From 1-to-1 to Many-to-Many: Bringing a Complex Systems Perspective to Organizational AI Adoption

Nathan Lloyd and Maria J. P. Peixoto and Peter R. Lewis
Ontario Tech University, Canada

Introduction

Artificial intelligence (AI) is pervasive (Benbya and Melville, 2025), integrating into various aspects of life, in workflows across many different industries, embedded in our infrastructure and cities, and increasingly shaping how we work, relax, communicate, and make decisions. Globally, around two-thirds of people believe that AI-powered products and services will significantly affect daily life within the next three to five years (Maslej et al., 2025, p.398). Moreover, evidence suggests that, in the United States, generative AI has been adopted more rapidly than the personal computer or the internet relative to the timing of each technology's initial mass-market product launch (Bick et al., 2024). McKinsey forecasted $2.6 trillion to $4.4 trillion of annual economic benefit from 2023 (Chui et al., 2023), and productivity gains for generative AI have been reported (Brynjolfsson et al., 2025). Accepting the reports and trajectory of AI adoption without skepticism, of which there is plenty (Frey, 2025), we face a pressing societal transition challenge: *Modern organizations are under growing pressure to adopt and leverage "AI"*. But what does it mean for an "organization" to adopt "AI"? In this work, we move beyond the monolithic framing of "AI" and "organizations", and argue that the study and design of AI adoption by organizations would benefit from a complex systems perspective.

From 1-to-1 to Many-to-Many

Unpacking this societal transition reveals that an organization's capacity to adopt and leverage AI is shaped by prevailing understandings of "AI" instances (technological AI) as well as understandings of AI in conversation and literature across public and scientific spheres (conceptual AI). Indeed, both "AI" and "organizations" function as umbrella concepts encompassing a wide range of meanings and interpretations, they are themselves complex systems. Indeed, "AI" serves as a monolithic device which obscures a technology's true capabilities (Lewis et al., 2021; Narayanan and Kapoor, 2024). This is particularly true as "intelligence" manifests in many ways, and the pursuit of it, including the tools, practices, and models we use, can be described as pluralistic rather than unified (Scott and Orlikowski, 2025). An organization, understood here as a *formal* organization, can be defined very broadly as a form of *social organisation that has been purposefully created to attain certain goals* (Doreian, 1970, p.89). From such a broad definition we can know very little about an organization's internal structure or how it interacts with its environment and other organizations. Thus, when using monolithic formulations such as "The government wants AI to fight wars and review your taxes" (MacMillan et al., 2025), the terms *government* and *AI* are tasked with carrying substantial conceptual weight; we require a shift in language from monolithic to pluralistic. In doing so, we may leverage a complex systems perspective.

A Complex Systems Perspective

A complex adaptive systems (CAS) is a *non-linear system that restructures systematically according to the environment* (Nguyen and Vostinar, 2024). A CAS exhibits the following six traits (Preiser et al., 2018): Relationality, Adaptability, Non-linearity, Openness, Environmental Dependency, Novel Emergence.

Artificial Intelligence

We argue that the concept of "AI", itself, is a CAS. It's meaning and perception is non-linear and adaptive, shifting across time: from ancient myths such as Talos of Crete, to literary figures like Robota, to the formal development of logic and expert systems, and onward to machine learning and today's generative AI. The introduction of LLMs represents a watershed moment in how the public interacts with and perceive "AI" (Powers et al., 2024). Across cycles of "winters" and "summers," repeated hype and disillusionment, its trajectory remains dynamic. From this, we may consider the environment of "AI" as the socio-cultural, political, and technological substrate upon which AI develops and operates. And the direction of travel or 'novel emergence' of the concept can neither be understood or predicted from its constituent parts alone. What "AI" signifies at one moment may differ entirely the next, and is at the mercy of global interest and concern; restructuring according to the environment.

A clear illustration of this complexity lies in the relational and environmental dependencies that have given rise to distinct power imbalances limiting openness. Global digital giants like Google, Apple, Meta, Microsoft, and Amazon (GAMMA), have amassed vast economic and societal influence, forming data-opolies that dominate the tech industry (Mirrlees, 2021). Indeed, advantages conferred in the platform economy have propelled some firms to the forefront of the generative AI race (Tyagi, 2025), with many exerting influence across multiple layers of the AI technology stack (Hagiu and Wright, 2025), which in turn has enabled these organizations to shape the conversation around AI. Those benefiting from the AI boom are the ones selling the shovels during the gold rush (Merchant, 2025). This consolidated power, is said to be a result of weak governance, regulation, and taxation, leading to the relationship of *techno-feudalism* between end-user and organization (Pitt, 2020), one supported by an iron triangle of mutual support between BigTech, parliament and academia (Pitt, 2020). Moreover, from this influence, particular types of organizations may leverage their wealth to attract the 'coding elite' (Burrell and Fourcade, 2021; Smit and Pitt, 2024); recent compensation packages are as high as $250 million for four years of work (Isaac et al., 2025), perhaps disadvantaging particular types or instances of organizations.

A dense web of interconnections across stakeholders from industry, academia, governance, and the broader public sphere drives complexity. From art or media that inspires (Disney's Baymax), to those that provoke concern (Terminator), or policies that regulate (European Parliament and Council of the European Union, 2024) or those that fail to (Samuelson, 2023). So too the sub-fields and interdisciplinary specializations (Explainable AI, Human Centered AI, Green AI, etc.) that have emerged to address the challenges posed by "AI" as a socio-technical-environmental system. Moreover, research and innovation generate new applications that diffuse outward, eventually being adopted by both organizations and the public as either *technological artifacts or speech acts*. Furthermore, we see disparities between those that reap the benefits of "AI", and those taken advantage of because of it (Hao and Hernández, 2022), each dimension discussed reveals the multidimensionality behind a monolithic "AI".

Organizations

Organizations are made up of interacting agents, including people, teams, roles, software, and routines. These interactions evolve when conditions change, such as during reorganizations, the implementation of new workflows, or the introduction of revised incentives. Small, localized changes can have a disproportionately large impact on the entire organization, leading to phenomena like cascades or tipping points. Also, the boundaries of organizations are often porous, involving contractors, platforms, as well as data and capital markets. Usually, the regulatory, technological, and cultural environments influence performance and behaviour. Additionally, culture, reputation, and routines develop at the macro level as a result of micro-level interactions and cannot be simplified to any single component; thus we may consider organizations as complex adaptive systems (CAS) (Anish and Gupta, 2009; Preiser et al., 2018).

Viewing organizations as CAS prompts us to understand that adopting "AI" is not a straightforward decision. It is a distributed, path-dependent process that modifies local interaction rules and creates feedback loops that resonate throughout the organization. An AI decision-support tool inserted into a claims team, a generative AI assistant added to a helpdesk, or an agentic scheduler inside a hospital ward immediately changes who talks to whom, about what, and when. Over time, these local rule changes accumulate into new organizational attractors: new routines (e.g., model-first triage), new roles (prompt engineers, model risk leads), and new boundaries (data-sharing agreements, API dependencies). Moreover, AI systems may become players within an organization's network by storing and reshaping organizational memory through logs and fine-tuned weights. They can also influence attention, decision-making and create new couplings to external ecosystems such as cloud services and foundation models. All this amplifies non-linearity and openness (Preiser et al., 2018; Nguyen and Vostinar, 2024) in the organizational landscape. Hence, the same "AI" artifact can yield very different system-level outcomes depending on organizational structure, coupling, and governance.

So, what next?

Given the interaction between two complex adaptive systems, we propose a research agenda is required to examine how organizations can adopt, integrate, and leverage "AI" effectively. This requires attending to organizational characteristics such as environment, structure, governance, and strategic goals, while also situating these within existing typologies of organizational forms. Accompanying this attention, we must consider "AI" and the organizations which adopt it as a heterogeneous and evolving assemblage of technologies, practices, and meanings; considering explicitly change and time (Baygi et al., 2021). To pursue this agenda, we may draw on complexity science methods, such as empirical and theoretical agent-based modeling, network analysis, causal loop diagrams, and evolutionary game theory, to generate insights; i.e., feedback loops and path dependencies. By considering the interplay between these two dynamic systems, our agenda seeks to generate insights into the conditions under which alignment, resilience, and responsible adoption are most likely to emerge, and, how these properties may be designed. We may further complement this with empirical data and case studies, using real-world applications of AI across organizational types to test, refine, and contextualize complexity-based models, thereby ensuring that theoretical insights remain relevant to practice.

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