



Opportunities and Challenges for Artificial Intelligence Applications in Infrastructure Management During the Anthropocene

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Pervasive and accelerating climatic, technological, social, economic, and institutional change dictate that the challenges of the future will likely be vastly different and more complex than they are today. As our infrastructure systems (and their surrounding environment) become increasingly complex and beyond the cognitive understanding of any group of individuals or institutions, artificial intelligence (AI) may offer critical cognitive insights to ensure that systems adapt, services continue to be provided, and needs continue to be met. This paper conceptually links AI to various tasks and leadership capabilities in order to critically examine potential roles that AI can play in the management and implementation of infrastructure systems under growing complexity and uncertainty. Ultimately, various AI techniques appear to be increasingly well-suited to make sense of and operate under both stable (predictable) and chaotic (unpredictable) conditions. The ability to dynamically and continuously shift between stable and chaotic conditions is critical for effectively navigating our complex world. Thus, moving forward, a key adaptation for engineers will be to place increasing emphasis on creating the structural, financial, and knowledge conditions for enabling this type of flexibility in our integrated human-AI-infrastructure systems. Ultimately, as AI systems continue to evolve and become further embedded in our infrastructure systems, we may be implicitly or explicitly releasing control to algorithms. The potential benefits of this arrangement may outweigh the drawbacks. However, it is important to have open and candid discussions about the potential implications of this shift and whether or not those implications are desirable.

Keywords: climate change, infrastructure, artificial intelligence, complexity, anthropocene

INTRODUCTION

If future infrastructure resembles that of the past, or even of today, it will represent a profound failure on the part of engineers and infrastructure managers. Pervasive and accelerating climatic, technological, social, economic, and institutional change signal that the challenges of the future will likely be vastly different and more complex than they are today (Allenby, 2011; Marchant et al., 2011; Markolf et al., 2018). The relationship of the human species to the planet is changing dramatically given a rapidly urbanizing global population of roughly 7.7 billion, and a parallel growing middle class with changing consumption and food demands. These dynamics play a

key role in driving and accelerating the integration of human, natural, and built systems to create complex, interlinked, and rapidly evolving systems at all scales—from local infrastructure to regional and global systems (Lo and Yeung, 1998; NRC (US National Research Council), 2003; Chester et al., 2019).

The need for infrastructure to adapt, transform, and perform competently under conditions of complexity and accelerating change is increasingly being met by integrating infrastructure and information systems [including various artificial intelligence (AI) capabilities] into infrastructure design, construction, operation, and maintenance. However, successfully implementing this strategy requires a clear and concise understanding of relevant information, communication, and computational frameworks, as well as how they functionally couple together in practice—a particularly difficult task in today's environment. Therefore, it is not surprising that the rise of a new global infrastructure with profound implications for humans, their institutions, and their planet has gone both unperceived and unremarked. This is the *cognitive infrastructure*, and it already permeates virtually every aspect of our world (Allenby, 2019). In particular, each infrastructure system and sector has its own companies, experts, investors, and users. But what is often not recognized is that many of these infrastructures and technologies are not only coherent entities themselves, but also being integrated into an emergent infrastructure that includes integrated functionality from many sources: the “cognitive infrastructure.”

Taking a functional definition of “cognition” (i.e., information processing, reasoning, remembering, learning, problem-solving, decision-making, etc.) (Squire, 2009), the accelerating rise of cognitive infrastructure becomes evident. For example, machine-to-machine connections are anticipated to increase from 6.1 billion in 2018 to 14.7 billion in 2023 (Cisco, 2020). Similarly, spending on sensors and other technologies related to the Internet-of-Things (IoT) is expected to reach \$1.2 Trillion in 2022 (Columbus, 2018). Most of these sensors and devices will generate vast amounts of data and integrate some cognitive capability via accelerating deployment of AI technology such as neural nets (Lee, 2018). In short, accelerating capability and capacity across a number of apparently unrelated infrastructures and technologies is generating an infrastructure, tied together by AI and a vast array of institutional structures, that (1) contains the functional components of cognition and ever-more powerful networks operationally linking them together, (2) is distributed around the world, and (3) contains evolving and emergent systemic and behavioral capabilities. Simply put, we are building a pervasive cognitive infrastructure without fully recognizing it, and we are doing so rapidly and at global scale.

Cognitive infrastructure offers challenges that more traditional infrastructure systems do not. For one, it operates at a level that humans can neither fully understand nor perceive—people are relatively low bandwidth cognitive mechanisms in a world where even contemporary cognitive infrastructure operates at far higher bandwidths, much faster speeds, and higher levels of complexity than individuals can access. This can unfortunately be seen in the tragic Lion Air Flight 610 and Ethiopian Airlines Flight 302 incidents. Although many factors appeared to have been at play, the disconnect between the development of the automated flight control systems in the

Boeing 737-MAX planes and the training and implementation by the pilots was a key element in the accidents (Gelles, 2019; Wise, 2019; Herkert et al., 2020; U.S. House Committee on Transportation Infrastructure., 2020). Thus, determining how to effectively integrate human and machine cognition into infrastructure systems becomes a significant professional challenge that, so far, appears to have not been adequately and effectively considered.

Integrating cognitive infrastructure is a critical capability as engineers, technologists, and policymakers try to develop infrastructure systems that are as resilient, agile, and adaptive as current (and future) conditions demand. But knowing that incorporating sensor and AI-driven adaptability into infrastructure can make it more efficient and responsive to changing conditions is only the beginning. Understanding the cognitive infrastructure as a whole is required to fully and responsibly meet the demands for better infrastructure. For example, designers of IoT devices embed sensors and communication capabilities in their products as a matter of required functionality. But, absent a systemic perspective on security and the devices' place within the overarching cognitive infrastructure, there is the potential for underappreciating/misunderstanding issues like the vulnerability to adversarial attacks that the embrace of AI technologies can create. These potential drawbacks are ultimately a symptom of understanding a few of the constituent technologies (e.g., AI) in isolation, but failing to understand that it is the cognitive infrastructure, not just those individual technologies, that their infrastructure design is integrating.

It is premature to consider tantalizing questions such as how humans should respond as critical cognitive functions migrate to higher level techno-human systems embedded in a global cognitive infrastructure. However, it is not premature to recognize that this new infrastructure, itself a reflection and driver of the complexity and challenges of the Anthropocene, is already emergent. Additionally, trying to perceive and understand some of these implications is an increasingly imperative and necessary professional responsibility. Without that first step, ethical, rational, and appropriate infrastructure design, construction, operation, maintenance (as well as the educational and institutional structures to support them) will remain beyond reach. As such, this paper provides a broad discussion about what AI is and how it relates to infrastructure. We then explore various tasks and services within infrastructure systems that may be enhanced and/or replaced by AI. Finally, we conclude with a discussion of some of the broader implications that may emerge as AI and infrastructure systems become increasingly entwined in the coming decades.

AI AND INFRASTRUCTURE LEADERSHIP IN THE CONTEXT OF COMPLEXITY

“AI” is a fuzzy term. As the U. S. National Science and Technology Council says in its 2016 report, “There is no single definition of AI that is universally accepted by practitioners. Some define AI loosely as a computerized system that exhibits behavior that is commonly thought of as requiring intelligence.

Others define AI as a system capable of rationally solving complex problems or taking appropriate actions to achieve its goals in whatever real world circumstances it encounters.” Herein, we use “AI” to include big data and analytics dimensions, but ultimately describe the leadership and intelligence capabilities that are needed to replace or augment people. In doing so we envision a future where humans employ AI to make sense of an increasingly complex world.

In managing dynamic and complex systems and environments, several leadership capabilities are needed to address continually changing conditions (Uhl-Bien et al., 2007). *Administrative Leadership*, what we largely practice today, is well-suited for stable conditions and is made up of bureaucracies that formalize the structure and function of organizations. However, in the changing or chaotic conditions that define complex environments, *Adaptive Leadership* is preferred. Under this approach, adaptability, creativity, and learning are emphasized in order to make sense of and navigate complex and uncertain conditions. Perhaps of most importance is *Enabling Leadership*, the ability to shift between *Administrative* and *Adaptive Leadership* practices as conditions shift from stable to chaotic. *Enabling Leadership* involves creating structural, financial, and knowledge conditions for flexibility (Uhl-Bien et al., 2007). In assessing the AI landscape, evaluating which techniques are best positioned to support each leadership style is increasingly useful.

Given this context, there are several tasks for which AI applications in infrastructure are well-suited, including pattern recognition, classification, clustering, categorization, system control, function approximation (e.g., regression analysis), optimization, and prediction/forecasting (Chen et al., 2008; Brynjolfsson and McAfee, 2017; Eggimann et al., 2017). In order to accomplish these tasks, a variety of techniques and approaches can be applied, such as rule-based systems (RBS), genetic algorithms, cellular automata, Fuzzy Systems, Multi-agent systems, Swarm Intelligence, Case-based reasoning (CBR), and Artificial Neural Networks (ANN) (Chen et al., 2008). For example, AI (particularly genetic algorithms, Artificial Neural Networks, and Deep Learning) has been applied in a variety of civil engineering contexts including optimum design of structures (Hajela and Berke, 1991; Adeli and Park, 1995; Camp et al., 2003; Hadi, 2003), concrete strength modeling (Yeh, 1999; Ni and Wang, 2000; Lee and Ahn, 2003; Al-Salloum et al., 2012), predicting geotechnical settlement and liquefaction (Shahin et al., 2002; Young-Su and Byung-Tak, 2006), earthquake engineering (Lee and Han, 2002; Arslan, 2010; Yilmaz, 2011), concrete design mix (Jayaram et al., 2009), prediction and forecasting of water resources and flooding (Maier and Dandy, 2000; Mitra et al., 2016; Alexander et al., 2018; Lin et al., 2018; Yu et al., 2018; Zamanisabzi et al., 2018; Li et al., 2019), water quality and sediment modeling (Nagy et al., 2002; Zhang et al., 2010; Barzegar et al., 2016; Sabouri et al., 2016), irrigation and water-delivery scheduling (Nixon et al., 2001; Karasekreter et al., 2013), rainfall-runoff modeling (Minns and Hall, 1996; Tokar and Johnson, 1999; Cheng et al., 2005, 2017; Dixon, 2005; Jeong and Kim, 2005; Abraham and See, 2007; Young et al., 2017), and evapotranspiration modeling (Tabari et al., 2010; Kumar et al., 2020)—additional examples can also be found in **Figure 1** (e.g., Liu et al.,

2016; Mounce et al., 2016; Amanollahi et al., 2017; Beh et al., 2017; Conniff, 2017; Ghalekhondabi et al., 2017; Matias, 2017; Rezaeianzadeh et al., 2017; Yang et al., 2017; Zhang et al., 2017, 2018; Corominas et al., 2018; Pisa et al., 2019; Rastegaripour et al., 2019; Suh, 2019). The scope and purpose of this article is not to provide a comprehensive overview and discussion of these different techniques. For that, we refer the readers to works by Flood and Kartam, 1994a,b; Kartam et al., 1997; Adeli, 2001; Flood, 2001; Flintsch and Chen, 2004; Chandwani et al., 2013; Ye et al., 2019); and (Falcone et al., 2020). Nonetheless, a brief discussion about the ways in which various AI techniques may (or may not) support infrastructure leadership in stable and chaotic environments appears warranted and is included below.

Some AI techniques may be well-suited for enhancing operations during stable conditions, while others may be more appropriate for supporting leadership during unstable times (e.g., extreme events, funding uncertainty, pandemics, etc.). For example, techniques that establish algorithms to solve novel problems by recalling and referencing similar problems from the past (e.g., CBR) are particularly suitable for the well-defined and stable conditions endemic of *Administrative Leadership*. In this context, these approaches can be particularly useful for applications related to system control, planning, prediction, and diagnosis (Chen et al., 2008). Conversely, techniques that mimic the manner in which human brains process information via a series of layered and interconnected processing units (e.g., ANN) are increasingly well-suited for the complex, data-intensive, multivariable, and dynamic conditions (i.e., instability) that warrant *Adaptive Leadership*. In this context, AI can help make predictions (based on a series of input patterns) and/or intuit relationships between various inputs—even in situations where the underlying rules and structure of the problem may be unknown or hard to express (Chen et al., 2008). Overall, various forms of AI appear poised to greatly complement (or even in some cases replace) *Administrative* and *Adaptive Leadership* activities and roles within our infrastructure systems. In turn, the humans and institutions that interact with and govern our infrastructure systems may play an increasingly important role as the primary source of *Enabling Leadership* within our systems. Thus, it will be crucial for humans and institutions to recognize the benefits and tradeoffs among the different types of leadership, roles, and services provided by various AI. Perhaps most importantly, additional consideration appears warranted regarding the frameworks, resources, structures, and knowledge systems that may be needed to facilitate the smooth and agile transition between leadership approaches as future conditions continually fluctuate between stable and chaotic. The following section explores this issue further by examining some of the various roles and tasks AI may fill in infrastructure systems moving forward.

AI INTELLIGENCES AND TASKS WITHIN INFRASTRUCTURE SYSTEMS

Evaluating the potential for AI to augment or replace existing capabilities requires a critical examination of the intelligences involved. Huang and Rust (2018) assert that AI job replacement

fundamentally occurs at the task level, and that “lower” intelligence tasks (e.g., repetitive, routine tasks) are easier for AI to replace than “higher” intelligence tasks (e.g., highly emotional/empathetic tasks). Given that, at their core, infrastructure systems are service providers, we adapt Huang and Rust’s framework to (1) link various infrastructure services to the four types of intelligences described by Huang and Rust (i.e., *Mechanical*, *Analytical*, *Intuitive*, and *Empathetic*), and (2) outline cases (and examples where possible) of how AI has and/or could potentially replace various infrastructure-related tasks at each level of intelligence—see **Figure 1**.

Mechanical Intelligence

The “lowest” level of intelligence is *Mechanical*, which is defined by routine and repeated tasks, minimal creativity, and an emphasis on efficiency and consistency (Huang and Rust, 2018). AI at this level are rule-based and are well-suited for homogenous tasks that are repetitive, performed often, and unsophisticated (Sawhney, 2016; Huang and Rust, 2018). As a result, AI at this level often have an advantage over humans with respect to consistency, reliability, and work-rate (Huang and Rust, 2018).

One of the primary challenges associated with *Mechanical* AI is that it can be difficult to scale to the systems level, which in turn can limit its applicability to the large-scale and dynamic infrastructure systems typical of modern cities. *Mechanical* tasks are typically conducted by a single unit (or small, tightly integrated group of components). As a result, this type of AI is best suited for well-bounded and tightly constrained situations. Thus, increasing the network, scale, and/or state of operations adds complexity that can eventually overwhelm the system. Under these circumstances, AI at higher levels of intelligence will likely be more appropriate and effective.

Analytical Intelligence

The second level of intelligence is *Analytical*, which relies on the ability to process information, make decisions, problem solve, and adjust to new information (Huang and Rust, 2018). *Analytical* Intelligence is defined by tasks that can be complex (often data-intensive), yet consistent and predictable. AI at this level use algorithms to iteratively learn and gain insights from large and/or continuous data sets. *Analytical* AI increasingly consist of networked units rather than a stand-alone machine. Human interpretation and intuition are still vital complements to AI at this level. AI provides increasingly varied and valuable decision support, but humans are still the ones ultimately making the decision.

One of the biggest potential challenges with *Analytical* AI is that it is likely not well-suited for problems that do not have similar analogs from the past (Chen et al., 2008). This drawback is particularly important to consider in the context of managing infrastructure systems under a changing climate. Non-stationarity, the concept that past conditions and data are not indicative of future trends and conditions, is increasingly a reality for urban and infrastructure systems (Milly et al., 2008; Koutsoyiannis, 2011; Lins, 2012). Thus, *Analytical* AI should not be treated as an “off-the-shelf” or “plug-and-play” solution for a wide range of problems. Engineers and

infrastructure managers should take great care to understand the nuances, strengths, and weaknesses of AI when applying it to infrastructure that has significant interaction with climatic variables (e.g., weather prediction, stormwater systems, flood management systems, etc.).

Intuitive Intelligence

The next level of intelligence is *Intuitive*, which relies on experience-based thinking and creativity. Tasks related to *Intuitive* Intelligence are contextual, chaotic, complex, and idiosyncratic (Huang and Rust, 2018). AI at this level function in a more human-like manner by learning and adapting based on previous experience and new information. Understanding a problem or situation based on context and prior experience is a hallmark characteristic of *Intuitive* Intelligence in both humans and AI.

One potential challenge with *Intuitive* AI is that the problems to which it may be applied are often “wickedly complex” and do not have one “right” solution (e.g., the allocation and management of natural resources) (Chester and Allenby, 2019a). The algorithms supporting this type of AI often learn from human-defined data as to what the outcome should be. Thus, the training of and learning by the AI can be severely inhibited in situations where the outcome/solution is not clear (Meserole, 2018). Under these circumstances, AI can still be very helpful in generating, exploring, and analyzing various scenarios. However, human stakeholders will ultimately be responsible for deciding on the final outcomes or course of action.

Another potential challenge associated with *Intuitive* AI is that there can be a “black-box” element to the analysis and outcomes due to the fact that it provides solutions and insights with minimal knowledge of the underlying systems and processes (Chen et al., 2008). For example, the AI may produce outputs that are non-intuitive and/or fail to converge on a solution, and it may be difficult to ascertain why. Ultimately, some level of this “black box” is likely unavoidable. Presumably, one of the main reasons to deploy *Intuitive* AI is because the system in question is already operating at a scale and/or level of complexity beyond human cognitive capabilities. If total understanding and mastery of system dynamics and complexity (i.e., elimination of the “black box”) is achievable, then *Intuitive* AI was likely not needed in the first place. Thus, the critical question is not “how do we eliminate the black-box?” but rather, “what degree of black-box are we comfortable with?” As AI systems continue to evolve and become further embedded in our infrastructure systems, we may be implicitly or explicitly releasing control of our infrastructure systems to software and algorithms. The potential benefits of this arrangement may very well outweigh the drawbacks in certain circumstances. However, it is important for communities, policy-makers, and infrastructure managers to have open and candid discussions about the potential implications of this shift in control and whether or not those implications are desirable.

Empathetic Intelligence

The “highest” level of intelligence is *Empathetic*, which relies on empathy, social interaction, and communication. *Empathetic* tasks relate to the ability to understand emotions, appropriately

respond to emotions in others, and influence other's emotions (Huang and Rust, 2018). AI at this level “relates to, arises from, or influences emotions (Picard, 1995),” and behaves as if it has feeling. *Empathetic* AI are still in the nascent stages of development, with initial applications tending to relate to emotional analytics (Abou-Zeid and Ben-Akiva, 2010; Quercia et al., 2014). Nonetheless, the high level of social and communication skills needed for *Empathetic* Intelligence seem to indicate that humans will remain integral at this level for the foreseeable future.

Similar to *Intuitive* AI, aspects of wicked complexity and wicked problems can be especially challenging for *Empathetic* AI. One of the elements of a wickedly complex problem is the presence of a wide degree of norms and values among the various stakeholders within the system. These values/interests may not always be clearly stipulated or coded in anyway. Additionally, they can shift and fluctuate over time. As a result, it is very difficult for the AI to understand the different (and often conflicting) values among the stakeholders, let alone “train” the AI around a centrally agreed upon solution/outcome (Baum, 2020).

Related to the issue above, *Empathetic* AI can be particularly susceptible to various biases. The biases may be implicit or explicit, and can be the result of the individuals who wrote the algorithms or the data from which the algorithm was trained (Tomer, 2019). For example, facial recognition AI has been found to contain racial bias (Grother et al., 2019). It is unlikely that biases can fully be eliminated from *Empathetic* (and other) AI systems. Thus, similar to the “black box” issue, perhaps the best approach is for citizens, decision makers, and AI developers to have open and candid discussions about the appropriate applications of *Empathetic* AI given the potential unintended consequences that may result from these biases.

Figure 1 provides a summary of the key elements of each intelligence, examples from infrastructure systems, and current/potential applications of AI in infrastructure across each level of intelligence.

How Might AI Disrupt Infrastructure Services and Introduce New Capabilities?

Exploration of the four levels of intelligences in the context of infrastructure systems reveals a few key insights. First, it appears that AI (or at least automation) has already been widely implemented for *Mechanical* tasks. Although there is still some potential for AI growth and evolution at this level, it appears that we may have already reached a saturation point, thereby making fundamental transformations less likely. This outcome further underscores the potential for AI to complement and supplement *Administrative Leadership* roles within infrastructure systems. On the other hand, *Analytical* tasks are where AI appears poised to have the largest disruption (at least in the near-to-medium term). As AI capabilities continue to improve (especially due to the combination of ever-increasing data availability, ever-decreasing computing costs, and advancements in techniques like ANNs), *Analytical* tasks (and *Adaptive Leadership* roles) will increasingly be accomplished by AI. Considering that

the vast majority of engineering and infrastructure jobs are analytical by nature, the augmentation and/or replacement of *Analytical* tasks by AI is likely to have a fundamental, profound, and transformative impact on infrastructure systems as we know them. Thus, moving forward, a key adaptation for engineers and infrastructure managers will be to strengthen and place increasing emphasis on *Intuitive* and *Empathetic* tasks/intelligences, which in turn should strengthen *Enabling Leadership* capabilities. This is particularly important, because even though humans exhibit much higher levels of *Intuitive* and *Empathetic* Intelligence than AI (and are likely to remain that way for quite a while), there is still room for improvement. Human error is always a concern when operating under both mundane and surprise conditions. Similarly, *Empathetic* Intelligence currently does not appear to be widely incorporated or considered in the development of engineered/infrastructure systems. Thus, in order to most 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*) advantages of humans, we (humans) will need to continually learn from past mistakes and develop skills to make effective decisions under surprise conditions. Additionally, substantial and continual efforts should be made toward enhancing our ability to incorporate social, emotional, and equity dynamics into engineering/infrastructure planning and implementation.

DISCUSSION AND CONCLUSION

It is useful to consider how AI technologies in infrastructure are likely to create new capabilities that, if leveraged correctly, can help us adapt to the rapidly changing conditions in which infrastructure systems must thrive. As evidence emerges of the accelerating and increasingly uncertain conditions that characterize infrastructure environments (Steffen et al., 2015), design and management must be able to respond to these conditions with agility and flexibility (Chester and Allenby, 2019b; Gilrein et al., 2019). With any new technology, control processes are created to harness and guide the new capabilities toward the goals of the managing institution (Beniger, 1989). For example, the advent of engines and novel processes during the industrial revolution released energy at rates and scales never before seen. In turn, these technological advancements required new institutions and processes to channel this power. Whether AI follows historical patterns of technological control is questionable. AI technologies are fundamentally focused on augmenting and replacing cognition. Cognitive infrastructure that learns and makes decisions for us implies that control may not be fully attainable (like it was for the steam engines in the industrial era). Instead, our control efforts may need to focus on establishing relationships with AI that recognize that cyber-technologies will be guiding us in ways that we may not always fully understand.

AI may be uniquely positioned to help us learn about and navigate increasingly complex environments. In designing knowledge systems, institutions enable sensing and analytical

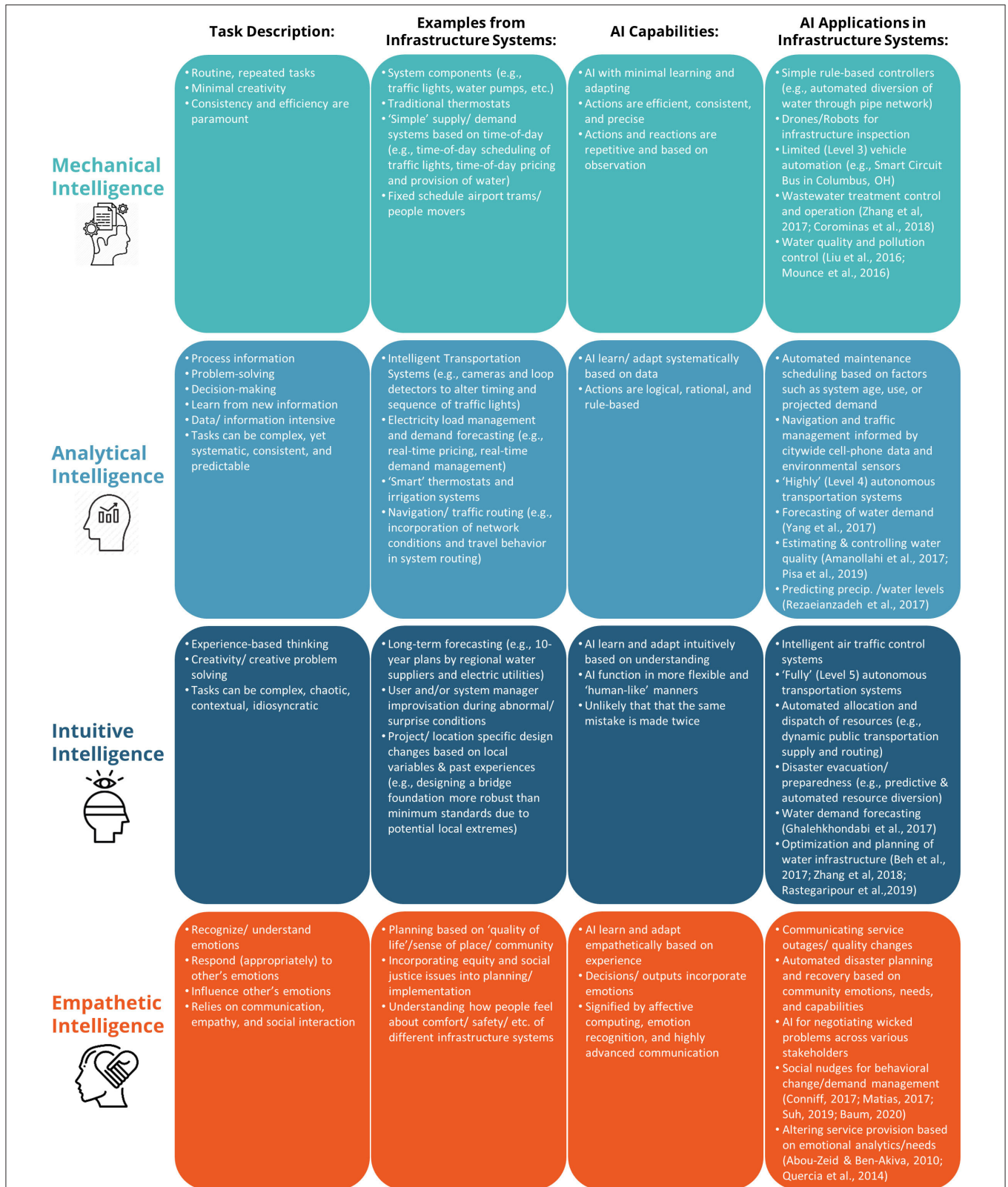


FIGURE 1 | Summary of the “Four Intelligences,” examples from infrastructure systems, and current/potential applications of AI to infrastructure systems across each level of intelligence.

capabilities (coupled with different leadership styles) to operate in both calm and chaotic environments (Miller and Munoz-Erickson, 2018). As our systems, and the environments in which they operate, become increasingly complex and beyond the cognitive understanding of any group of individuals or institutions, AI may offer critical cognitive insights to ensure that systems adapt, services continue to be provided, and needs continue to be met.

The mapping of AI applications to intelligences and leadership roles appears to support the varying approaches needed to address domains of complexity. The Cynefin framework classifies systems as *simple*, *complicated*, *complex*, or *chaotic*, and as we transition from one domain to another, disorder governs (Snowden and Boone, 2007; Chester and Allenby, 2019a). Each domain requires a fundamentally different approach to address challenges. Infrastructure have historically been *complicated* systems and are now increasingly viewed as *complex* (Chester and Allenby, 2019b). A *complicated* system calls for data collection, analyzing and decision-making, while a *complex* system shifts toward probing, testing, and a commitment to adaptability and transformation. The intelligence mapping presented in **Figure 1** provides a useful set of AI applications that can be applied to infrastructure in *complicated* and *complex* environments. The *Mechanical* and *Analytical* Intelligences appear to align well with *complicated* situations where the emergent behaviors of systems are predictable and their environments somewhat stable. The *Intuitive* and *Empathetic* Intelligences appear to align with *complex* systems, where perturbations can result in unpredictable emergent behaviors, and “*satisficing*” is needed to manage wicked problems across technical and social requirements (Chester and Allenby, 2019a). While all intelligences are needed at various times during the operation of a system, the development and deployment of *Intuitive* and *Empathetic* Intelligences (and *Enabling Leadership*) in humans and institutions, as well as the development and deployment of *Administrative* and *Adaptive Leadership* via AI appears necessary to address the growing complexity and non-stationarity of our systems and the environments in which they operate.

Ultimately, we are in the nascent stages of AI development and application to infrastructure systems. The topics in this paper are intended to be an initial discussion of some of the key

opportunities and challenges associated with AI in infrastructure systems—especially in the context of the leadership and skills needed to face the complex challenges of the Anthropocene. Avenues for future work that can build on this endeavor include interviews and surveys aimed at gaining a better understanding of infrastructure practitioner’s current thoughts and expectations about the possible benefits and downsides of AI. Additionally, it would be beneficial to further explore which level of intelligence appears most appropriate for specific problems/contexts, as well as a more detailed assessment of the specific AI techniques likely to be most effective/appropriate in these circumstances. Finally, in conjunction with (if not prior to) these efforts, open, candid, and iterative discussions are required amongst society writ large to debate what level of cognitive infrastructure we are comfortable with and the level of “control” (or at least perceived control) we are comfortable offloading to cognitive infrastructure. By doing so, engineers and infrastructure users/managers can hopefully ensure that they are striking the right balance between human and AI capabilities required to effectively and equitably navigate our increasingly complex world.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary materials, further inquiries can be directed to the corresponding author/s.

AUTHOR CONTRIBUTIONS

SM: conception of the work, drafting of the work, and revisions. MC: conception of the work, drafting of the work, and review and editing of the work. BA: drafting of the work and review and editing of the work. All authors contributed to the article and approved the submitted version.

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Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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