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Towards Autonomous Infrastructure Management: A Survey of AI-driven Approaches in Platform Engineering

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Abstract

The rapid evolution of digital infrastructure demands innovative solutions to streamline management processes. This survey explores the emerging paradigm of autonomous infrastructure management, focusing on AI-driven approaches within platform engineering. By synthesizing current research and industry practices, we delineate the landscape of autonomous infrastructure management, examining its key components, challenges, and potential benefits. We discuss various AI techniques, including machine learning, optimization algorithms, and cognitive computing, employed to enable autonomy in infrastructure management tasks. Furthermore, we analyze real-world implementations and assess their effectiveness in enhancing system reliability, scalability, and efficiency. Through this comprehensive review, we aim to provide insights into the trajectory of autonomous infrastructure management and highlight avenues for future research and development.

Keywords: Autonomous Infrastructure Management, AI-driven Approaches, Platform Engineering, Machine Learning, Optimization Algorithms, Cognitive Computing, Reliability, Scalability, Efficiency.

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Introduction

In the digital era, where businesses rely heavily on complex infrastructures to support their operations, the efficient management of these infrastructures becomes paramount. Traditional methods of infrastructure management often struggle to keep pace with the dynamic nature of modern systems, leading to inefficiencies, vulnerabilities, and increased operational costs. To address these challenges, a paradigm shift towards autonomous infrastructure management has emerged, leveraging the capabilities of artificial intelligence (AI) to automate and optimize various aspects of infrastructure operations.

Platform engineering plays a crucial role in shaping the architecture and functionality of modern infrastructures, serving as the foundation upon which applications and services are built and deployed. As the complexity of platforms continues to grow, there is a pressing need for innovative approaches to manage and maintain them effectively. AI-driven techniques offer promising solutions by enabling platforms to adapt, self-optimize, and autonomously respond to changing conditions and demands.

This survey aims to provide a comprehensive overview of the state-of-the-art AI-driven approaches in autonomous infrastructure management within the context of platform engineering. By synthesizing insights from both academic research and industry practices, we seek to elucidate the key concepts, methodologies, challenges, and potential benefits associated with this emerging paradigm. Through a systematic examination of relevant literature and real-world implementations, we aim to shed light on the current landscape of autonomous infrastructure management and its implications for the future of platform engineering.

In this introduction, we first define the concept of autonomous infrastructure management and highlight its significance in the context of modern digital ecosystems. We then outline the objectives and scope of this survey, followed by an overview of the structure of the paper. Finally, we discuss the anticipated contributions and potential implications of our research in advancing the understanding and adoption of AI-driven approaches in platform engineering and infrastructure management.

Objectives:

1. Examine the Current State of Autonomous Infrastructure Management: The primary objective is to assess the existing landscape of autonomous infrastructure management, focusing on AI-driven approaches within platform engineering. This involves analysing the literature, frameworks, and real-world implementations to understand the scope, capabilities, and limitations of autonomous infrastructure management systems.

2. Identify Key AI Techniques and Methodologies: Another objective is to identify and categorize the AI techniques

and methodologies utilized in autonomous infrastructure management. This includes exploring machine learning algorithms, optimization techniques, cognitive computing models, and other AI-driven approaches deployed to enable automation, self-optimization, and intelligent decision-making in managing complex digital infrastructures.

3. Evaluate the Effectiveness and Impact of AI-driven Approaches: The survey aims to evaluate the effectiveness and impact of AI-driven approaches on the performance, reliability, scalability, and efficiency of platform engineering and infrastructure management. By analysing case studies, experimental results, and industry best practices, we seek to assess how AI technologies enhance system resilience, reduce operational overhead, and enable proactive maintenance and optimization strategies.

Methodology

1. Selection Criteria: A set of inclusion and exclusion criteria are established to guide the selection of literature for analysis. Inclusion criteria may include relevance to autonomous infrastructure management, focus on AI-driven approaches, recent publication dates, and empirical studies or case studies demonstrating real-world implementations. Exclusion criteria may involve outdated or irrelevant publications, non-peer-reviewed sources, and works lacking empirical evidence or practical relevance.

2. Data Extraction and Synthesis: Relevant information, including key concepts, methodologies, AI techniques, case studies, and findings, is extracted from selected literature sources. This data is synthesized to identify common themes, trends, challenges, and opportunities within the field of autonomous infrastructure management. Information extraction may involve categorizing AI techniques, summarizing experimental results, and comparing different approaches based on performance metrics and effectiveness.

3. Classification of AI Techniques: I techniques utilized in autonomous infrastructure management are classified and categorized based on their functionality and application domains. This classification may include machine learning algorithms (e.g., supervised learning, unsupervised learning, reinforcement learning), optimization techniques (e.g., genetic algorithms, simulated annealing), natural language processing (NLP) models, and cognitive computing frameworks.

4. Analysis and Interpretation: The synthesized data is analysed to provide insights into the current state of autonomous infrastructure management and the role of AI-driven approaches in platform engineering. This involves interpreting the findings, identifying gaps in the literature, discussing challenges and limitations, and highlighting potential avenues for future research and development.

5. Validation and Peer Review: The methodology and findings of the survey are validated through peer review and expert feedback. Peer reviewers assess the rigor, validity, and relevance of the methodology, data analysis, and interpretations, providing constructive criticism and suggestions for improvement. This iterative process helps ensure the reliability and credibility of the survey results.

Background:

If the infrastructure of the future mirrors that of the past or present, it would signify a substantial failure on the part of engineers and infrastructure managers. The constant and escalating changes in climate, technology, society, economy, and institutions suggest that the challenges ahead will likely be vastly different and more intricate than those faced today (Allenby, 2011; Marchant et al., 2011; Markolf et al., 2018). With a rapidly urbanizing global population of roughly 7.7 billion and a concurrent rise in the middle class with evolving consumption patterns and food demands, the relationship between humanity and the planet is undergoing significant transformation. These dynamics are pivotal in propelling and hastening the integration of human, natural, and built systems, resulting in complex, interconnected, and rapidly evolving systems at all levels—from local infrastructures to regional and global networks (Lo and Yeung, 1998; NRC (US National Research Council), 2003; Chester et al., 2019).

Addressing the need for infrastructure to adapt, transform, and function effectively amidst complexity and rapid change increasingly involves the integration of infrastructure and information systems, including various artificial intelligence (AI) capabilities, into the design, construction, operation, and maintenance processes. However, implementing this strategy successfully necessitates a clear understanding of relevant information, communication, and computational frameworks, and how they interact in practice—a challenging task in today's environment. Consequently, the rise of a new global infrastructure with profound implications for humanity, its institutions, and the planet has largely gone unnoticed and unacknowledged. This new infrastructure, referred to as cognitive infrastructure, already permeates nearly every aspect of the world we inhabit (Allenby, 2019).

While each infrastructure system and sector has its own distinct characteristics, what often goes unrecognized is that many of these infrastructures and technologies are not just standalone entities but are also being integrated into an emerging infrastructure known as the "cognitive infrastructure." Functionally defined as encompassing information processing, reasoning, learning, problem-solving, decision-making, and other cognitive processes (Squire, 2009), the cognitive infrastructure is rapidly ascending. For instance, the proliferation of machine-to-machine connections is projected to rise from 6.1 billion in 2018 to 14.7 billion by 2023 (Cisco, 2020). Similarly, expenditure on sensors and IoT-related technologies is expected to reach $1.2 trillion by 2022 (Columbus, 2018), with many of these devices integrating cognitive capabilities through the accelerated deployment of AI technologies such as neural networks (Lee, 2018). Essentially, the confluence of advancing capabilities across seemingly disparate infrastructures and technologies is engendering a cognitive infrastructure, bound together by AI and a myriad of institutional structures, distributed globally, and evolving emergent systemic and behavioral capabilities.

Cognitive infrastructure presents challenges that traditional infrastructure systems do not. Operating at a level beyond human comprehension or perception, cognitive infrastructure operates at significantly higher bandwidths, speeds, and complexity levels than individuals can access. Unfortunately, this disconnect was apparent in tragic incidents like the Lion Air Flight 610 and Ethiopian Airlines Flight 302 accidents, where the divergence between the development of automated flight control systems in Boeing 737-MAX planes and pilot training and implementation contributed significantly to the accidents (Gelles, 2019; Wise, 2019; Herkert et al., 2020; U.S. House Committee on Transportation Infrastructure, 2020). Effectively integrating human and machine cognition into infrastructure systems thus emerges as a significant professional challenge that has yet to be adequately addressed.

Integrating cognitive infrastructure is crucial for engineers, technologists, and policymakers striving to develop resilient, agile, and adaptive infrastructure systems capable of meeting present and future demands. However, recognizing the cognitive infrastructure as a whole is imperative to responsibly meeting the demand for better infrastructure. Without a systemic perspective, issues like security vulnerabilities stemming from the adoption of AI technologies may be overlooked. Designers of IoT devices, for example, may embed sensors and communication capabilities without fully understanding their place within the overarching cognitive infrastructure, risking vulnerability to adversarial attacks.

While it may be premature to ponder how humans should respond as critical cognitive functions transition to higher-level techno-human systems embedded in a global cognitive infrastructure, it is not too early to acknowledge the emergence of this new infrastructure. Understanding and anticipating its implications is increasingly vital. Without this initial step, ethical, rational, and appropriate infrastructure design, construction, operation, maintenance, and the necessary educational and institutional structures to support them will remain elusive. Thus, this paper initiates a broad discussion on AI and its relationship to infrastructure, exploring various tasks and services within infrastructure systems that may be augmented or replaced by AI, and concludes with a discussion on broader implications as AI and infrastructure systems become increasingly intertwined in the forthcoming decades.

AI and Infrastructure Leadership in the Context of Complexity

Defining "AI" proves elusive, as acknowledged by the U.S. National Science and Technology Council in its 2016 report. Some define AI broadly as computerized systems displaying behaviors traditionally associated with intelligence, while others define it as systems capable of solving complex problems or achieving goals in diverse real-world circumstances. Here, we use "AI" to encompass big data and analytics dimensions, envisioning a future where humans leverage AI to navigate an increasingly intricate world.

In managing dynamic and complex systems, specific leadership capabilities are essential. Administrative Leadership, prevalent in stable conditions, relies on formalized structures to govern organizations. Conversely, Adaptive Leadership thrives in changing or chaotic environments, emphasizing adaptability, creativity, and learning. Enabling Leadership, crucial for shifting between Administrative and Adaptive practices as conditions evolve, entails creating conditions for flexibility. Evaluating which AI techniques best support each leadership style becomes increasingly pertinent in the evolving landscape of AI applications in infrastructure.

Several tasks align with AI applications in infrastructure, including pattern recognition, system control, optimization, and prediction. A variety of techniques such as rule-based systems, genetic algorithms, and artificial neural networks have been applied across various civil engineering domains. While not exhaustive, these applications highlight the diverse capabilities of AI in infrastructure management.

Different AI techniques may suit stable and unstable conditions differently. Techniques like Case-Based Reasoning (CBR), adept at solving novel problems by referencing similar past cases, align well with stable Administrative Leadership contexts, aiding in system control, planning, and prediction. Conversely, techniques like Artificial Neural Networks (ANN), which mimic human brain processing, excel in complex, data-intensive, and dynamic scenarios typical of Adaptive Leadership.

Overall, AI complements and, in some cases, replaces Administrative and Adaptive Leadership roles within infrastructure systems. Humans and institutions must recognize the benefits and tradeoffs among different leadership approaches and AI roles. Furthermore, considerations are warranted regarding the frameworks, resources, and knowledge systems necessary to facilitate seamless transitions between leadership approaches as future conditions fluctuate.

The following section delves deeper into the roles and tasks AI may undertake in infrastructure systems moving forward, examining how AI can support infrastructure leadership amidst complexity.

AI Intelligences and Tasks within Infrastructure Systems

Assessing AI's potential to enhance or replace existing capabilities necessitates a thorough examination of the intelligences involved. Huang and Rust (2018) posit that AI job replacement primarily occurs at the task level, with "lower" intelligence tasks—such as repetitive and routine tasks—being more susceptible to AI replacement than "higher" intelligence tasks, which may involve emotional or empathetic aspects. Adapting Huang and Rust's framework to the context of infrastructure systems—primarily service providers—allows us to link various infrastructure services to four types of intelligences: Mechanical, Analytical, Intuitive, and Empathetic. We outline cases, supported by examples where feasible, of how AI has or could potentially replace various infrastructure-related tasks at each intelligence level.

Mechanical Intelligence

At the lowest level of intelligence lies Mechanical Intelligence, characterized by routine tasks, minimal creativity, and a focus on efficiency and consistency (Huang and Rust, 2018). AI at this level operate based on rules and excel in performing repetitive, homogenous tasks efficiently and reliably. They often outperform humans in consistency, reliability, and work-rate.

However, Mechanical AI encounters challenges in scaling to the systems level, limiting its applicability to the large-scale and dynamic infrastructure systems typical of modern cities. These AI are optimized for well-bounded and tightly constrained situations, typically operated by a single unit or a small, integrated group of components. As operations expand in network, scale, or complexity, Mechanical AI may struggle to cope, leading to potential overwhelm. In such scenarios, AI at higher intelligence levels may prove more suitable and effective.

Analytical Intelligence

The second tier of intelligence, Analytical Intelligence, relies on processing information, making decisions, problem-solving, and adapting to new data (Huang and Rust, 2018). Tasks at this level are often complex, requiring substantial data analysis, yet they possess a level of consistency and predictability. AI operating at this level utilize algorithms to iteratively learn from and extract insights from extensive or continuous datasets. These Analytical AI systems are increasingly interconnected units rather than standalone entities. Despite their capabilities, human interpretation and intuition remain essential complements to AI at this level. While AI offers diverse and valuable decision support, humans retain ultimate decision-making authority.

One significant challenge with Analytical AI is its limited adaptability to problems lacking historical parallels (Chen et al., 2008). This limitation becomes particularly pertinent in managing infrastructure systems amidst a changing climate. Non-stationarity, the concept that past data may not accurately predict future trends and conditions, poses a significant challenge for urban and infrastructure systems (Milly et al., 2008; Koutsoyiannis, 2011; Lins, 2012). Consequently, Analytical AI should not be viewed as an "off-the-shelf" solution for a broad array of problems. Engineers and infrastructure managers must carefully consider the nuances, strengths, and weaknesses of AI when applying it to infrastructure significantly impacted by climatic variables like weather prediction, stormwater systems, and flood management.

Intuitive Intelligence

The subsequent level of intelligence, Intuitive Intelligence, relies on experience-based thinking and creativity, addressing contextual, chaotic, and idiosyncratic tasks (Huang and Rust, 2018). AI functioning at this level emulate human-like learning and adaptation based on prior experiences and new information, emphasizing problem understanding within specific contexts—a characteristic shared by both human and AI Intuitive Intelligence.

However, applying Intuitive AI faces challenges in solving "wickedly complex" problems devoid of singular "right" solutions, such as natural resource allocation and management (Chester and Allenby, 2019a). The algorithms supporting Intuitive AI often rely on human-defined data to determine desired outcomes, hindering AI training and learning in situations with unclear solutions. Despite these challenges, AI remains invaluable for generating, exploring, and analysing various scenarios, with human stakeholders retaining responsibility for final decisions.

Another challenge lies in the "black-box" nature of Intuitive AI, where it may produce opaque outcomes without a deep understanding of underlying systems and processes (Chen et al., 2008). While some level of opacity may be inevitable due to complexities surpassing human cognitive capabilities, discussions on the acceptable level of "black-box" transparency are essential as AI becomes increasingly embedded in infrastructure systems. Communities, policymakers, and infrastructure managers must engage in open discussions about the potential implications of relinquishing control to software and algorithms, weighing potential benefits against drawbacks in diverse contexts.

Empathetic Intelligence

At the pinnacle of intelligence lies Empathetic Intelligence, which hinges on empathy, social interaction, and communication. Tasks involving Empathetic Intelligence revolve around comprehending emotions, responding appropriately to others' emotions, and influencing the emotions of others (Huang and Rust, 2018). AI operating at this level exhibits behaviors akin to having feelings and strives to understand, resonate with, and influence human emotions. Although still in its infancy, initial applications of Empathetic AI often center on emotional analytics (Abou-Zeid and Ben-Akiva, 2010; Quercia et al., 2014). However, the high demand for social and communication skills at this level suggests that human involvement will remain indispensable in the foreseeable future.

Similar to Intuitive AI, Empathetic AI faces considerable challenges when dealing with wickedly complex problems. These challenges stem from the diverse norms and values held by stakeholders within a system, which may not be clearly defined or codified and can evolve over time. Consequently, Empathetic AI struggles to comprehend the varying and sometimes conflicting values among stakeholders and lacks the ability to be trained around a universally agreed-upon solution or outcome (Baum, 2020).

Furthermore, Empathetic AI is susceptible to various biases, whether implicit or explicit, originating from the individuals who develop the algorithms or the data used for training (Tomer, 2019). For instance, facial recognition AI has exhibited racial biases (Grother et al., 2019). Fully eliminating biases from Empathetic AI systems is unlikely. Hence, it is imperative for citizens, decision-makers, and AI developers to engage in transparent discussions regarding the appropriate applications of Empathetic AI, considering the potential unintended consequences arising from biases.

Figure 1 offers a concise overview of the key characteristics of each intelligence level, exemplifying instances from infrastructure systems, and current/potential AI applications across each intelligence level.

How Could AI Revolutionize Infrastructure Services and Introduce Novel Capabilities?

An examination of the four levels of intelligence within infrastructure systems offers valuable insights. Firstly, it is evident that AI, particularly in terms of automation, has already found extensive application in Mechanical tasks. While there remains room for AI growth and development at this level, it seems that we have largely reached a saturation point, reducing the likelihood of significant transformative changes. This underscores the potential for AI to support and enhance Administrative Leadership roles within infrastructure systems. Conversely, Analytical tasks represent the arena where AI is poised to exert the greatest disruption in the foreseeable future. As AI capabilities continue to advance, fueled by increasing data accessibility, decreasing computing costs, and advancements in techniques like Artificial Neural Networks (ANNs), Analytical tasks (and the roles of Adaptive Leadership) are increasingly susceptible to AI intervention. Given that a considerable portion of engineering and infrastructure tasks are analytical in nature, the augmentation or replacement of Analytical tasks by AI is anticipated to bring about fundamental and transformative changes to infrastructure systems as we currently understand them.

Therefore, looking ahead, engineers and infrastructure managers must prioritize strengthening and emphasizing Intuitive and Empathetic tasks and intelligences, thereby enhancing Enabling Leadership capabilities. This is crucial because, despite humans exhibiting higher levels of Intuitive and Empathetic Intelligence compared to AI (a trend likely to persist for the foreseeable future), there is still room for improvement. Human error remains a concern, both in routine and unexpected circumstances. Additionally, Empathetic Intelligence is presently not widely integrated or considered in the development of engineered and infrastructure systems. Consequently, to effectively balance the Mechanical (i.e., Administrative Leadership) and Analytical (i.e., Adaptive Leadership) advantages of AI with the Intuitive and Empathetic (i.e., Enabling Leadership) strengths of humans, continuous learning from past errors and the cultivation of skills to make proficient decisions under unforeseen conditions are imperative. Moreover, concerted and ongoing efforts should be directed towards enhancing our capacity to incorporate social, emotional, and equity dynamics into engineering and infrastructure planning and implementation.

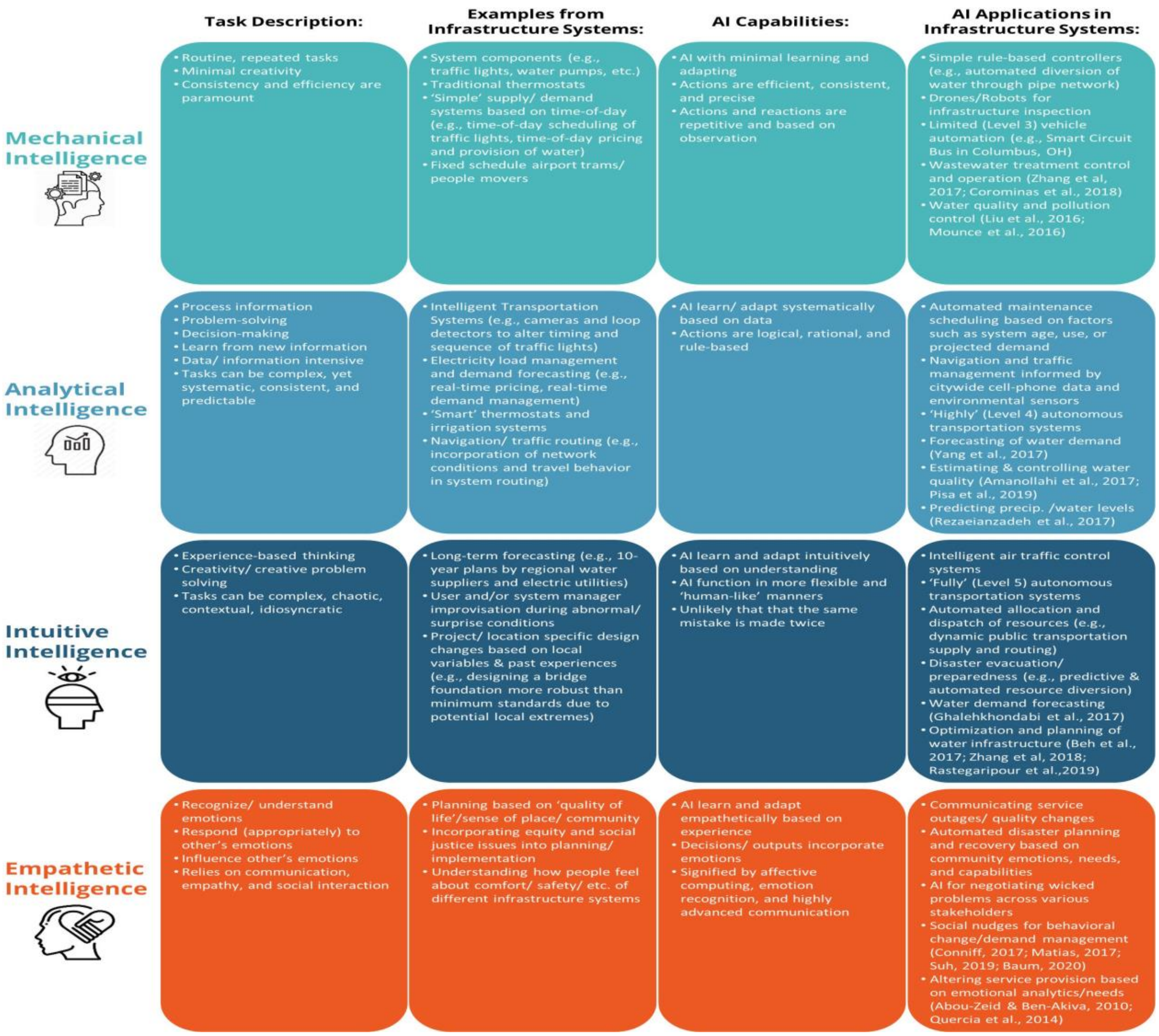
Discussion and Conclusion

Understanding how AI technologies are likely to revolutionize infrastructure is crucial for adapting to the dynamic conditions in which these systems operate. As evidence mounts of the accelerating and unpredictable nature of infrastructure environments, it becomes imperative for design and management strategies to exhibit agility and flexibility. Historically, new technologies have necessitated the creation of control processes to harness their capabilities towards institutional goals. For instance, the industrial revolution brought about engines and novel processes, prompting the establishment of new institutions and procedures to regulate their unprecedented energy output.

However, the control dynamics surrounding AI technologies may deviate from historical patterns. AI, fundamentally centered on augmenting and potentially replacing cognition, presents unique challenges. Unlike earlier technological advancements where control was attainable, the cognitive infrastructure facilitated by AI implies a shift in our understanding of control. Instead of exerting full control, efforts may need to focus on establishing symbiotic relationships with AI, acknowledging that these cyber-technologies will guide us in ways that may not always be fully comprehensible.

Nevertheless, AI holds the potential to assist us in navigating increasingly intricate environments. By designing knowledge systems, institutions can empower sensing and analytical capabilities to adapt to evolving conditions. Leveraging AI technologies effectively can empower infrastructure systems to respond adeptly to the multifaceted challenges posed by modern society.

In conclusion, while AI introduces novel capabilities and challenges traditional notions of control, embracing these technologies with a forward-thinking mindset can enable us to navigate the complexities of the future infrastructure landscape. It is imperative for institutions and stakeholders to remain proactive in understanding and harnessing the transformative potential of AI in infrastructure design and management.



Capabilities (paired with different leadership styles) are essential for operating in both calm and chaotic environments (Miller and Munoz-Erickson, 2018). As our systems and their operating environments grow increasingly complex, surpassing the cognitive grasp of any single group or institution, AI may provide indispensable cognitive insights to ensure system adaptability, continued service provision, and meeting evolving needs.

The mapping of AI applications to intelligences and leadership roles appears to endorse the varied approaches necessary for addressing domains of complexity. The Cynefin framework categorizes systems as simple, complicated, complex, or chaotic, with disorder governing transitions between domains (Snowden and Boone, 2007; Chester and

Allenby, 2019a). Each domain necessitates a distinct approach to tackling challenges. While infrastructure traditionally belonged to the domain of complicated systems, they are now increasingly perceived as complex (Chester and Allenby, 2019b). Complicated systems demand data collection, analysis, and decision-making, while complex systems require probing, testing, and a commitment to adaptability and transformation. The intelligence mapping in Figure 1 offers a valuable array of AI applications applicable to infrastructure in both complicated and complex environments. Mechanical and Analytical Intelligences align well with complicated situations, where system behaviors are predictable and environments relatively stable. Intuitive and Empathetic Intelligences correspond to complex systems, where perturbations can lead to unpredictable behaviors, and "satisficing" is necessary to manage wicked problems across technical and social domains (Chester and Allenby, 2019a). While all intelligences are essential at different times during system operation, developing and deploying Intuitive and Empathetic Intelligences (and Enabling Leadership) in humans and institutions, alongside the deployment of Administrative and Adaptive Leadership via AI, seems imperative to address the increasing complexity and non-stationarity of our systems and their environments.

Ultimately, we are at the early stages of AI development and application in infrastructure systems. The topics discussed in this paper serve as an initial exploration of some of the key opportunities and challenges associated with AI in infrastructure systems—especially concerning the leadership and skills required to confront the complex challenges of the Anthropocene. Future avenues of inquiry could include interviews and surveys aimed at understanding infrastructure practitioners' current perspectives on the potential benefits and drawbacks of AI. Additionally, further investigation into which level of intelligence is most suitable for specific problems/contexts, as well as a detailed assessment of the AI techniques likely to be most effective/appropriate, would be beneficial. Prior to or in conjunction with these efforts, open, candid, and iterative discussions across society are necessary to deliberate on the level of cognitive infrastructure we are comfortable with and the degree of "control" we are willing to delegate to cognitive infrastructure. Through these actions, engineers and infrastructure stakeholders can strive to strike the right balance between human and AI capabilities necessary to navigate our increasingly complex world effectively and equitably.

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