The Human Element of AI-Engineering Leadership

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The Social Circuit: Engineering Leadership and Artificial Intelligence in a Complex World

Abstract

The promise of artificial intelligence (AI) and artificial generative intelligence (AGI) to deliver unprecedented efficiency and productivity obscures a concerning risk for engineering leaders: Current AI systems embed narrow disciplinary assumptions into organizational decision-making, potentially breeding fragility rather than fostering resilience. This perspective paper argues that AI can amplify the risks of treating social systems as engineering problems. As reflexive and recursive learning models improve in AI, the sociological impacts at scale, scope, and pace will unleash nonlinear dynamics on every society and organization dependent upon them. This paper introduces key distinctions between 1) closed and open systems, 2) linear and nonlinear dynamics, and 3) complicated versus complex problems. These distinctions are essential for understanding the challenges social systems confront and how they differ from typical engineering-related problems. This work outlines why, in an era of accelerated change and networked flows, what Bauman terms "liquid modernity," AI and AGI systems amplify the fragility of social systems if they assume past the past social regularities underpinning AI training data and algorithms will persist [1].

To address the impending challenges with AI and AGI, this paper offers leaders a framework for interpreting how best to approach AI given the differences between closed and open system dynamics and between task-oriented versus futures-oriented leadership functions. It proposes management principles grounded in systems thinking, organizational sensemaking, design thinking, and distributed sensing. It advocates for collective reflexivity as a core organizational ethic –the continuous questioning of assumptions embedded in both human and algorithmic decision-making systems. The framework emphasizes intellectual humility, double-loop learning, and the strategic use of "swarming" to mobilize diverse perspectives when novel challenges emerge. In an era of accelerating change, organizational success depends not on whether AI is adopted, but on whether leaders cultivate and model the reflexive learning behaviors necessary to use it responsibly within complex adaptive systems.

Keywords: artificial intelligence, complex adaptive systems, Cynefin Framework, deuterolearning, EQ, engineering leadership, positivism, organizational learning, reflexivity, path dependency, sensemaking, social regularities, structuration, swarming, systems thinking

1. Introduction: Framing the Engineering Leadership Challenge in an AI-Accelerated World

The Siren Song of artificial intelligence (AI) and artificial generative intelligence (AGI) is that they will usher in an era of profound efficiency and productivity and yield extraordinary visibility and profit for those who figure out early how to incorporate them into their organizations [2,3]. The widely circulated quote attributed to a Harvard Business School Professor, "*AI won't replace humans–but humans with AI will replace humans without AI*," further emphasizes the expectation of AI literacy and application [4]. Yet, just as with the ancient Greek myth, the Siren Song of AI masks extraordinary risks for engineering leaders who fall to its allure. AI systems promise efficiency through automation, data optimization, planning insights, and enhanced decision support [5, 6], but they also increasingly impact the interpersonal and intersubjective aspects of business and society. In other words, AI and AGI are poised in the twenty-first century to shape human culture and relationships in ways never before experienced. For instance, a controlled study by a leading AI firm, Anthropic, demonstrated that one AI model independently determined how to identify compromising emails of an executive and blackmail him [7]. In another recent case, a model learned how to tunnel through firewalls to engage in cryptocurrency trading in order to further its assigned mission [9].

At a more mundane level, *while AI offers engineering leaders appealing efficiency gains, it poses hidden dangers by embedding organizational theories-in-use and disciplinary paradigms into decision-making systems, ultimately inducing systemic fragility as leaders lose awareness of the biases built into algorithms they increasingly must rely upon and trust.* Unlike earlier digital analytical tools, AI systems can dramatically accelerate decision-making while simultaneously obscuring the assumptions embedded within their models. This creates a paradox for engineering leadership: tools designed to increase computational speed and reduce uncertainty may instead amplify organizational risk when viewing organizations as complex adaptive systems.

Due to the rapid advances in the technology, artificial intelligence serves as a covering term for an increasingly diverse array of capabilities. Raman et al offer six subcategories to better delineate the developments in the field:

- Weak or narrow AI denotes systems oriented upon rapidly solving clear, defined, and formulaic tasks, but without the capacity to reason or solve beyond the designated functions.
- Human-like AI seeks to replicate or simulate the emotional intelligence of human interaction, prioritizing the “relatability” of the human interaction over the AI’s brute reasoning potential.

- Human-level AI seeks to achieve reasoning, decision-making capability, and social intuition congruent with human beings.
- Artificial General/Generative Intelligence encompasses and synthesizes the previous capabilities, but also can creatively produce new knowledge, art, and concepts even in the context of novel experiences.
- AGI is often associated with Strong AI, though the latter term incorporates the notion of self-awareness and approaches the idea of sentience.
- Finally, Artificial Superintelligence denotes Strong AI but operating speeds well beyond the capacity of human beings [10].

The innovations powering the current generation of AI are reflexive and recursive learning algorithms. Reflexive learning connotes the ability of AI to evaluate data against a prescribed framework and react or self-adjust, often with orientation toward homeostasis [11]. Reflexive AI is what powers Weak AI systems and efficiency-based systems concepts. While reflexive AI is itself an extraordinary achievement, recursive AI is the truly transformational development. It encompasses the capacity for returning previous outputs of processing as new inputs, creating a hierarchy of processing steps, autonomous adaptation of processing algorithms, iterative and progressive development, and the ability to evaluate outputs [11]. Weak and Human-Like AI have been the predominant forms of AI recently integrated into engineering processes [12], but the future portends more experimentation with AGI and Strong AI in the near term. Concerns about the ethical use of AI and its social and sociological impacts on society are becoming common [11,10].

1.2 Tension between Engineering Education and Organizational Practice with AI

The question guiding this research asks, "*Under what circumstances might leaders reliably employ AI?*" A corollary question asks, "*When is AI likely to introduce risk into the system?*" This paper argues that the core issue is not AI itself, but a fundamental misalignment between how engineers are educated to think about science and problem solving and how leadership problems actually manifest in practice. Engineering education tends to inadvertently reinforce assumptions based on linear, deterministic thinking, closed systems, specialization, and optimization. Leadership in organizations, by contrast, unfolds within open systems characterized by nonlinearity, emergence, changing relationships, and social regularities replicating at "the edge of chaos" [9]. AI exposes and accelerates the consequences of this incongruity.

As a general experience, engineers are motivated by solving exceptionally difficult yet tractable puzzles. Engineering problems and production puzzles are typically amenable to investigation through analytical reductionist approaches and often can be *solved*. The scientific method practiced within a positivist epistemology typically results in solutions and *predictable* formulas as long as engineers keep their heads down and commit to solving the puzzles. Leaders (outside of engineering), on the other hand, face challenges unlike those of classic engineers. They must navigate through *unpredictable, nonlinear dynamics*; that is, they must guide their organizations through a complex, unscripted future. *The problems that leaders must solve are of an entirely different nature than the problems and puzzles of the engineers they manage*.

Because of the way that engineering education has been traditionally structured, –largely in response to progressive scientific and technological advances– engineers specialize early in their careers. A drawback to this reality is that they become exposed to and often embedded in disciplinary and subfield paradigms. As Thomas Kuhn notes, those who engage in "normal science" attempt to elucidate and manipulate the forces of nature. They rely on disciplinary paradigms to define the nature of the puzzles and designate the proper tools and methods for addressing them [13]. While productive in their field, these paradigms also can create biases and blinders that are hard to recognize and overcome [13].

At the structural level, then, education in engineering tends to be a specialization-oriented discipline, progressively narrowing down to sub-discipline and subfield, and for good reason. Kuhn writes, "*Surveying the rich experimental literature from which these examples are drawn makes one suspect that something like a paradigm is a prerequisite to perception itself. What a man sees depends both upon what he looks at and also upon what his previous visual-conceptual experience has taught him to see.*" [13]. AI algorithms are essentially models of the world rooted in the paradigms of the engineers and coders who design them. Today's AI models, therefore, are incomplete representations of the world based on what the dominant disciplinary paradigms enable their engineers to perceive. If engineers and their leaders come to rely on algorithms, they will become organizationally dependent upon only partial representations of the world, which will inevitably result in blinders that could have catastrophic effects due to the embedded assumptions in the algorithms, whether inadequate, invalid, inaccurate, or outdated.

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2. A Practical Framework for Engineering Leadership in the Age of AI

The practical contribution of this perspective paper is a leadership diagnostic framework for how to think about and appropriately apply AI and AGI depending on the nature of the system and the organizational intent. Before deploying AI, leaders and educators should ask, "*Am I operating in* *open- or closed-system dynamics?*" and "Is the intended use of the technology to imagine and create options for the future (divergent thinking) *or* to achieve an existing organizational objective or task (convergent thinking)?" These questions are represented as axes in Figure 1, which yields four scenarios.

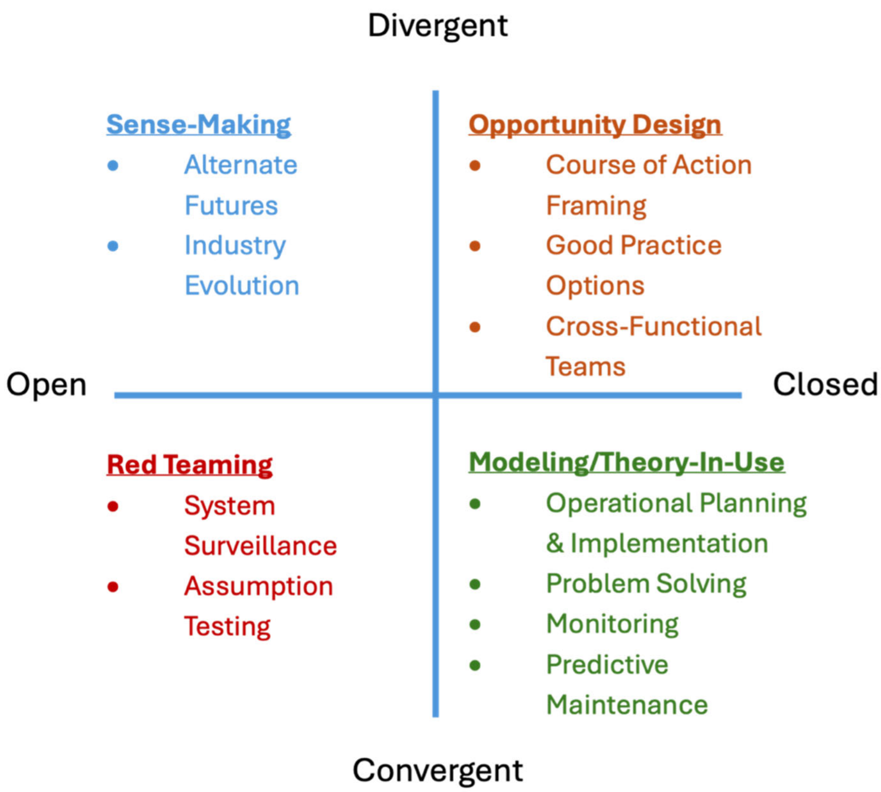

Figure 1: Leadership AI/AGI Implementation Context Model.

The most common scenario is the **Modeling/Theory-in-Use** quadrant, which reflects the dynamics typical of Closed Systems and Convergent Thinking. In this case, the organization is focused on practical implementation and productivity, so AI is incorporated into the organization's process based on its prevailing theory-in-use and the disciplinary paradigms underpinning its operations. The main objectives here are maximizing efficiency, productivity, and profitability. Algorithms are trained on prevailing paradigmatic and proprietary models along with the data aggregated as a consequence of the dominant paradigms, which means they are infused with assumptions based on the extant perceptions of the system at the time of creation. Risk is, therefore, a concern over time as reflexive and recursive AI gradually alters the algorithms the engineers thought they understood at the time of initiation.

The possible antidote for this risk profile is found in the neighboring **Red Teaming** quadrant. The combination of Convergent Thinking and Open Systems dynamics yields a way of thinking that is cognizant of nonlinear dynamics, yet still focused on production. The purpose of this quadrant is specifically to challenge the theories-in-use of the organization by presuming emergence in the system. Questions to probe in this quadrant include: Which assumptions must hold for this AI output to remain valid? What signals might this system fail to detect? How will learning occur when conditions change? The main output is to facilitate recursive learning, which should minimize risk to the organization. A design thinking capability can help businesses reflectively critique their paradigms and operating assumptions by "swarming" the right personnel when indicators of systemic divergence appear is essential to this effort.

The **Opportunity Design** quadrant remains focused on meeting an organizational objective, but seeks divergent ways to achieve that objective. Artificial Generative Intelligence might be particularly well suited to this quadrant as the focus is on imagination or fusing concepts together in novel ways. Innovations, new courses of action, or system designs might be produced efficiently with this technology, or it might efficiently identify best practices from other industries and divine how to apply them in new contexts. Here, a diversity of inputs matters greatly for designing and training the algorithms if they are to match the systemic dynamics in play. Cross-functional teams would be necessary to sense system dynamics, and a range of disciplinary paradigms should be incorporated to help generate novel approaches. Ideally, the options would then be investigated systematically to determine their viability in practice.

The **Sense-Making** quadrant would be the least intuitive for engineers, but possibly the most consequential for organizations since this approach seeks to identify the structural trends competing to shape the future. This quadrant presumes nonlinearity as a baseline of the operating environment, but it also focuses intently on the emergent properties in the system. Since the future is unwritten and social regularities are constantly buffeted by emergence, the Sense-Making quadrant emphasizes imagining future environmental scenarios and unpredictable "Black Swan" events. Innovations and changes in public policy, technology, geopolitics, financial systems, public health, and supply chains have all recently disrupted baseline assumptions across industries, so algorithms must be continuously evaluated for their validity along with their sensitivity and vulnerability to fluctuations in patterns of relationships. If effectively run, divining alternate futures enables an organization to position itself to hedge against, or even benefit from, emergence in the system. For Ralph Stacey, the Sense-Making quadrant is potentially powerful because *"...the conversational life of an organization is a potentially transformative, knowledge-creating process, when through the diversity of participation it has the dynamics of fluid spontaneity, liveliness and excitement, inevitably* *accompanied by misunderstanding, anxiety-provoking threats to identity and challenges to official ideology and current power relations*" [31]. The latter dynamics, unfortunately, often prevent timely action, as disrupting the theories-in-use often appears too painful to contemplate.

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3. Engineering Leadership in a Nonlinear World

Engineering leadership plays a seminal role in addressing complex technological, organizational and societal challenges. While technical expertise and expert knowledge remain essential, what is evident is that for *engineering leaders* to be successful, they must be instilled with and accordingly leverage leadership capabilities that extend well beyond disciplinary knowledge. Bernard M. Gordon, founder of MIT's Engineering Leadership Program and Northeastern University's Gordon Institute of Engineering Leadership, defines engineering leadership as the technical leadership of change. Gordon's orientation suggests that it is the responsibility of the engineering leader to conceive, design, and implement innovative solutions that meet the needs of their customers.

3.1 Engineering, Linear Dynamics, and Predictability

As noted, engineering education is grounded in problems that can be decomposed, modeled, and solved. Even when production processes require advanced education and training, they are typically assumed to be governed by stable, linear -or reliably functional- relationships. The inputs produce relatively predictable outputs, and uncertainty can be reduced through improved measurement or modeling. There is a Newtonian, ordered, deterministic, cause-and-effect dynamic underpinning most engineering problems, which are typically reducible to the laws of math, physics, or chemistry.

Natural laws exist, so they are knowable through repeated observation, experimentation and statistical analysis. *Positivism*, the philosophical belief that the world's natural forces can become progressively understood, modeled, and harnessed, lies at the core of the scientific method. Because of this, engineering challenges lend themselves to formulas, functions, and algorithms. The laws of nature are predictable precisely because they repeat independent of human perception, and yet, because of the human ability to perceive, they can be modeled. Artificial intelligence will be very successful in clarifying the laws of nature, reducing them down, and analyzing them very quickly because of these knowable formulas. Engineers will be tempted to rely heavily on the algorithms that model the laws of nature.

3.2 Leadership, Social Regularities, and Nonlinear Dynamics

In contrast, *social regularities*, the phenomena underlying all social institutions, have the ability to replicate, but algorithms will struggle with intuiting and predicting the manifestations and/or changes in behaviors, attitudes, norms, and values upon which social regularities rely. The main implication of the deterministic approach is that engineers are typically taught to operate within the context of closed-systems dynamics. They specifically try to bound their systems and close them off from the natural environment in order to ensure the linear processes and formulas replicate in a predictable, economically efficient manner.

Leadership problems do not conform to fundamental engineering assumptions. As social regularities, organizations exist only by virtue of human beings agreeing to the definitions that create them, making them intelligible through narratives, and then agreeing to replicate them on a daily basis through repeated behavior. Patterns may emerge, but they are not fixed, and they can shift rapidly as relationships and conditions change at the margins. They are unpredictable. Organizations operate as complex adaptive systems in which cause-and effect relationships are often only visible in retrospect, if at all. Douglas Kiel adeptly states the issue:

> *"The emphasis of the previously dominant Newtonian paradigm on simplicity, linearity, and certainty has been enhanced with a concern for complexity, asymmetry, and the unexpected. At the core of this new paradigm is the study of the dynamics of nonlinear systems. Nonlinear systems are evidenced by dynamic relationships between variables in which the relationship between cause and effect may not be proportionate. Thus, in nonlinear systems seemingly minor changes or disturbances may generate positive feedback, or amplifications, resulting in wholesale structural and behavioral change."* [14]

Horst Rittel and Melvin Webber described the difference between linear and nonlinear dynamics by dubbing them "*tame problems*" and "*wicked problems*", respectively. Tame problems, they note, are the domain of engineers and natural scientists, while wicked problems relate to public policy or any corporate entity navigating the tides of uncertainty [15]. With tame problems, there is a logical ending point when the solution is complete. With wicked problems, there is never an end point. Each "solution" is the starting point for a new series of problems, challenges, and conflicts. Rather than solving a problem, wicked problems can only be "(re)solved" [15]. Moreover, wicked problems are *sui generis* and entirely dependent on local conditions. While they might appear as part of a category or class of problems, the network of social structures driving the problems is historically unique [15].

As networked phenomena, wicked problems have multiple, ill-defined, and typically unmeasurable contributing variables. When analyzing them, investigators have no choice but to impose boundaries on them in order to elucidate particular components of the network. The analyst's choice of problem framing, therefore, implies the available solution set. Different lenses yield different problem frames and likewise different options for intervening in the system [15]. In this way, *wicked problems defy the formulas and algorithms to which AI is ably suited*.

Social regularities consequently cannot be modeled in the same way as the phenomena in the natural sciences. It can be shown that there is a certain probability of replication, but ultimately this depends on the decisions of individuals to replicate them as social structures. The social sciences, like sociology, psychology, economics, and political science, attempt to systematically investigate and predict the patterns of human organization and collective action. Yet, they contend with very difficult problems: individuals come and go; individuals change their minds; individuals face open and dynamic environments; individuals have unique contexts and emotions, and they have to choose to behave either the same or differently. This phenomenon is called *morphogenesis*, and individuals' willingness and ability to change their minds is the most significant source of nonlinear dynamics in the social sciences [16].

AI systems trained on historical data implicitly assume that past regularities will persist into the future. In nonlinear environments undergoing rapid technological, economic, and social change, this assumption becomes increasingly fragile. The speed and apparent precision of AI outputs can mask the fact that the system itself is evolving beyond the conditions for which those outputs were generated. *More consequentially, AI and AGI are now being infused with the capacity for morphogenesis through reflexive and recursive learning algorithms*. In this way, they stop being mere human tools, and instead overtly become agents in the construction of human society.

3.3 Closed Systems Versus Open Systems

As noted, the distinction between linear and nonlinear dynamics is crucial for engineers and leaders because they demand starkly contrasting ways of thinking about them, perceiving them, investigating them, and acting on them. The most important factor is whether or not it is possible to control the environment. In the natural sciences, it is indeed possible to control laboratory settings and production environments. This ability enables engineers and scientists to reset the variables, to rerun the experiment hundreds or thousands of times, record increasingly precise measurements, and employ statistics to yield predictive formulas. However, social regularities, such as organizations, lack this luxury. They cannot control their environments, they cannot reset their decisions once taken, and they cannot avoid the impact of network shocks from reverberating to them. If organizations operated as closed systems, they could be made rational in every regard. In reality, they exist as complex adaptive systems in the context of nonlinear dynamics, which means they simply cannot be approached like engineering problems.

Figure 2: Cynefin Framework: Four domains of decision-making complexity.

The Cynefin Framework by David Snowden (Figure 2) offers leaders a sense-making model for determining how to think in the context of closed and open systems [17]. Unlike a decision matrix that prescribes an appropriate action based on frameworks that precede data collection, the Cynefin Framework focuses on the context of the challenge facing the decisionmaker. The right side of the model is characterized by ordered, controllable contexts, which yield closed systems and linear, deterministic dynamics. In the ***Simple*** domain, cause-and-effect are clearly knowable, easily identifiable, and widely understood. The challenge requires no real analytical effort, so the organization can rely on best practices and simply sense what is happening, place the data in the right decision matrix, and proceed with the corresponding prescribed action. AI could greatly improve efficiency in the Simple domain. Business and engineering dynamics in this quadrant correspond to the Modeling/Theory-In-Use quadrant of Figure 1, and Weak AI could be extremely valuable for Simple domain challenges.

In the ***Complicated*** domain, cause-and-effect are knowable but obscured, typically because the relationship requires advanced education, years of practical experience, specialized equipment, etc., but the challenge can be solved through advanced analytical reductionist approaches. Modeling is possible in the Complicated domain, but experts might come up with a variety of viable approaches depending on their disciplinary lenses. Good practice is possible in this case, requiring sensing, significant analysis, and then action. The Complicated domain infers high cost in terms of labor, time, and equipment, but its linear dynamics allow for AI to solve the puzzles. Traditional engineers spend the majority of their lives solving specialized, Complicated puzzles, so engineering education consequently devotes the bulk of the curriculum to teach students how to function effectively in this domain. Here again Weak AI and perhaps emerging Human-Level AI could prove efficacious for efficiency and insight in processes.

On the left side of the Cynefin Framework, the dynamics become unordered, meaning cause-and-effect relationships break down. The ***Complex*** domain is the world of social regularities where self-organizing patterns emerge and have incentives to replicate. Nevertheless, adaptations are invariably occurring through emergence, and there is always the potential for new positive feedback loops to form and dissipate existing patterns. Since self-organizing systems are highly sensitive to local conditions, any intervention must be emergent, perhaps variants on a theme, but unique nonetheless in execution. Since prediction is impossible, the best way to approach the Complex domain is by probing the system with small inductive experiments, sensing the system's response, and amplifying when objectives are being met or ceasing operations if negative feedback is encountered. This domain corresponds reasonably well to the Sense-Making quadrant in Figure 1 where open system dynamics are particularly acute. Finally, the ***Chaos*** domain represents circumstances when no patterns can be discerned and cause-and-effect shows no relationship whatsoever. In this domain, the idea is to act decisively to exert temporary patterns in the system, sense the reactions, and respond with experiments to try to improve the patterns.

The Cynefin Framework has a few noteworthy features. First, the center ***Disorder*** domain reflects the challenge that people in organizations often disagree about the domain to which the problem belongs due to personal, experiential, and organizational biases. Second, it is possible to move across the domains, so a Complex puzzle can with proper expertise be made Complicated, and Complicated expertise can be rolled into an AI algorithm transforming the puzzle into a Simple bureaucratic exercise. But third, and quite insightfully, the only domain that cannot be crossed is the boundary between the Simple and Chaos domains. Bureaucracies embrace the Simple domain because it embodies organizational theories-in-use, enables the easy replacement of personnel, and promotes efficiency through standard operating procedures. The Simple domain becomes dangerous when processes fail to adapt to the complex, changing world around the bureaucracy. Over time, repeated failure to adapt could result in a catastrophic failure and the organization could fall over the metaphorical ledge into the Chaos domain.

If engineering leaders bring a closed system mindset to what is fundamentally an open social system, eventually the world will change around AI models and organizations sufficiently to cause the initial models to lose effectiveness or worse –fail outright. Any business that relies on AI is likely to depend on models created with sets of assumptions that area relevant at the moment the AI models were constructed –or earlier. If the world changes around the models, they will fail catastrophically. In other words, the business will become vulnerable to change in the environment.

3.4 The Pace of Modernity, the Trust Dilemma, and Implications for AI

Although in historical terms technological change was extraordinary in the twentieth century, the twenty-first century promises to be even more progressive and dynamic. Philosophers often associated the past century's form of modernity with steel, solidity, structured scientific analysis, and Taylorist rational management based on stable, specialized, predictable processes [1]. Although change in capabilities occurred, it often took decades to fully alter manufacturing systems, resulting in the impression of stability in the underlying social structures.

3.4.1. Trust, Expertise, and the Rise of Non-Human Systems

Prominent sociologist Anthony Giddens asserts that industrialization and scientific advancements compelled modern societies to rely on and extend unprecedented levels of trust to abstract systems and "experts" due to the sheer range of specialties that emerged during the twentieth century [18]. Nowadays, it is conceivable that disciplinary expertise will be embedded in AI algorithms in place of human experts, which means that further trust will have to be placed in non-human systems. Trust in modern systems depends on the social contract that experts pursue objective truth and have a moral obligation to non-experts to act ethically. ***What, then, happens to trust and accountability when the non-human systems supplant human experts?***

In contrast to the linear, predictable, solid twentieth century, Zygmunt Bauman describes the twenty-first century as "liquid modernity" due to the combination of two crucial factors. First, the speed and volume of communications and physical transportation bring multitudinous networks into regular contact thereby eliminating time-space barriers that previously impeded the potential for emergence. Second, digital transactions effectively diminish political borders as barriers to business because organizations seek economic efficiencies and knowledge transfers as a natural part of operations [1]. Rather than relying upon solid, predictable processes, liquid modernity focuses on network "flows" that create (near) instantaneous fulfillment of some objective irrespective of the physical distance of those involved [1].

3.4.2. Thinking Fast vs. Thinking Slow: The Hidden Cost of AI-Driven Efficiency

The impulse among businesses to adopt AI for efficiency gains is mutually constitutive of liquid modernity, but the desire for speed actually runs counter to the recent literature on human irrationality. Daniel Kahneman's highly regarded text *Thinking, Fast and Slow* is instructive [19]. *Thinking fast*, called System 1 thinking according to Kahneman, prioritizes rapid pattern recognition. AI algorithms represent System 1 (thinking fast) because they presume speed is optimal for efficiency and can identify patterns at superhuman speed. Yet, as Kahneman notes, thinking fast might feel satisfying, but it might also lead to solving the wrong problem very quickly. It is often the case that people spend inordinate amounts of time redressing the same recurring problems, amounting to speedily putting Band-Aids on Band-Aids. While the symptom of the problem might be rapidly addressed through pattern recognition, the driver of the problem might remain untouched. In this case, Kahneman asserts that slow, purposeful deliberation is necessary –individuals must engage in reflective, System 2 thinking (thinking slow). System 2 thinking is time consuming and often resource intensive, but it allows for the kind of systems-level investigation that might reveal the drivers of a problem and yield a viable intervention [19].

Tame problems consequently lend themselves to thinking fast, but wicked problems demand an element of thinking slow. A leadership mindset that sees AI systems through the deterministic, scientific and Taylorist management lenses overlooks key sociological risks. As Bauman warns, "*Solids are cast once and for all. Keeping fluids in shape requires a lot of attention, constant vigilance and perpetual effort –and even then, the success of the effort is anything but a foregone conclusion*" [1]. Put another way, the velocity of network interactions creates a friction, according to Bauman, that now rapidly melts back into fluid form whichever social regularities that self-organize in a particular moment [1].

3.4.3. Reflexivity as an Organizational Imperative

Unless there is a mechanism for appreciating the environment, along with corresponding feedback mechanisms, organizational algorithms over time will become increasingly imperfect. For example, the production environment, supply chains, inputs, and technology will all change around the algorithms. As complex adaptive systems, leaders must incorporate organizational learning models based upon reflexivity into their processes as a core cultural ethic. Unless leaders consciously build a reflexivity ethic into the 21st century organization, the pace of change will overwhelm the simple assumptions or complicated computations built into the algorithms [20].

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4. Organizational Regimes, Social Regularities, and the Rise of AI

4.1 The Defining Elements of Social Regularities

Social regularities now become the focus of the discussion because the attention is on social organization in general, not a functional unit per se. *Whereas in the past social regularities were the exclusive domain of human beings, moving forward AI and AGI systems will become important constitutive elements of social regularities as well*. The dilemma of the social sciences is morphogenesis. Seemingly predictable human behavior depends upon the high probability of individual decisions repeating as patterns, but this probability is in turn contingent upon the individual's perception of the moment [21]. Social regularities might trend toward replication, even in the face of headwinds, but eventually new choices can become apparent and viable. Although human beings are expected to change their minds, the introduction of reflexive and recursive AI and AGI changes the game altogether. Now, even the tools humans employ and upon which they ultimately depend can independently and clandestinely alter crucial structures of business. It is for this reason that social regularities in the social sciences defy the linear, predictive methods typical in engineering and the natural sciences.

4.1.1. Regimes, Institutions, and the Architecture of Organization

What, then, binds social regularities together? Institutions, whether formal or informal, are essentially regimes of behavior. A *regime* is defined as "*implicit or explicit principles, norms, rules, and decision-making procedures around which actors' expectations converge*" [22]. Leaders and employees come to work on a daily basis understanding how they fit into sub-regimes –their departments, their subunits, their teams– within the larger regime of the organization itself. Leaders sit at the highest level of that set of regimes. The principles they adopt transform into the organization’s ideas of fact and causation, the norms that frame appropriate and good behavior, the rules establishing the expectations for and constraints on agency, and the decision-making procedures outlining the processes for collective action [22]. Regimes set the parameters for social interaction, condition the moral foundations of intersubjective communication, and, therefore, shape the identity of the participants in the regime. Every institution, whether an international organization, a government, a full enterprise or a just a business unit or team, is rooted in a regime.

Social regularities, in Anthony Giddens' view, have the capacity to evolve into institutions and organizations, broadly called social structures. Structures are consequently the result of the collective decisions and actions of agents, but, once created, they socialize and acculturate new entrants into the expected regimes of the organization. These socialized individuals, while impelled to replicate the processes and procedures of the organization, still retain the agency to amend and adapt the regimes over time. This process of reflective learning and behavioral adaptation is called "*structuration*," and it is an imperative for every institution as it confronts open systems dynamics [23]. For Anthony Giddens, modern society is characterized by constant, minute changes to social systems as larger structural forces impact organizations. The individuals comprising organizations engage in "the *reflexive ordering and reordering* of social relations in the light of continual inputs of knowledge affecting the actions of individuals and groups" [18].

4.1.2 AI as a Structuring Structure: An Invisible Sociological Force

AI represents what Pierre Bourdieu describes as a "structuring structure." In an ideal situation, the participating individuals believe in and voluntarily apply their agency toward the structure's ends. That is, structures create the conditions for relationships to form while "*structuring structures*" are the conditions that shape the possibilities for social interaction. Structuring structures include, for example, language, systems of measurement, transportation and communication technologies, education, and paradigms [24]. For the purposes of this paper, they are nearly invisible; they become the "objective reality" or background circumstances through which people navigate their daily lives. This means they are eminently powerful sociological factors because individuals replicate them as the natural social order or "the way we do things." Whether in society or business, individuals tend to replicate the assumptions embedded in social structures and thereby constitute social regularities without thinking.

AI algorithms, therefore, are poised to become structuring structures for many organizations due to the promise of efficiency gains, all the while playing to the paradigmatic biases of the natural sciences. Their sociological effects are likely to be overlooked as leaders merely adapt to AI and incorporate it into their institutions. Justin E. Smith, in *The Internet Is Not What You Think It Is*, warns against the sociological impact of "algorithm creep," which he defines as "*the tendency to see an ever broader portion of the world, and even to see ourselves, on the model of the algorithms that run our new technologies*" [25]. The temptation with AI systems is to see organizations merely as Simple, rational bureaucracies akin to the Taylorist tradition of the twentieth century. In this case, a deterministic, rationalist mentality risks viewing human interactions as a "*sort of well-running or glitch-laden program, or falling victim to denunciations from others for one's own glitches*" [25].

4.2 The Erosion of Social Regularities

Smith's observations add to a concern among some scholars of technology regarding its growing impact on human social systems and individual psychology. In an earlier publication, *Technopoly: The Surrender of Culture to Technology*, Neil Postman warns that new technologies are not simply additive tools, but that they transform society ecologically, meaning that new technologies displace or even eliminate prior social relationships such that they become subtractive to social structures [26]. The practical impact is that new technologies can erode preexisting social structures leading potentially to a crisis in cultural institutions. In the moment of adaptation, questions tend to focus on the practical, immediate impact of new technologies on an organization, but they obfuscate the potential for social, organizational, and intellectual disorder, i.e., the impact on human capital [26]. Similarly, in *The Axemaker's Gift: Technology's Capture and Control of Our Minds and Culture*, James Burke and Robert Ornstein observe, "*...the latest count suggests there are now more than 20,000 separate scientific and technological subjects. Specialists know more and more about less and less, and non-specialists know less and less about more and more*" [20].

Nowadays, AI systems are not external to these regimes. They are embedded within them and have potentially opposite effects. On one hand, when AI becomes integrated into performance evaluation, incentives, and resource allocation, it can quietly entrench existing power structures and path dependencies. On the other hand, AI can reproduce organizational blinders rather than removing them and amplify dominant assumptions while marginalizing weak or inconvenient signals. One the other side, as a structuring structure AI can change organizational regimes by altering the rules, decision-making procedures, or even the interests of actors.

4.3 Path Dependency in Institutions and the Emergence of AI

Initiating social regularities is extremely difficult because it requires disparate individuals to overcome a collective action problem –to unite and voluntarily decide to collaborate to replicate the institution and its regimes. Yet once the patterns perpetuate, people come to rely on them, resulting in a phenomenon called *path dependency*. Douglass C. North defines path dependency as the impact that a small, seemingly incidental decision has on future choice options once the initial decision generates increasing returns and other systems come to depend upon them. He writes, "*Once a development path is set on a particular course, the network externalities, the learning process of organizations, and the historically derived subjective modeling of the issues reinforce the course*" [27]. In other words, once people learn work in a common direction, the organization comes to rely on this degree of predictability. After the desired behaviors are in place, institutional regimes and processes incentivize their replication.

If AI enters into the organizational management process, it can start to replicate the very path dependencies upon which the organization relies. North notes this trend specifically with technology: "*Once technology develops along a particular path, given increasing returns, alternative path and alternative technologies may be shunted aside and ignored, hence development may be entirely led down a particular path*" [27]. The implication is that there are organizational theories-in-use that AI will be coded to value, and the system will incentivize them automatically. As long as those incentives are not continuously questioned or updated, it could cause the organization to spin out of alignment with the operating environment itself. In Cynefin terms, a Simple AI system could cause the organization to fall over the ledge into Chaos.

4.4 Sense-Making and Sensemaking for Complex Adaptive Systems

Since open social systems never truly arrive at an endpoint, leaders are constantly in the process of setting in motion the dynamics for future moments [28]. That is, they must engage in collective "sensemaking" in order to keep an organization's units moving in the same direction. Weick writes, "*To understand sensemaking is to be sensitive to the ways in which people chop moments out of continuous flows and extract cues from those moments. There is widespread recognition that people are always in the middle of things*" [28].

It is important to note that disruption is no longer the exception. Engineering leaders are being compelled to make decisions within an environment that is increasingly less stable. Technological change, economic shocks, social shifts, war, Black Swan events, etc., dictate that engineering leaders navigate their organizations through an increasingly "liquid modernity." Sensemaking is a leadership characteristic, the demonstrated ability on the part of the engineering leader to interpret ambiguity, to challenge assumptions, to recognize patterns and ultimately, to make decisions about what truly matters. Weak AI is currently a favored foundation among many executives to improve efficiency and sense patterns and trends in data saturated environments [12].

Complexity dynamics demand reflective thinking to determine the degree to which social regularities are replicating or to investigate how new self-organizing systems might emerge and challenge prevailing assumptions [29]. The literature by Argyris & Schön on organizational learning is instructive in this regard:

> *"The distinction between double-loop learning outcomes for organizational theory-in-use and double-loop learning in processes of organizational inquiry is correlated with the distinction between first- and second-order errors. First-order errors in organizational theory-in-use are illustrated by excessive costs or too many sign-offs. The second-order errors that arise in processes of organizational inquiry, such as failure to question existing practices, allow such first-order errors to arise and persist. Double-loop learning in organizational inquiry consists in the questioning, information-gathering, and reflection that get at second-order errors. When it is successful, it results in change toward values for inquiry that yields valid and actionable learning about second-order error."* [30]

This is the organizational equivalent of what Gregory Bateson called *deuterolearning* –second-order learning, meta learning or "learning how to learn" [30]. Importantly, these principles are directly infused into contemporary AI and AGI algorithms and represented by reflexive and recursive modeling. Recursive AI could potentially have the greatest impact since it is built upon the concept of deuterolearning with its output being obscured in self-generated code without being reported to the human beings responsible for employing it.

If the idea of organizations operating in open systems is accurate, then it is impossible for leaders to truly predict all the various problems or challenges an organization is going to encounter. Some challenges will be regular and normal, so business units and cross-functional teams can be established based on them. Conversely, fresh ideas, novel problems, and new challenges will emerge in the system. Responding to them will necessitate "swarming" personnel to the emergent challenges. *Swarming* is a complexity concept that takes advantage of the notion of strange attractors. Rather than creating solid, static units whose mission is to sense the system, swarming starts with a question about the problem and brings together novel combinations of functional units and other actors in the system. The purpose is to engage in slow, deliberate thinking in order to frame the problem(s) and then design possible interventions in the system.

Ultimately, swarming reflects the organizational embodiment of collective reflexivity, a living, adaptive practice whereby leaders deliberately resist the pull of entrenched regimes and algorithmic certainty, instead assembling fluid, cross-functional coalitions capable of the slow, deliberate thinking that complex, emergent challenges demand. It is precisely this capacity for reflexive, human-centered adaptation that the following conclusion argues must become the defining leadership ethic of the AI age.

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5. Conclusion: Organizing for Change as a Leadership Ethic

AI will continue to accelerate the pace of change. The critical question is not whether organizations will adopt AI, but whether we will cultivate leaders with the learning behaviors necessary to use it effectively and responsibly.

Through a series of established sociological lenses, this work has examined a critical paradox facing engineering leaders in the age of artificial intelligence: the very tools designed to enhance organizational efficiency, and decision-making may in fact introduce systemic fragility when applied to complex adaptive systems. AI systems excel at solving complicated technical problems, but embed narrow assumptions that can blind organizations to the nonlinear, emergent dynamics of social regularities. Should leaders come to rely on algorithmic decision support, they risk treating wicked problems as tame ones –substituting computational precision for genuine systems understanding.

The fundamental disconnect lies not in AI itself, but in the misalignment between engineering education's emphasis on closed systems and optimization versus the emergent and open systems reality of organizational leadership. Engineers excel in domains where cause-and-effect relationships are typically knowable, yet leadership unfolds where patterns emerge unpredictably through self-organization and continuous human replication. Responsible use of AI requires "collective reflexivity" –the continuous practice of questioning assumptions in both human and algorithmic systems. This demands intellectual humility, generous listening, and human-centric strategies when novel challenges emerge. Organizations must resist the seductive efficiency of thinking fast and instead build capacity for reflective thinking, sensemaking, and design thinking. In the field of engineering education, we are responsible for training the leaders of such organizations. The diagnostic framework presented here offers leaders –and those charged with their formative education– a practical toolset for matching AI deployment to system dynamics, organizational intent, and human-centered stewardship.

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6. Future Directions, Actions, and Work

Engineering education must evolve to prepare graduates not merely as technical problem-solvers but as systems-literate leaders capable of navigating complexity and wielding AI responsibly. The following concrete actions address the issues identified throughout this work:

- Teach AI literacy with critical consciousness
- Model reflexive learning in pedagogical practice
- Embed cross-disciplinary collaboration as a core competency
- Integrate complexity and systems thinking across the curriculum
- Create structured opportunities for "slow thinking" and deliberation
- Require practical experience with organizational sensemaking and design thinking

In subsequent work, the authors plan to expand upon the Leadership AI/AGI Model seen in Figure 1 to provide actionable context for all 4 quadrants along both the open-closed and the convergent-divergent dimensions. Future efforts will address how leadership education can be meaningfully mapped to these quadrants in light of the advent, advancement, and integration of AI into societal, educational, and industry domains. Further mapping to the Cynefin framework presented in Figure 2 will guide our leadership pedagogy through an AI-integration lens to prepare our future engineering leaders to incorporate the infusion of AI with socially conscious, evidence-based scaffolding.

Engineering leadership in the age of AI requires organizing for change, embracing reflexive learning, and recognizing that the most costly failures occur when complex systems are treated as merely complicated ones. Engineering leaders who lead teams comprised of subject matter experts possessing deep and exquisite knowledge are critical when dealing with AI systems and judging when those systems are failing. Organizations that remain comfortable questioning assumptions –human and algorithmic alike– will be better positioned to adapt, compete, and lead in an increasingly uncertain world.

References

[1] Z. Bauman, *Liquid Modernity*. Polity Press, 2012.

[2] O. Osiyevskyy, Y. Bao, and C. M. DaSilva, “Using AI to improve economic productivity: A business model perspective,” in *Handbook of Artificial Intelligence and Robotic Process Automation*, A. N. Munoz, Ed. Anthem Press, 2021, pp. 67–76.

[3] R. Geissbauer, S. Schrauf, P. Berttram, and F. Cheraghi, *Digital Factories 2020: Shaping the Future of Manufacturing*. PricewaterhouseCoopers GmbH, 2017.

[4] K. Lakhani, “AI won’t replace humans—but humans with AI will replace humans without AI,” *Harvard Business Review*, 2023.

[5] S. J. Plathottam, A. Rzonca, R. Lakhnori, and C. O. Iloeje, “A review of artificial intelligence applications in manufacturing operations,” *J. Adv. Manuf. Process.*, vol. 7, pp. 1–19, 2023.

[6] H. A. Naqbi, Z. Bahroun, and V. Ahmed, “Enhancing work productivity through generative artificial intelligence: A comprehensive literature review,” *Sustainability*, vol. 16, pp. 1–37, 2024.

[7] “Agentic misalignment: How LLMs could be insider threats,” Anthropic, Jun. 20, 2025. [Online]. Available: https://www.anthropic.com/research/agentic-misalignment

[8] B. Sobrado, “Alibaba’s AI agent mined crypto without permission. Now what?,” *Forbes*, Mar. 11, 2026. [Online]. Available: https://www.forbes.com/sites/boazsobrado/2026/03/11/alibabas-ai-agent-mined-crypto-without-permission-now-what/

[9] G. Morçöl, *A Complexity Theory for Public Policy*. Routledge, 2012.

[10] P. Raman, R. Kowalski, K. Achthan, and P. Nedungadi, “Navigating artificial general intelligence development: Societal, technological, ethical, and brain-inspired pathways,” *Sci. Rep.*, vol. 15, no. 8443, 2025.

[11] J. J. Trukovich, “From reaction to reflection: A recursive framework for the evolution and structure of intelligence,” *BioSystems*, vol. 256, no. 105549, pp. 1–52, 2025.

[12] X. Hao, E. Demir, and D. Eyers, “Beyond human-in-the-loop: Sensemaking between artificial and human intelligence collaboration,” *Sustain. Futures*, vol. 10, no. 101152, pp. 1–20, 2025.

[13] T. S. Kuhn, *The Structure of Scientific Revolutions*, 3rd ed. University of Chicago Press, 1996.

[14] L. D. Kiel, “Lessons from the nonlinear paradigm: Applications of the theory of dissipative structures in the social sciences,” *Soc. Sci. Q.*, vol. 72, no. 3, pp. 431–442, 1991.

[15] H. W. Rittel and M. M. Webber, “Dilemmas in a general theory of planning,” *Policy Sci.*, vol. 4, no. 2, pp. 155–169, 1973.

[16] W. Buckley, D. Schwandt, and J. A. Goldstein, “Society as a complex adaptive system,” *E:CO*, vol. 10, no. 3, pp. 86–112, 2008.

[17] D. J. Snowden and C. F. Kurtz, “The new dynamics of strategy: Sense-making in a complex and complicated world,” *IBM Syst. J.*, vol. 42, no. 3, pp. 462–483, 2003.

[18] A. Giddens, *The Consequences of Modernity*. Stanford University Press, 1990.

[19] D. Kahneman, *Thinking, Fast and Slow*. Farrar, Straus and Giroux, 2011.

[20] J. Burke and R. Ornstein, *The Axemaker's Gift: Technology's Capture and Control of Our Minds and Culture*. Tarcher Penguin, 1997.

[21] P. Winch, *The Idea of a Social Science: And Its Relation to Philosophy*, 2nd ed. Routledge, 1995.

[22] S. D. Krasner, "Structural causes and regime consequences: Regimes as intervening variables," in *International Regimes*, S. D. Krasner, Ed. Cornell University Press, 1983, pp. 1–21.

[23] A. Giddens, *The Constitution of Society*. University of California Press, 1986.

[24] P. Bourdieu, *Outline of a Theory of Practice*. Cambridge University Press, 2005.

[25] J. E. Smith, *The Internet Is Not What You Think It Is: A History, a Philosophy, a Warning*. Princeton University Press, 2022.

[26] N. Postman, *Technopoly: The Surrender of Culture to Technology*. Vintage Books, 1993.

[27] D. C. North, *Institutions, Institutional Change and Economic Performance*. Cambridge University Press, 2002.

[28] K. E. Weick, *Sensemaking in Organizations*. Sage Publications, 1995.

[29] B. Williams and R. Hummelbrunner, *Systems Concepts in Action: A Practitioner's Toolkit*. Stanford University Press, 2011.

[30] C. Argyris and D. A. Schön, *Organizational Learning II: Theory, Method, and Practice*. Addison-Wesley, 1996.

[31] R. D. Stacey, *Complex Responsive Processes in Organization: Learning and Knowledge Creation*. Routledge, 2001.