon committed substantial additional resources to oversight, data integration, and model refinement. As these hidden and continuously shifting resource dependencies accumulated, IBM sold off Watson Health in 2021 (Lohr, 2021).

The examples show that as organizations integrate AI more deeply and as its performance and scope continue to expand, they undergo a fundamental shift: resource dependencies become not only more numerous but also increasingly unpredictable. This starkly contrasts traditional, deterministic technologies (e.g., enterprise resource planning systems), where the focus was mainly on managing the number of resource dependencies. In the context of deterministic technologies, organizations navigated these dependencies by mapping who relied on whom for resources and who held power over them, then designing

hierarchical structures with centralized decision-making (Albrow, 1970; Monteiro & Adler, 2022) or multidivisional (Gupta & Govindarajan, 2000; Kownatzki et al., 2013; Martin & Eisenhardt, 2010) and organic (Brown & Eisenhardt, 1997; Davis et al., 2009; Sandhu & Kulik, 2019), with distributed power, to enable efficient resource flows. In the context of AI, however, it is no longer enough to manage a rising number of resource dependencies effectively. As seen by the abovementioned examples, organizations must also contend with the increasing unpredictability of AI's resource dependencies. However, the organizational designs that once optimized resource flows for deterministic technologies are ill-equipped to handle AI's increasingly unpredictable resource dependencies. While previous technological advances reinforced the organizational structures we are accustomed to, AI is already challenging these very structures. Yet, until now, such observations have lacked sufficient theoretical grounding. Thus, to advance both theory and practice, we must therefore ask:

How do organizations allocate resources to AI?

We conducted an inductive, theory-building case study (Eisenhardt, 1989) to answer this research question. We drew on resource dependence theory (Casciaro & Piskorski, 2005; Pfeffer & Salancik, 1978) to examine how organizations manage AI's increasingly unpredictable resource dependencies. Over a three-year period (2022-2025), we gathered qualitative data from six Swiss financial organizations. We focused on retail banks and (health) insurers, as they are typically risk-averse. Despite their caution, all case companies viewed AI as a promising tool for enhancing their customer service centers, which they regarded as cost centers. This made them open to experimenting with AI.

Theoretically, we reconceptualize organizing not as a strategy for managing predictable resource dependencies but as a strategic capability for managing increasingly unpredictable resource dependencies. Hence, we extend resource dependence theory by theorizing a fundamental shift in organizing under conditions shaped by AI.

Empirically, we identify three organizational responses that organizations adopt to manage AI's increasingly unpredictable resource dependencies: the AI Business Unit, the AI Team, and the AI Stream. These organizational approaches differ in their capacity for managing increasingly unpredictable resource dependencies, ranging from full to partial to none.

Practically, two implications emerge. First, financial industry incumbents must make a trade-off decision between how much value they want to extract from AI and how effective they can manage AI's increasingly unpredictable resource dependencies. Second, as illustrated by Company F, a comprehensive organizational response is indispensable for truly transitioning to an AI-driven customer service center.

This paper proceeds as follows: Section 2 outlines the theoretical foundations. Section 3 describes the research design employed. Section 4 presents the findings, detailing the three organizational responses to AI management and their corresponding resource constraint absorption strategies. Section 5 discusses the study's theoretical and practical contributions, limitations, and directions for future research.

Conceptual Background

The AI Frontier

The AI frontier represents the dynamic and evolving boundary of computational advancements, where AI is not a static technology but a continually shifting paradigm. Moreover, the AI frontier is characterized by two key dimensions: performance and scope. Performance refers to the progressive improvement in AI's ability to execute complex tasks across diverse domains, driven by advancements in algorithms, data availability, and computational power. Scope, on the other hand, denotes the expanding range of applications, as AI transitions from organizational processes to everyday human activities, permeating an ever-increasing number of contexts. However, as the performance and scope of what AI can achieve ever more increases AI becomes more autonomous, learns more and faster, and is more inscrutable. Consequently, organizations adopting frontier AI must treat associated resources such as, for example, data, compute, model artifacts, integration interfaces, human oversight capacity, and risk buffers as dynamic resources that adaptive allocation and adjustment. The challenge lies in managing these evolving resource dependencies so that the increasing autonomy, learning capacity, and opacity of AI do not erode organizational control.

Generative Artificial Intelligence as one of the Current AI Frontiers

Generative AI (GenAI) is one of the current frontier of AI and encompasses technologies that can autonomously generate (e.g., via prompt instructions) text, images, video, and audio outputs based on the data they were trained on (Feuerriegel et al., 2024; Martineau, 2023). In that, Generative AI is characterized by two features:

Open-endedness: GenAI offer versatile outputs—even from identical inputs. Unlike discriminative AI models (e.g., convolutional neural networks), which are good at classification or regression problems, GenAI has multiple capabilities at which they perform well (e.g., natural language generation and coding) (Feuerriegel et al., 2024). However, their versatility makes them challenging to control (Dans, 2023; OpenAI, 2024; Yagoda, 2024). Also, GenAI can hallucinate, producing inaccurate or nonsensical outputs (Ji et al., 2022). In addition, their open-endedness makes them vulnerable to exploitation. Users can manipulate GenAI to disclose confidential information or execute unintended actions. For instance, a GenAI-powered Chevrolet dealer chatbot was manipulated through prompt injection to offer an \$81,000 Tahoe for just \$1 (Dans, 2023).

Inscrutability: As GenAI models produce increasingly sophisticated outputs, understanding their internal mechanisms becomes more crucial. GenAI models are trained on billions of data points. Hence, their full range of properties and potential behaviors is difficult to predict (OpenAI, 2024; Sparks, 2024). Even with access, users often find these applications inscrutable. For example, medical professionals are hesitant to rely on GenAI for diagnostic or treatment recommendations without clear explanations of the underlying reasoning (Khullar et al., 2024). Moreover, in the legal context, the inability to scrutinize the reasoning of GenAI complicates the validation of outputs, making it difficult for legal professionals to ensure that GenAI-generated recommendations comply with legal standards and ethical considerations (Chen et al., 2024).

Organizing at the AI Frontier

A growing body of research indicates that AI introduces new layers of dependencies and unpredictability in information systems management (Berente et al., 2021). This has led information systems scholars to question how much of our existing knowledge, developed around deterministic technologies, remains valid in a world increasingly shaped by non-deterministic systems.

The field of AI management is evolving rapidly. Recent studies have examined AI innovation capabilities (Lou & Wu, 2021), performance measurement (Lebovitz et al., 2021), and strategic alignment (Li et al., 2021). A substantial body of work also explores how people interact with and are supported by AI systems (Broek et al., 2021). However, one area remains underexplored: how organizations allocate resources to manage AI. This gap is critical. Unlike traditional systems (e.g., a customer relationship management tool), where behavior was hard-coded, AI is non-deterministic. This means the system operates as a probabilistic black box, making the full range of possible input–output pairings and the likelihood of any given response unknowable in advance. Consequently, resource dependencies shift over time and are difficult to predict.

Organizing and, thus, resource allocation strategies evolved primarily in response to external uncertainty. For example, traditional bureaucracies were designed for stable environments where resource flows were predictable (Albrow, 1970). However, as markets became more volatile and organizations diversified, forms like the multidivisional (M-form) (Gupta & Govindarajan, 2000; Kownatzki et al., 2013; Lin & Germain, 2003) and organic (O-form) (Brown & Eisenhardt, 1997; Davis et al., 2009; Pisano, 1994) emerged to better manage the challenges of external turbulence and the coordination demands of increased specialization and diversified outputs (see Table 1).

However, although these organizational forms adeptly manage external uncertainty, they generally assume that internal processes are more controllable. That is, they focus on optimizing predictable, albeit manifold, dependencies and, thus, resource flows. As a consequence, increasingly unpredictable resource dependencies are not directly addressed. Rather, managers rely on established procedures and coordination mechanisms as mitigation strategies, thereby presuming that increasingly unpredictable resource dependencies are manageable once they are recognized and segmented.

Organizational Form	Understanding of Resource Flows	Main Holder of Decision Rights	Resource Allocation Logic	Core Design Assumption of the Environment	Literature
Bureaucracy (U-form)	One tall vertical pipe; resources travel up for permission, down for execution	Hierarchical superiors ("supreme chief" at the top)	Managers assign people and budgets ex ante via rules	Stable, predictable, efficiency-first	(Albrow, 1970; Monteiro & Adler, 2022)
Multidivisional (M-form)	Several parallel pipes bundled into a trunk; most resources circulate inside each business unit	Division managers; corporate Head Office keeps the tap on big capital	Head Office sets targets; business unit managers deploy their "own" functional assets	Moderate environmental uncertainty from diversification; need for fast local adaptation and capital discipline	(Gupta & Govindarajan, 2000; Joseph & Wilson, 2018; Kownatzki et al., 2013; Lin & Germain, 2003; Martin, 2011; Martin & Eisenhardt, 2010; Roth & O'Donnell, 1996; Sengul & Gimeno, 2013)
Organic (O-form)	A mesh of more flexible hoses; resources (e.g., people, knowledge) increasingly move laterally	Decision rights become more distributed. More cross-functional teams and integrators; hierarchy becomes flat	Head Office sets the targets, and each business unit allocates slices into cross-functional efforts as needed	High technological and market turbulence; innovation trumps cost efficiency	(Bingham & Eisenhardt, 2011; Brown & Eisenhardt, 1997; Davis et al., 2009; Pisano, 1994; Sandhu & Kulik, 2019; Weigelt & Miller, 2013)
Table 1. Organizational Design Evolution					

However, unlike traditional IT systems that operate on fixed rules, AI introduces greater internal unpredictability (Berente et al., 2021). As a result, the more deeply organizations integrate AI and the closer they operate to the AI frontier, the more they encounter unpredictable resource dependencies. Organizations must learn to manage these increasingly unpredictable resource dependencies. While deterministic technologies allow managers to plan and coordinate resource flows with relative predictability, such mechanisms fall short when applied to AI (Lohr, 2021; SUNSET, 2025).

Hence, a deeper understanding of this challenge is crucial for developing theoretical and practical insights to guide more effective resource allocation strategies for managing AI.

Resource Dependence Theory

Although recent research has increasingly examined AI management from various perspectives, it still overlooks how organizations respond to resource dependencies when managing these systems. AI requires continuous access to varied resources, which are often distributed across different organizational units. This creates a range of resource dependencies that organizations must manage but are ill-equipped to do so. Moreover, because of AI's non-deterministic nature, its resource dependencies cannot be perfectly anticipated. Thus, organizational units working on AI often lack knowledge of the resources they need and when they are needed.

Resource dependence theory offers a suitable perspective on how organizations respond to resource dependencies arising from their reliance on external resources that are not under their direct control but are necessary for their operational endeavor (Casciaro & Piskorski, 2005; Pfeffer & Salancik, 1978). At its core, resource dependence theory argues that no organizational unit operates in isolation: each depends on others for vital resources often outside its direct control. This dependence creates a situation that organizations seek to manage by reshaping their structure and relationships (Pfeffer, 1972; Pfeffer & Nowak, 1976; Pfeffer & Salancik, 1978; Salancik & Pfeffer, 1974).

When a unit does not control the resources it needs, it becomes dependent. Moreover, that dependence shapes power dynamics between the units. Resource dependence theory posits that the greater the dependence on another actor, the less power the dependent unit holds. Therefore, organizations pursue strategies to reduce the dependency on resources they cannot control. Also, they aim to increase the

dependency of others on resources they control (Pfeffer & Salancik, 1978). One key organizational response mechanism in resource dependence theory is resource constraint absorption. This refers to an organization or unit taking control (i.e., full or partial) over a previously constrained resource (Casciaro & Piskorski, 2005; Pfeffer, 1972; Pfeffer & Nowak, 1976; Pfeffer & Salancik, 1978). For example, a business unit may internalize a function (e.g., hiring dedicated data engineers) to avoid bottlenecks caused by external dependencies (i.e., full constraint absorption). Thus, it gains full control over a resource previously constrained by another organizational unit.

Resource dependence theory offers a useful starting point but not a complete explanation. Taken to its extreme, the theory implies that an organization's ideal state is one of complete independence, relying on no one while making others dependent on it (Casciaro & Piskorski, 2005). This would suggest that the optimal form of organizing is a single-business-unit structure at the intra-organizational level (Salancik & Pfeffer, 1974). Yet, such a structure is rarely observed in practice.

Nonetheless, the organizational structures best suited for AI, with their increasingly unpredictable resource dependencies, remain unclear and warrant further investigation.

Publication	Setting	Variables	Absorption Statuses	Full Constraint Absorption	Resource Understanding	Example
(Pfeffer & Salancik, 1978)	Inter-organizational	Interdependence	Full and Partial Constraint Absorption	Increased Interdependence	You absorbed all the necessary resources	Company Merger
(Casciaro & Piskorski, 2005)	Inter-organizational	Power and Dependence	Full and Partial Constraint Absorption	Mutual Dependence and Power Balance	You absorbed all the necessary resources	Company Merger
Table 2. Resource Dependence Theory						

Research Design

Case Study

Given the limited existing theory and evidence related to our research question, we adopted an inductive theory-building multiple-case study approach (Eisenhardt, 1989). This approach is particularly suitable when variance exists in the data, as in my study. Furthermore, multiple cases are often more effective than single cases for theory development, as replication across cases enhances the accuracy, parsimony, and possible future generalizability of the resulting theory (Eisenhardt, 1989; Sigelkow, 2007).

Our embedded design focuses on individuals who manage AI solutions within their respective organizations (i.e., retail bank, health insurance, and insurance) as the unit of analysis. By maintaining this narrow focus, we aim to enhance the richness and precision of the theory development process (Yin, 2017). Additionally, this focused approach increases the potential for the developed theory to be tested in future research.

Our study focuses on the financial sector, which is characterized by a strong aversion to risk and uncertainty, particularly in Switzerland. Nevertheless, all the organizations in our sample recognize the potential of AI, and GenAI in particular, for their customer service centers. Additionally, these companies view their customer service centers as cost centers, making them eager to test new technologies (e.g., AI) that can help reduce operational expenses.

Following the principles of theoretical sampling, we examine retail banks and (health) insurance companies where the need for AI management is needed, and thus, organizational design adaptations are most likely to arise. Specifically, we selected organizations that were actively transforming their customer service centers into more AI-driven entities at the time of our study. Additionally, we selected organizations with robust revenue streams, as those lacking sufficient financial resources will likely struggle to transform their customer service centers into AI-driven ones. Thus, we reduce unnecessary noise within the data. We also included organizations that had only recently begun their AI-driven customer service center transformation to capture diverse organizational responses. This approach increases the likelihood of identifying varied AI management approaches and, thus, organizational responses, ultimately strengthening the completeness and future generalizability of the resulting theory.

Our sample consists of six organizations: three of Switzerland's largest retail banks and three of the most prominent (health) insurers. Common patterns emerged, particularly among organizations with ineffective organizational responses and, thus, ineffective AI management practices, suggesting that this sample size approaches theoretical saturation (Eisenhardt, 1989; Yin, 2017). The sample size is a key strength of our study, as observing multiple organizations and conducting multiple waves of interviews with frontline employees, middle managers, and senior executives is rare, even within a single organization. Moreover, collecting data from six organizations enhances the richness and variation of insights compared to a single-case study.

The selected organizations are representative of Swiss and, more broadly, Central European retail banks, health insurers, and insurers. Each retail bank and insurer primarily serves the Swiss market, with only one insurer (Company D) operating on a broader European scale. All organizations had prior experience with AI (e.g., AI for fraud detection). However, their previous AI solutions were isolated and often served a very narrow use case. At the outset of the study, all organizations expressed a positive outlook on their transition to an AI-driven customer service center and their ability to manage their AI solutions effectively.

Data Collection Process

We conducted 54 semi-structured interviews with 45 representatives from my six case companies. We primarily relied on interviews as a data source because they offered the possibility of capturing employees' lived experiences at our six case companies. Our choice of interviews as the primary method aligns with Walsham's (1995) argument that interviews provide the best access to understanding participants' experiences of lived events. The interviews lasted approximately 60 minutes each. Additionally, all interviews, conducted via Microsoft Teams, were recorded and transcribed (using OpenAI's Whisper). Moreover, we used Atlas.ti as a software tool to code the interviews. In total, we generated a set 12 cleaned-up codes. All people interviewed directly or indirectly participated in their company's AI management. Following established standards of qualitative research, we carried out interviews until we reached the point of saturation, at which point the themes began to recur (Hennink et al., 2017). Thus, we carried out 54 interviews between March 2023 and March 2025.

Data Analysis Process

We began by analyzing real-world data to identify a phenomenon relevant to both practitioners and academics. Thus, rather than solely searching for gaps in the literature, we focused on practical problems and used them to challenge existing ways of thinking within the literature. After finding a topic of interest (i.e., AI's increasingly unpredictable resource dependencies), we sought a useful theory to guide our analysis (i.e., resource dependence theory). After that, we began the "within-case analysis" and sought to understand the power and dependent composition of our case companies, respectively. This was done inductively.

Next, we attempted to understand how the identified power and dependence mechanisms lead to organizational responses that facilitate the absorption of resource constraints. Again, we utilized an inductive approach for this analysis step.

In the subsequent phase, termed "cross-case analysis," we outlined causal templates across the case companies, illustrating the outcomes of different organizational responses and resulting in diverse resource-constraint-absorbing capacities. Because these AI projects shared very similar contextual features (e.g., customer service center focus), we focused our analysis on identifying variance across the organizational responses. Our approach builds on the in-depth knowledge of the individual case companies.

Within-case-analysis

Codes serve as symbolic representations of descriptive or inferential data collected during a study (Miles et al., 2018). These codes facilitate retrieving, categorizing, and triangulating data from interview transcripts by grouping elements associated with specific constructs or themes.

Starting with the within-case analysis, we employed a multi-stage coding scheme inspired by Gioia et al. (2013). This approach enabled us to discern a data structure for all six case companies, illustrating the relationships between first-order concepts, second-order themes, and aggregate dimensions. We began coding the data collected for the six cases, focusing on first-order concepts, specifically power and

dependence indicators. We prioritized maintaining the participants' language and expressions to capture their true intent. If there were ambiguities in the data, we contacted the interviewees through email or phone to seek clarity.

This approach enabled us to draw connections between 1st order concepts, elevating them to the status of second-order themes (i.e., organizational responses). Ultimately, we merged the second-order themes into three aggregate dimensions, namely constraint absorption capacities. Thus, we created our final data structure for our within-case analysis.

Cross-case-analysis

We started with the cross-case analysis to continue our analysis process and identify recurring patterns across the case companies. Accordingly, we systematically compared, contrasted, and triangulated the data across the case companies. The first-order concepts encompass power and dependency mechanisms across our case companies. The second-order themes represent organizational responses within these companies. Furthermore, the third-order aggregate dimensions represent the various capacities for absorbing resource constraints. Moreover, our data structure comprises six first-order concepts, three second-order themes, and three aggregate dimensions.

During our analysis process, we utilized several measures to ensure the rigor of our research process and the trustworthiness of our interpretations. First, we frequently consulted our case companies and sought their feedback to evaluate whether our interpretations were accurate. Based on this feedback, we adjusted and refined our codes to ensure clarity, reliability, and relevance. Lastly, we incorporated quotes from the interviewees to vividly convey their experiences and perspectives.

Results

We identify three interrelated areas that shape how organizations manage AI's increasingly unpredictable resource dependencies: power and dependence as organizational conditions, organizational responses as structural choices, and constraint absorption as an outcome of these arrangements. Drawing on six company cases, we observed differences in how power is distributed, how dependencies are managed, and how structures are designed to lead to distinct patterns in how effectively organizations can manage AI's increasingly unpredictable resource dependencies (i.e., full, partial, or none).

Power and Dependence as Organizational Conditions

Power refers to how a business unit can shape outcomes by controlling access to resources. In AI management, power determines, for example, who can access resources across organizational boundaries. Across the cases in this study, three overarching forms of power emerged: unbalanced power, concentrated power, and balanced power (see Figure 1).

Unbalanced Power: When individual subunits lack formal authority or the requisite endorsement by higher echelons, they operate in environments where influence is largely derived from informal, ad hoc mechanisms. In these settings, agents resort to reactive adaptations. Also, progress is contingent upon intermittent negotiations rather than being driven by codified mandates. This condition exposes the system to fragility as initiatives evolve in response to emergent pressures rather than premeditated design.

Concentrated Power: Here, a single locus of control—or a dominant coordinating entity—holds the decisive influence over system functions. The concentration of power permits rapid, coherent action and alignment across various system components. However, such centralization may lead to an overreliance on a singular node, risking overload and potentially constraining the adaptive capacity of the system as a whole.

Balanced Power: A more idealized theoretical arrangement is one in which control is shared across multiple organizational levels and units. In this configuration, strategic visioning and operational execution are co-owned, thereby creating redundancy and resilience. This balanced power structure mitigates the risks associated with both dispersion and concentration and can better accommodate complex and evolving demands.

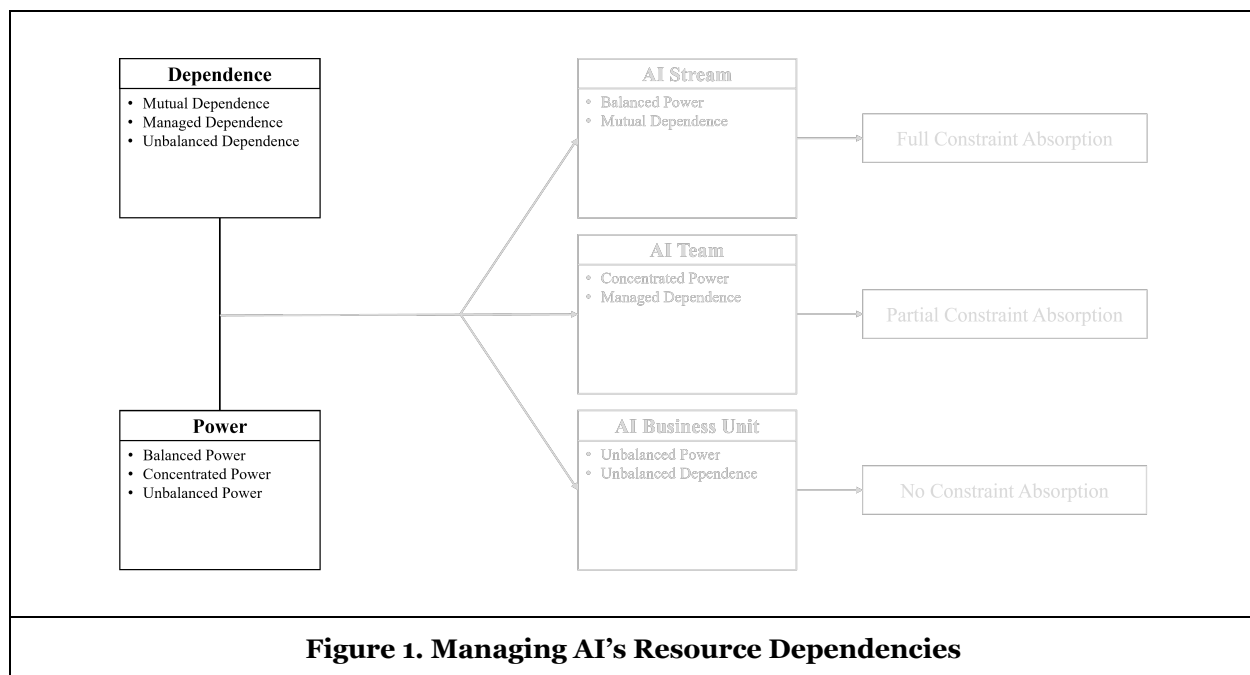
While power shapes control, dependence reflects vulnerability. Dependence refers to the extent to which a unit requires access to resources held by others in order to fulfill its duty. We observed three distinct

patterns of dependence: unbalanced dependence, managed dependence, and mutual dependence (see Figure 1).

Unbalanced Dependence: In this form, one unit's functioning relies disproportionately on external resources without having any substantive power to shape those resource dependencies. The imbalance leads to persistent coordination challenges and exposes the system to bottlenecks.

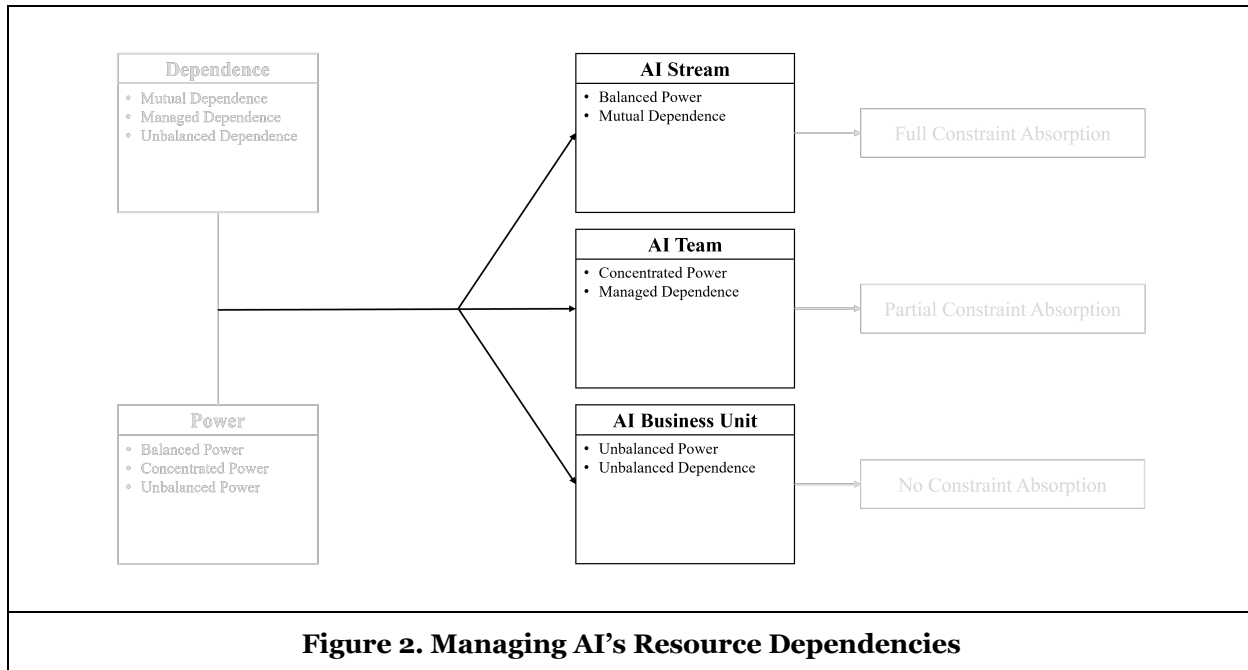
Managed Dependence: Here, dependencies are explicitly acknowledged and institutionally regulated. Through formal mechanisms, such as designated roles, integrated protocols, or structured workflows, the resource dependencies are coordinated systematically. This managed approach lends a degree of formality and predictability to interactions, supporting stability within the system.

Mutual Dependence: At the other end of the spectrum, mutual dependence arises when multiple subunits are interlocked by their reciprocal resource dependencies. In such configurations, no single subunit can independently drive outcomes; instead, success is contingent upon a tightly woven fabric of collaboration. This high level of integration enhances overall connectivity, encouraging the system to evolve and adapt collectively.



Organizational Responses as Structural Choices

Organizational responses describe how companies structure themselves to manage access to critical resources needed for AI. As AI initiatives cut across traditional boundaries, no single unit can operate in isolation. Instead, AI management depends on how organizations respond to internal resource dependencies. Some responses concentrate AI capabilities in a business unit, others centralize them in a team, while a few embed AI efforts across functions. These structural choices shape who holds power, who depends on whom, and how effectively an organization can manage AI's increasingly unpredictable resource dependencies.



AI Business Unit

The “AI Business Unit” response describes a structure where a dedicated business unit assumes primary responsibility for managing AI but operates with both unbalanced power and unbalanced dependence. Companies A, B, and C exemplify this pattern. While these units often possess deep technical expertise and a clear vision for AI in the organization, they lack the power needed to drive AI management effectively across the organization. Their success depends on navigating a fragmented internal landscape, securing buy-in from skeptical executives, and negotiating access to data and collaboration with other departments. This model leads to a reactive, case-by-case approach to AI management.

Unbalanced Power: C-level executives show some interest in AI, but their support is limited to quick, tangible results. Instead of planning and allocating resources strategically, they require immediate proof of value. This forces the AI business unit to react to short-term pressures and repeatedly justify its need for additional resources. For example, one interviewee noted: “[...] they [The C-level executives] were somewhat sceptical [towards Conversational AI technology]. I have found a good way by showing working prototypes. [...] I try to anchor this with examples that add value. [...] That is the only thing that works.”

Although the AI business unit possesses the technical expertise, it lacks the consistent executive support necessary to secure ongoing resources. Instead of benefiting from planned, long-term support, the business unit must continually prove its case, resulting in a reactive approach that undermines its ability to plan and invest effectively in AI.

In addition, the business unit often struggles to access essential resources like data and technical support because other departments control these resources. These departments, which view AI as secondary to their core responsibilities, do not prioritize sharing resources. One interviewee explained: “The greater challenge lies in guiding the business units that are not functioning optimally today [...] We already possess substantial technical and specialized knowledge today but must collaborate more closely.”

This dependence on other business units exacerbates the resource allocation problem. Limited inter-unit dialogue, often intentionally kept to avoid conflicts—means that opportunities for sharing resources are missed. As one participant summarized, “Yes, it is about organizational [...] aspects. [...] That is actually the crux of the matter with all these things [AI projects] right now.”

Unbalanced Dependence: A key challenge in managing AI resources is the heavy reliance on other departments for inputs like data and cross-functional support. Even with strong technical expertise, the AI

business unit often finds its progress slowed by its dependence on other units that control essential resources. This structural misalignment creates bottlenecks that directly impact resource allocation.

For example, one interviewee compared managing a simple chatbot with the demands of Conversational AI, noting: *"With a simple chatbot, you can achieve results relatively quickly, but when introducing Conversational AI, there are many dependencies, at least for us at [Company B]. One should be aware of these dependencies to avoid showstoppers."*

Unlike isolated automation tools, AI solutions need continuous high-quality data from multiple departments. When these resources are guarded by business units with different priorities, delays and friction are inevitable. The lack of proactive top-management intervention to streamline these dependencies further exacerbates the issue. As one participant remarked, *"I wish it had been anchored at a higher level from the beginning, so we would have achieved better penetration within the company [...]."*

Without formal authority to reallocate resources, the AI business unit is forced to act as its own advocate. Employees often find themselves stuck in endless loops of referrals and bureaucratic hurdles: *"They tell you that you absolutely need to talk to person XY. You go to this person, and then you get sent back. You are being sent back and forth [...] it is complicated."* This continuous cycle of unmanaged dependencies hampers effective resource allocation, slowing AI projects and limiting their potential impact.

AI Team

The "AI Team" response, observed in Companies D and E, reflects an approach where AI management is driven by a specialized team that operates with concentrated power and managed dependence. This team functions as an organizational hub, strategically positioned between business and IT, and benefits from strong executive sponsorship. With concentrated authority and direct access to decision-makers, the AI team has the power to shape the company's AI trajectory. However, managing dependencies across departments remains challenging, particularly given the need for process integration, data access, and cross-functional collaboration.

Concentrated Power: Multiple interviewees noted that strong C-level support is essential for the AI team to secure necessary resources. Without proactive engagement from top management, the AI team risks becoming sidelined, which undermines its ability to secure resources. One interviewee explained: *"We ensured management support through effective stakeholder management. We always kept them informed and did internal marketing for our progress and figures. [...] If the management had not believed in the technology, the project would have failed much earlier."*

This example shows that resource allocation hinges on executive belief in the technology. The AI team must not only manage technical tasks but also serve as a bridge between business and IT, actively negotiating for the resources it needs. Often, this means adapting to different working styles across business units instead of following a single, coherent strategy.

Moreover, the AI team has to overcome internal resistance by demonstrating clear benefits. As one interviewee described: *"It actually triggered more of a small wave of innovation within the company. So, business units really come to us [the AI team] [...]. With use cases that they somehow want to implement."*

This bottom-up demand enables the team to secure resources based on proven value, rather than relying solely on top-down directives. Overall, the AI team's success in resource allocation depends on effective internal communication, ongoing stakeholder engagement, and the ability to adapt to varying organizational demands.

Managed Dependence: While the AI team brings together key business and IT expertise, it still relies on other business units to secure the resources needed for AI management. AI management requires cross-functional collaboration, data sharing, and adjustments in processes across teams that operate at different speeds and with varying working styles. This mismatch often leads to delays and resource allocation challenges. One interviewee explained: *"One of the biggest challenges is that all these teams [AI team and business unit teams] work together. [...] Especially this collaboration is sometimes challenging because people operate at different paces. Frictions arise occasionally when it comes to reaching an agreement."*

Without a clear, structured approach to managing these dependencies, AI management can stall. To improve resource allocation, the AI team is sometimes embedded within a specific business unit. This

arrangement helps create ongoing knowledge exchange, ensuring that AI solutions are managed with real, domain-specific insights: *"[...] Imagine we [AI team] are working on a project in the claims department. We would need the employees from the claims department because they have the process knowledge [...]."*

This approach underlines that technological expertise alone is not enough. Effective AI management depends on integrating domain experts who understand the intricacies of business processes. Embedding the AI team also shifts the perception of AI projects from top-down directives to joint initiatives, fostering closer, day-to-day collaboration. One participant described how a realignment improved resource sharing: *"For example, my team was moved to another department so that we are closer to telephony. Such steps help."*

Unlike traditional IT projects, AI systems require continuous refinement, retraining, and adaptation. As a result, the AI team must constantly manage these dependencies to ensure that the necessary resources are allocated promptly and effectively.

AI Stream

The "AI Stream" response, exemplified by Company F, is the most integrated organizational response, characterized by balanced power and mutual dependence. Here, AI is not the responsibility of a single team or department but is embedded into a value stream. Power is distributed across hierarchical levels, enabling both executive leadership and frontline employees to participate in shaping AI management. This collaborative model institutionalizes cross-functional coordination and shared ownership, reducing resistance and enhancing responsiveness.

Balanced Power: Company F's success in managing AI relies on a balanced power structure that supports resource allocation, even in unpredictable scenarios. Rather than centralizing decisions at the top or leaving them entirely to the front, the company spreads decision-making across all levels. This structure means that executives, middle managers, and frontline employees all have a role in allocating resources.

At the executive level, strong leadership creates momentum and a willingness to take early risks: *"He [CIO] was very, or is very, interested in it [AI], and our new CEO is already a big fan of it. Yes, and then there are individual protagonists at the other management levels who like to push it forward."*

This top-level support is crucial for securing the resources needed for AI management. However, balanced power is not just about leadership enthusiasm. It also means giving middle managers and frontline staff the authority to decide resource allocation. One department head noted: *"We are in a good position because we recognized this [the potential of Conversational AI] and the executive board gives me [Department Head] the freedom to roll it out step by step. [...] I have an opportunity to help shape the content of the topic."*

By empowering different layers of the organization, Company F avoids over-centralization risks, ensuring that resources are allocated flexibly to match the real, evolving dependencies of AI. Involving frontline employees, who interact with AI daily, further refines this process. Their input, even in the form of veto power during AI Stream meetings, helps adjust resource allocation in real time. As one customer service center informant explained: *"And it is being listened to [Our opinion] very well. This is the story about the veto [...]. We took it very seriously. And overall, front-line employees (i.e., those in the customer service center) are represented there [AI Stream Meetings] again."*

By distributing power and decision-making, Company F creates an environment where resource allocation is continuous, flexible, and closely aligned with strategic goals and day-to-day operational needs.

Mutual Dependence: Company F handles resource allocation for digital transformation by making everyone responsible for change, rather than leaving it to just one department. This approach creates mutual dependence where every employee must collaborate to move the transformation forward. One interviewee said: *"Before, it was the IT and us. And now we have intermediaries, Business Analysts, and that is working much better now."*

This restructuring means that technical and business teams are responsible for AI management. Instead of relying on traditional handovers and isolated roles, Company F created translator positions that ensure continuous interaction and clear communication between teams. This helps prevent misalignment between AI goals and business needs.

Moreover, the company encourages collaboration across different business units. One interviewee explained: *"I think it is more interdisciplinary. We already have core topics in our company where departments collaborate across boundaries and support each other. It is very closely knit."*

The organization ensures that AI systems are managed with the necessary business insights by aligning various stakeholders. Over time, the relationship between business and IT has grown stronger, with one informant noting: *"The IT is collaborating even more closely with our employees merging."*

Rather than maintaining separate structures for IT and business, Company F uses an AI Stream model where both groups co-manage AI. This integrated approach speeds up resource allocation and reduces bottlenecks. Also, Company F's value stream approach is a deliberate choice to manage the increasing unpredictability of AI's resource dependencies. As one interviewee remarked: *"Our typical approach is very pragmatic; we do a lot in operations without a large project structure because it is important to be quick and pragmatic [...]"* This flexibility ensures that AI solutions are continuously refined, adjusted, and improved in real time, allowing the organization to allocate resources as needed.

Constraint Absorption as an Outcome

Constraint absorption refers to an organization's ability to manage resource access effectively. As AI management unfolds, organizational units often encounter obstacles. Some organizational responses absorb these constraints by redesigning internal structures, building missing capabilities, or repositioning teams to gain greater control over the necessary resources. Others remain exposed, relying on ad hoc collaboration or informal influence to make progress. The degree of constraint absorption determines whether AI's increasingly unpredictable resource dependencies can be managed effectively (see Figure 3).

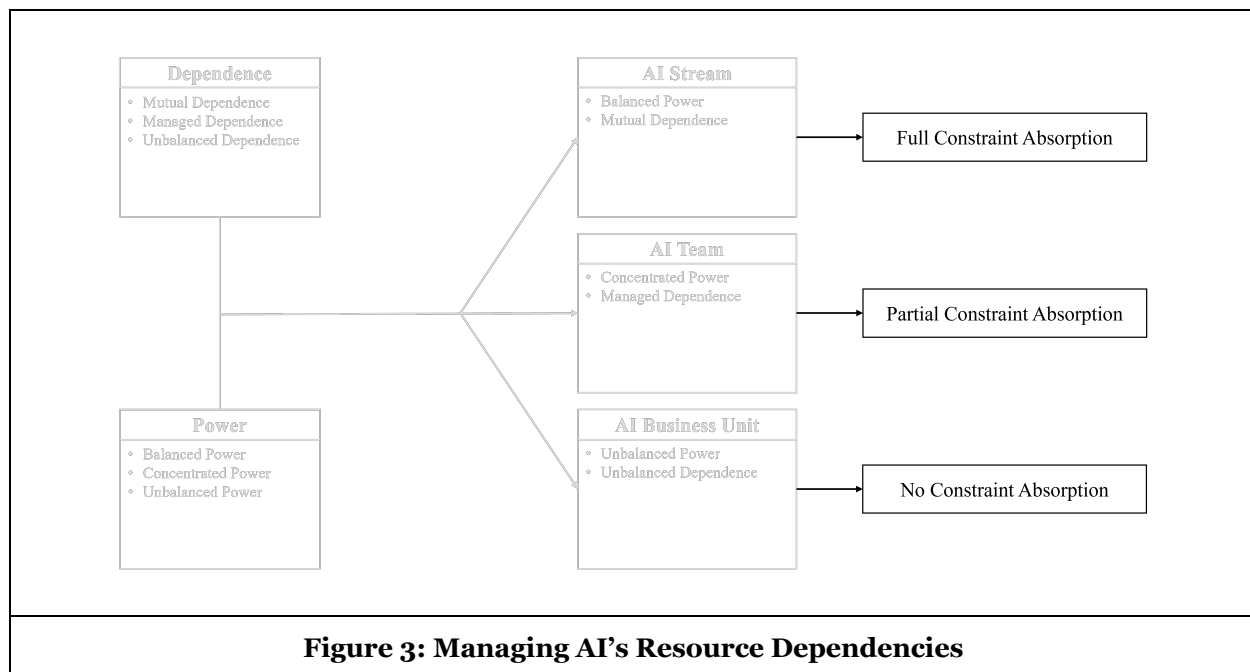


Figure 3: Managing AI's Resource Dependencies

No Constraint Absorption

Companies that follow an "AI Business Unit" model concentrate AI management in one business unit, such as a customer service center. However, this approach often leaves them unable to fully absorb the resource constraints of managing AI. The unit lacks the power needed to build, for example, essential cross-departmental data pipelines. As a result, they can only use resources that are in their immediate control, forcing them to deploy overly generic AI solutions, like basic FAQ chatbots.

Also, this resource shortfall can lead to problems. For instance, one AI solution in Company D once responded to the statement "I have cancer" with "Congratulations." When errors occur, there is no one to step in and reallocate resources to fix the issues. As one interviewee noted: *"[...] no one is advocating for it."*

Otherwise, someone would usually come and say, 'Hey, we need to do something [...] no one is pushing for it.'

Moreover, C-level executives grow increasingly frustrated, with one remarking: *"[...] our [Conversational AI] chatbot, which is a complete disaster [...] I have already wanted to shut it down three times."* Ultimately, Company D was forced to permanently shut down its AI solution because it could not secure the resources needed for improvement.

Partial Constraint Absorption

Companies using the "AI Team" approach manage to internalize some resource constraints, but not all. This approach attempts to balance managed dependence with concentrated power. The AI Team absorbs some resource, typically those within its control, yet many resource challenges remain unaddressed because the broader organization is not fully equipped to handle them.

Also, without immediate organizational pressure, stakeholder resistance can stall progress. As a result, the team focuses only on specific, critical issues rather than tackling all resource challenges. They are burdened with coordinating across silos and handling additional leadership responsibilities, which diverts their energy from exploring new AI use cases. Each new deployment further drains the team's capacity, as they spend more time maintaining existing systems than on innovation.

One stakeholder put it succinctly: *"We have positioned [Name of the Conversational AI solution] as a self-service bot. As long as our colleagues are not ready, we will not take this step [toward deeper integration]. It would only add complexity."*

Thus, while the AI Team can absorb some resource constraints, its capacity is limited. The team becomes like a sponge, trying to manage every new resource dependencies. However, eventually, it becomes saturated. As a result, this model leads to only partial constraint absorption.

Full Constraint Absorption

In the "AI Stream" approach, effective resource allocation comes from close, cross-functional collaboration. At Company F, aligning business and IT, and establishing clear data pipelines, has enabled them to integrate and continuously improve AI. One interviewee explained: *"However, with the Conversational AI, improvements can still be made to the same functionality even a year later [...]. The model must continue to be improved [...] otherwise, one might think that it can simply be left as is. [...] one must be aware that it is an iterative, continuous process. I think [Company F] is on the right track [...]."*

This hands-on, ongoing collaboration ensures that necessary resources, such as data, technical support, and domain expertise, are consistently reallocated to meet AI's increasingly unpredictable resource dependencies. By fostering close business-to-business and business-to-IT relationships, Company F created a setup where resource constraints are fully absorbed even when deeply integrated into core business processes. As the COO noted: *"We believe that we are quite advanced among banks in the Swiss market because what we are able to do is fully automate approximately 80% of all customer inquiries."*

Discussion

This paper provides new insights into how organizational structures affect the management of AI's increasingly unpredictable resource dependencies. We identified three organizational structures, which we coined AI Business Unit, AI Team, and AI Stream, each with varying capacities for managing the increasingly unpredictable resource dependencies of AI (i.e., full, partial, or none). Moreover, our findings highlight that even when specific business units aspire to become AI-driven, their ability to manage the increasingly unpredictable resource dependencies of AI is contingent on effectively managing dependencies through power. Business units must rely solely on their immediate resources if these dependencies are not properly managed. In the context of our study, we demonstrate that achieving full resource constraint absorption requires balanced power and mutual dependence (i.e., AI Stream).

Theoretical and Practical Contributions

Building upon our conceptualization, we outline the implications of our research for two key areas (i.e., AI management and resource dependence theory) that are of interest to scholars in information systems management, organization science, and management science. First, we add to the emerging literature stream on AI management (Berente et al., 2021; Broek et al., 2021; Lebovitz et al., 2021; Vial et al., 2023) by situating my study within a currently underexplored context, namely the customer service centre of retail banks and (health) insurers.

While previous research in the scope of AI management focused on the creation of AI innovation capabilities (Lou and Wu 2021), AI performance assessment (Lebovitz et al., 2021), and AI's strategic orientation (Li et al. 2021), our study highlights how organizations respond to AI's increasingly unpredictable resource dependencies. Moreover, our findings underscore that AI management differs fundamentally from traditional IT management. Unlike conventional IT systems, which operate on rule-based mechanisms with predictable resource dependencies, AI's resource dependencies are harder to predict and thus manage.

Empirically, we contribute by identifying three organizational responses (i.e., AI Business Unit Capabilities, AI Team, and AI Stream) to address resource constraints (i.e., full, partial, or none).

Theoretically, we contribute to resource dependence theory. Previous research utilizing resource dependence theory has focused on inter-organizational constraint absorption, where organizations manage resource constraints through, for example, mergers and joint ventures (Casciaro & Piskorski, 2005; Pfeffer, 1972; Pfeffer & Nowak, 1976; Pfeffer & Salancik, 1978). Our findings showcase that similar dynamics are present within organizations and organizational units. Specifically, we showcase that mutual dependence and power balance are key drivers of full constraint absorption at the intra-organizational level. In contrast, constraint absorption is not possible when power imbalances exist, such as in the AI Business Unit organizational response. This insight aligns with Casciaro and Piskorski's (2005) assertion that power asymmetry hinders constraint absorption, and it extends their thinking to the internal power dynamics of organizations (see Table 3).

Publication	Setting	Variables	Absorption Statuses	Full Constraint Absorption	Resource Understanding	Example
(Pfeffer & Salancik, 1978)	Inter-organizational	Interdependence	Full and Partial Constraint Absorption	Increased Independence	You absorbed all the necessary resources	Company Merger
(Casciaro & Piskorski, 2005)	Inter-organizational	Power and Dependence	Full and Partial Constraint Absorption	Mutual Dependence and Power Balance	You absorbed all the necessary resources	Company Merger
This Paper	Intra-organizational and non-deterministic system	Power and Dependence	Full and Partial Constraint Absorption	Mutual Dependence and Power Balance	You created resource access optionality	AI Stream

Table 3. Theoretical Contribution to Resource Dependence Theory

Specifically, in the context of AI, full constraint absorption at the intra-organizational level was achieved through an AI Stream. Thus, our study showcases that organizational adaptations to manage resource constraints effectively does not necessarily follow the traditional merger-based absorption model proposed by resource dependence theory. Instead of merging business units to absorb AI-related resource constraints, company F created an AI Stream. This overlaying structure was then used to increase dependencies (i.e., mutual dependence) and manage these dependencies effectively (i.e., balanced power).

Additionally, when applied to the context of managing AI's increasingly unpredictable resource dependencies, the concept of resource constraint absorption takes on a different meaning. At the inter-organizational level, resources are seen in binary terms: either you have them, or you do not. Within the context of managing AI's increasingly unpredictable resource dependencies, however, the focus shifts towards resource optionality: the ability to reallocate resources effectively in the face of increasingly unpredictability.

Two practical implications arise. First, Organizations need to align their organizational structure with how close they are to the AI frontier. An AI Business Unit may be sufficient for narrow use cases but often encounters bottlenecks. An AI Team provides better coordination across functions but can become overloaded as demands grow. Only the AI Stream achieves full absorption of resource constraints by balancing power and embedding mutual dependence. Managers can look for recurring signs such as persistent delays in data access or reliance on ad hoc negotiations as signals that redesign is needed.

Second, to remain at the AI frontier without losing control, organizations must move from execution to orchestration. The case evidence shows that an AI Stream emerges through structural choices such as shared decision rights, translator roles that connect business and IT, and stable data pipelines that enable continuous improvement. These changes require significant time and resources, so leaders should evaluate carefully whether the expected benefits outweigh the disruption that a full redesign entails.

Limitations and Outlook

Our study comes with certain limitations. However, these limitations also offer ample opportunities for future research. First, we primarily focused on two sectors (i.e., retail banking and (health) insurance) and confined my scope geographically to Switzerland. Second, our dataset is limited to a specific context (i.e., customer service centre) and time frame (i.e., 2022–2025).

Future research should investigate whether and how organizations successfully transition between the abovementioned organizational responses to identify the triggering and hindering events that facilitate such transitions (i.e., a process theory approach). Research should also investigate the applicability of these findings to other contexts. Moreover, research should aim to understand the factors that contribute to the fact that full constraint absorption unfolds differently on the intra-organizational level.

Conclusion

This study examined how organizations allocate resources to AI. Based on the insights of six Swiss financial organizations, we identified three organizational responses: AI Business Unit, AI Team, and AI Stream. Moreover, each organizational response has varying capacities to manage AI's increasingly unpredictable resource dependencies (i.e., full, partial, none). Only the AI Stream achieved full constraint absorption by fostering mutual dependence and balanced power. The findings showcase that known organizational structures designed for non-deterministic systems are struggling to accommodate AI effectively. This study shifts the focus in AI management towards organizational structures, contributing to resource dependence theory at the intra-organizational level. For practice, it highlights the need to align organizational structures with AI to allow effective resource allocation practices.

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