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The Kirk-Spock Leadership Framework for Balanced Human-AI Collaboration in Construction Project Management

Elyar Pourrahimian[1], Diana Salhab[2], Farook Hamzeh[3]

Abstract

Question: What leadership approach can sustain human adaptability and resilience in construction project management in the age of Artificial Intelligence (AI)?

Purpose: The purpose is to develop and demonstrate a framework that helps construction project managers effectively use AI while actively preserving their critical thinking, intuition, and emotional intelligence.

Research Method: This study adopts a Design Science Research (DSR) approach to develop the Kirk–Spock Leadership Framework (KSLF) for balanced human–AI collaboration in construction management.

Findings: The paper proposes that while AI offers efficiency, only a balanced human–AI leadership model can prevent skill loss and build more resilient leaders.

Limitations: The paper's limitations stem from its conceptual nature, limited case evidence, reliance on cross-industry analogies, and lack of longitudinal validation for the proposed framework.

Implications: The paper suggests that sustaining human cognitive engagement alongside AI is crucial for both theory and practice, resulting in stronger leaders, healthier teams, and more adaptable organizations.

Value for authors: The authors' value lies in creating a new leadership framework (KSLF) and providing both theoretical and practical guidance for sustaining human leadership capacity in AI-augmented construction management.

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[1] Post-Doctoral fellow, Dept. of Civil and Environmental Engineering, Univ. of Alberta. 9105 116 St., 7-369 DICE, Edmonton T6G 2W2, AB, Canada. elyar@ualberta.ca

[2] Post-Doctoral fellow, Dept. of Civil and Environmental Engineering, Univ. of Alberta. 9105 116 St., 7-369 DICE, Edmonton T6G 2W2, AB, Canada. Salhab@ualberta.ca

[3] Professor, Dept. of Civil and Environmental Engineering, Univ. of Alberta. 9105 116 St., 7-287 DICE, Edmonton T6G 2W2, AB, Canada. Hamzeh@ualberta.ca

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Introduction

The rapid uptake of AI and advanced analytics in construction project management has fundamentally altered how decisions are made and tasks are executed. AI-powered tools now assist with scheduling, cost estimation, risk assessment, and real-time project monitoring. These innovations have yielded efficiency gains, but they also introduce new challenges for human leadership. One emerging concern is cognitive outsourcing, wherein project managers and teams become so dependent on AI recommendations that they gradually disengage their critical thinking and intuition. Over-reliance on automated decision support can limit opportunities for leaders to develop problem-solving, strategic planning, and interpersonal judgment skills that are traditionally acquired through experience and reflection. When humans yield too much control to AI, there is a risk of diminished cognitive engagement, sometimes described as a form of "neural atrophy" or loss of mental agility over time (Dergaa et al., 2024).

Neuroplasticity, the brain's ability to form and reorganize synaptic connections in response to learning and experience, is at the heart of this issue (Draganski & May, 2008). Just as muscles weaken from disuse, neural circuits for complex cognitive tasks can weaken if not regularly exercised. Leaders who let algorithms take over adaptive decision-making may inadvertently neglect the mental processes that keep them sharp and creative. Recent neuroscience studies support the principle of "use it or lose it"; frequent utilization of specific skills strengthens the corresponding neural networks (Voss et al., 2011), whereas prolonged disuse can cause those networks to degrade. For instance, studies have shown that training in new skills induces measurable changes in brain structure (Draganski et al., 2004), and, conversely, that technological aids like GPS navigation can diminish our innate spatial memory over time (Ruginski et al., 2019).

AI within Construction 4.0 warns that adoption often sidelines social impacts. A human-centric stance, framed as Lean Construction 4.0, calls for technologies that augment people, protect autonomy, and translate lean values into digital practice. This explicitly includes AI as part of a wider stack that must be evaluated for human consequences before and after adoption (Noueihed & Hamzeh, 2022). Recent studies highlight metrics that can shift control from a reactive to a proactive approach. Exposure to such metrics enhances capacity planning but can also lead to over-allocation, underscoring the need for human judgment to complement analytics. This is the natural substrate for AI tools that forecast, recommend, and simulate, while humans keep authority (Shehab et al., 2024; Pourrahimian et al., 2024). These findings raise important questions for leadership in the age of AI: How can we leverage AI's capabilities without eroding the human expertise and adaptability that are crucial in complex projects? In this paper, we aim to present a conceptual framework rather than empirically validated findings; its purpose is to synthesize theory, provoke reflection, and provide actionable guidance for practitioners, pending longitudinal empirical validation.

Within this context, we draw inspiration from the contrasting leadership styles of two iconic fictional characters, Captain James T. Kirk and Commander Spock from Star Trek, as an analogy for balancing intuition and analysis in decision-making. The Kirk-Spock Leadership Framework (KSLF), introduced in prior work on construction leadership, suggests that effective project management requires a blend of Kirk's intuitive, experiential judgment with Spock's logical, data-driven reasoning. Kirk's approach exemplifies courage, creativity, and emotional intelligence in the face of uncertainty, while Spock's approach represents rigorous analysis, objectivity, and technical precision. Each style has its strengths and limitations; when combined, they can complement each other to improve team outcomes (Betsch & Glöckner, 2010; Patton, 2003).

Building on this framework, the present paper adds a new dimension: the role of neuroplasticity in sustaining leadership effectiveness. We argue that a balanced human–AI collaboration modelled on the Kirk-Spock paradigm can actively foster neuroplasticity by ensuring that human team members remain cognitively and emotionally engaged, rather than passively deferring to AI. By consciously pairing AI tools with human intuition and critical thinking, construction leaders can leverage the best of both worlds – the computational power of AI and the adaptive intelligence of the human brain, while continually reinforcing the neural pathways that underlie decision-making and social skills. In essence, AI should augment, not replace, the human element in leadership.

This paper is structured as follows. First, we review relevant literature on leadership theories, neuroplasticity, and the impacts of AI on human skills. Next, we present the Kirk-Spock Leadership Paradigm in detail, explaining how intuitive and analytical strategies, together with deliberate practice, can safeguard cognitive agility. We then illustrate these concepts with case studies from construction project management, as well as analogous examples from other industries. Finally, we discuss the broader implications of sustaining neuroplasticity in an AI-driven world, offer recommendations for practitioners and policymakers, and conclude with suggestions for future research on integrating AI with leadership development in the construction industry.

Literature review

Leadership theories

Leadership theories provide frameworks for understanding how leaders influence and guide their teams. They encompass a range of approaches, from trait-based theories, which focus on the inherent qualities of leaders, to behavioral theories, which emphasize the actions and decisions leaders make. Transformational leadership theory highlights the ability of leaders to inspire and motivate their teams, while transactional leadership focuses on structured tasks and rewards. Other theories, such as servant leadership and contingency theory, explore the importance of context and the leader's role in serving others or adapting to specific situations. Together, these theories offer valuable insights into the dynamics of leadership and how various leadership styles can impact team performance (Bass & Stogdill, 1990).

Trait-based leadership models propose that effective leaders possess specific innate traits that distinguish them from non-leaders. The Great Man Theory suggests leaders are born with inherent heroic qualities. Trait Theory further refines this by identifying precise attributes such as confidence and intelligence, characteristics more closely associated with logic and intelligence (Spector, 2016; Bass & Stogdill, 1990; Digman, 1990).

Behavioral leadership theories shift focus from innate traits to the observable actions and behaviors of leaders. Lewin's Leadership Styles categorize leadership into autocratic, democratic, and laissez-faire styles (Bond, 2015; Schriesheim, 1979). Democratic leadership encourages team participation and collaboration, while autocratic leadership involves structured, controlled decision-making. Similarly, the Blake-Mouton Grid categorizes leaders based on their concern for people versus their concern for tasks (Blake, 1975). High people-oriented leadership fosters team harmony and motivation, whereas high task-oriented leadership focuses primarily on productivity and efficiency.

Situational and contingency leadership models highlight the importance of context in effective leadership. Fiedler's Contingency Model emphasizes aligning leadership style with situational demands (Fiedler, 1978). The Hersey-Blanchard model proposes adjusting leadership styles according to follower maturity (Wang, 1991; House, 1971).

Transformational and transactional leadership theories provide contrasting approaches. Transformational leadership, exemplified by Bass's model, emphasizes inspiring followers through visionary motivation and charisma. Transactional leadership, meanwhile, utilizes systematic reward and punishment systems, aligning with a logical, rule-based management style (Odumeru & Ogbonna, 2013).

Modern and hybrid leadership models integrate various approaches to address contemporary leadership challenges (Ghosh et al., 2025). Servant leadership, prioritizing empathy and follower empowerment, and authentic leadership, promoting transparency and ethical awareness, both align with an empathetic and genuine style. Ambidextrous leadership balances exploration (innovation) and exploitation (efficiency).

Functional leadership models emphasize specific leadership functions (Burke et al., 2006). Charismatic leadership, relying on charm and emotional appeal, and crisis leadership, emphasizing decisiveness under pressure.

Emerging or niche leadership models address specialized leadership contexts (Tabassum et al., 2023). Leader-Member Exchange (LMX) theory, focusing on in-group versus out-group dynamics, aligns with a meritocratic and structured approach. Complexity leadership addresses adaptive leadership within complex systems. Digital leadership, which focuses on managing technological disruptions and remote teams, closely aligns with an analytical and data-driven approach.

AI and leadership

AI has substantially transformed leadership by enhancing decision-making accuracy, speed, and predictive capabilities. Leaders equipped with AI tools can rapidly process vast datasets, enabling more informed and efficient decisions (Aziz et al., 2024). In construction project management, AI aids in tasks such as resource allocation, risk assessment, and predictive scheduling, thereby significantly reducing uncertainties and errors (Shamim, 2024; Pourrahimian et al., 2025). However, excessive dependence on AI can pose substantial risks, including cognitive deskilling, where leaders become overly reliant on automated systems, gradually diminishing their problem-solving abilities and analytical thinking. Additionally, emotional detachment may occur, as leaders may become less engaged in direct interpersonal interactions, potentially eroding empathy and emotional intelligence, crucial elements for effective team leadership and motivation. Balancing AI integration with active human engagement is therefore critical to preserving the essential cognitive and emotional competencies necessary for sustainable leadership effectiveness (Von Krogh, 2018).

Lean construction: definition, origins, and relevance

Lean Construction emerged from applying lean production principles to the construction industry, though it quickly evolved beyond a simple transplant of manufacturing methods (Howell, 1999; Mossman, 2018). Koskela (1992) laid the theoretical foundation by proposing that construction should be understood not merely as a transformation of inputs into outputs, but as a system of interdependent flows and value generation processes. This Transformation-Flow-Value (TFV) model recognized that waste in construction arises not only from inefficient tasks but from unreliable workflows, poor coordination, and misaligned value delivery (Koskela, 1992; Abdelhamid, 2004). Building on this foundation, the Lean Construction Institute (LCI) and the International Group for Lean Construction (IGLC) formalized a body of practice centered on two pillars: respect for people and continuous improvement (Abdelhamid and Copeland, 2022).

The most widely adopted operational tool within Lean Construction is the Last Planner System® (LPS), developed by Ballard (2000). LPS shifts planning authority toward those closest to the work, foremen, trade supervisors, and project managers, through a commitment-based planning process. Weekly Work Plans are developed collaboratively, with teams making reliable promises about what will be completed, and variances are systematically analyzed to identify and remove constraints. The resulting metric, Percent Plan Complete (PPC), serves as a learning signal rather than merely a performance indicator. Hamzeh et al. (2012) found that inadequate lookahead planning and sluggish constraint removal are among the primary causes of planning failure, underscoring the irreplaceable role of human judgment in the make-ready process. Ballard and Tommelein (2021) further extended LPS to encompass both production- and project-level planning and control, reinforcing that the system fundamentally depends on practitioners actively reasoning through constraints and commitments at each planning horizon. Shehab et al. (2024) also reported that exposure to LPS metrics significantly improves capacity planning outcomes but also noted that this exposure can lead to over-allocation when human judgment is not actively engaged, highlighting the essential role of the human planner as a counterweight to algorithmic outputs. This learning orientation reflects the broader imperative of continuous improvement that underpins Lean thinking; as Rother (2009) articulates through the Toyota Kata framework, sustaining improvement requires the deliberate practice of adaptive routines rather than passive reliance on tools, a principle Tapase (2019) connects explicitly to construction learning environments.

The Lean Construction field has increasingly grappled with the implications of digitalization and Construction 4.0 for these human-centered practices. Noueihed and Hamzeh (2022) warned that the social impacts of Construction 4.0 technologies, including AI, are frequently overlooked in the rush to adopt new digital tools, and called explicitly for a human-centric approach that places people at the center of technological adoption rather than treating them as passive recipients. This concern is not peripheral to Lean Construction but central to it: the field's effectiveness depends on the cognitive and social engagement of its practitioners. Value in Lean Construction is inherently human-centered and relational, defined through the perspectives of owners, users, and society rather than reducible to algorithmic outputs (Salvatierra-Garrido & Pasquire, 2011). The collaborative reasoning required in pull planning sessions, the interpersonal judgment involved in commitment-based scheduling, and the reflective capacity needed to learn from variance analysis are precisely the human capabilities that AI-induced cognitive deskilling threatens. This extends beyond on-site operational waste to what Sarhan et al. (2017) term institutional waste, systemic inefficiencies embedded in organizational structures and practices that suppress human agency and learning. Lean's emphasis on learning organizations, where culture fosters continuous experimentation, acknowledges failure, and rewards shared responsibility, similarly depends on practitioners who remain cognitively active and self-directed (Hamzeh, 2011).

The Kirk-Spock Leadership Framework (KSLF) is therefore situated within Lean Construction, not as an external addition but as an extension of its core values. Just as Lean insists that workers closest to the work must remain actively engaged in planning and control, KSLF insists that leaders closest to decision-making must remain cognitively and emotionally engaged alongside AI systems. In this sense, protecting neuroplasticity is a Lean imperative; the learning loops that Lean depends upon cannot function if the humans within them have outsourced their judgment to algorithms. The KSLF offers a practical framework for ensuring that AI tools are used to augment human planners and project managers within Lean workflows, rather than displacing the very cognitive engagement on which those workflows depend.

Neuroplasticity and skill retention

Neuroplasticity refers to the brain’s capacity to change its structure and function in response to learning and experience. This plasticity enables the acquisition of new skills and the adaptation to new environments. However, it also implies that a lack of practice can weaken previously established neural connections. In the context of professional skills, the adage "use it or lose it" has a neurological basis. Draganski et al. (2004) provided a landmark demonstration of experience-driven brain change. After adults learned a new complex motor task (juggling), researchers observed an increase in gray matter volume in brain regions associated with visual-motor coordination. Notably, when the participants stopped practicing for a few months, these brain changes partially receded, indicating that continuous engagement in the activity was necessary to maintain the neural development. Similarly, Maguire et al. (2000) found that London taxi drivers, who undergo intensive training to memorize the city's labyrinthine streets, had significantly enlarged posterior hippocampi (the brain region key to spatial memory) compared to non-taxi drivers. This enlargement correlated with their navigational experience, suggesting that the brain had reorganized itself to accommodate the cognitive demands of wayfinding. Both studies underscore an important point: active use of skills leads to stronger neural pathways, whereas inactivity leads to regression.

By translating these insights into leadership and management skills, it can be inferred that regularly exercising cognitive functions, such as problem-solving, strategic planning, and emotional regulation, will strengthen the underlying neural circuits. On the other hand, if leaders rely too heavily on external aids (for example, delegating all data analysis to software or all interpersonal communication to digital platforms), they might experience a decline in their innate abilities to analyze complex situations or read social cues. This phenomenon has been observed in everyday technologies; Ruginski et al. (2019) reported that habitual GPS navigation can impair a person's ability to form cognitive maps of their environment. In effect, outsourcing the spatial reasoning to a device can cause the brain to invest less in those neural networks. Over time, such cognitive offloading may result in a tangible decrease in skill level when the technology is unavailable. In project management, a related risk is that overreliance on AI planning tools could atrophy a manager's ability to foresee project issues or to brainstorm creative solutions independently.

Intuition, analysis, and emotional intelligence in leadership

Leadership research has long debated the relative merits of intuitive versus analytical decision-making (Armstrong & Priola, 2001; Patton, 2003). Intuition in this context refers to the ability to make quick, experience-informed judgments without extensive conscious deliberation, a process often linked to pattern recognition and tacit knowledge. By contrast, analytical thinking involves systematic evaluation of data and options, aligning with rational choice models. Effective leaders often blend both modes, using intuition to swiftly assess situations and analysis to validate or refine their insights (Betsch & Glöckner, 2010). Intuition is also closely tied to emotional intelligence (EI), the capacity to understand and manage one's own and others' emotions (Goleman, 1995). High EI enables leaders to gauge team morale, show empathy, and inspire confidence, all of which are critical in construction projects where collaboration and trust are paramount. These intuitive and emotional skills draw on brain processes in regions such as the amygdala and other limbic system structures that process emotions, as well as the prefrontal cortex, which integrates emotional and rational inputs during decision-making. Neuroscience suggests that leaders who frequently engage in social interaction and empathy are effectively training the neural pathways associated with social cognition. For example, the discovery of mirror neurons, brain cells that fire both when an individual performs an action and when they observe someone else performing it, provides a biological basis for empathy and learning through observation (Rizzolatti & Craighero, 2004). Regular face-to-face engagement and team communication can activate these circuits, reinforcing a leader's capacity to understand and relate to others.

On the other hand, an overly analytical approach that overlooks emotional considerations may lead to decisions that appear optimal on paper but fail in practice due to poor team buy-in or ethical blind spots. Thus, contemporary leadership models emphasize cognitive flexibility, the ability to shift between intuitive, interpersonal, and analytical modes as needed (Norton, 2010; Zaccaro et al., 1991). Cognitive flexibility itself can be viewed as a neuroplastic outcome; a brain that has been challenged to handle both creative intuition and logical analysis becomes more adaptable. By regularly toggling between these modes, leaders strengthen a wider network of neural connections, potentially enhancing their problem-solving repertoire. This balance is especially vital in construction management, where project conditions can change rapidly, and leaders must make decisions that are both technically sound and organizationally acceptable.

AI, automation, and the risk of cognitive deskilling

The rise of AI and automation in management brings to the forefront the concern of cognitive deskilling, a reduction in human expertise due to over-reliance on automated systems. In construction project management, AI-driven systems now perform tasks like schedule optimization, risk analysis, resource allocation, and even aspects of design coordination. These tools can process vast amounts of data faster than any human, often providing recommendations or decisions that humans approve. While this has clear benefits for efficiency and evidence-based planning, there is a double-edged sword; if project managers become mere overseers of algorithms, their active involvement in problem-solving diminishes. Over time, they may lose the sharpness required to effectively question the AI's output or to intervene when the AI encounters novel situations outside its training data. Endsley (2017) warns that operators can become satisfied and suffer loss of situation awareness when automation handles the bulk of tasks, a phenomenon known as the "out-of-the-loop" problem. In the context of semi-autonomous vehicles, for example, drivers can become less adept at reacting to emergencies because they assume the autopilot will handle everything (Endsley, 2017). By analogy, a project manager might become less vigilant in monitoring project details or less skilled in crafting contingency plans if they assume an AI will flag all potential issues.

Evidence from multiple domains supports these concerns. In healthcare, the heavy reliance on AI diagnostics and decision support has sparked concerns that clinicians' diagnostic reasoning skills may deteriorate. If doctors trust an AI's judgment without exercising their own critical analysis, their ability to make independent diagnoses may weaken over time (Paranjape et al., 2019). In education, studies have noted that the widespread use of calculators and learning apps can hinder the development of mental arithmetic and problem-solving strategies among students (OECD, 2015). These scenarios illustrate automation-induced complacency, in which the human agent's role shifts from an active problem-solver to a passive monitor of an AI. The result is a form of deskilling that might not be immediately apparent; after all, everything works smoothly when the AI performs well, but it becomes painfully apparent when the AI fails or is unavailable. In construction, imagine an AI scheduling system that operates flawlessly under normal conditions. However, if a crisis (e.g., an unanticipated supply chain collapse or a pandemic shutdown) invalidates the AI's learned patterns, a project manager who has not practiced manual replanning skills may find themselves unprepared to develop a quick solution. Thus, maintaining a human in the loop is not just about oversight to prevent errors, but also about keeping the human mind trained and ready to take control when necessary.

Despite extensive literature on leadership theories and AI integration, a notable research gap remains regarding frameworks explicitly designed to balance intuitive and analytical leadership styles while actively promoting neuroplasticity. Current leadership models rarely address how to systematically maintain human cognitive and emotional skills in AI-enhanced environments. This gap highlights the need for an integrative model like the proposed KSLF, which explicitly aims to bridge intuition and analysis, thereby ensuring sustainable leadership practices amid increasing AI adoption.

Research Methodology

This study adopts a Design Science Research (DSR) methodology to structure the development and validation of the proposed Kirk–Spock Leadership Framework (KSLF) for balanced human–AI collaboration in construction project management. DSR is particularly suited for research that seeks not only to understand phenomena but also to create actionable solutions that address complex, real-world problems. In line with established DSR guidelines (Hevner et al., 2004), our approach followed three core principles: problem relevance, design as an artifact, and evaluation.

The motivation for this study stems from the observed risks of over-reliance on AI in project management, including cognitive outsourcing and potential neuroplasticity atrophy among leaders. The practical problem is how to integrate AI tools into leadership practice without undermining essential human cognitive and emotional competencies. This aligns with the DSR principle of addressing a relevant organizational challenge with tangible managerial implications.

The central artifact developed in this research is the Kirk–Spock Leadership Framework (KSLF). It integrates intuitive and analytical leadership modes with deliberate safeguards for neuroplasticity to ensure that human leaders remain cognitively and emotionally engaged alongside AI systems. The design of this artifact was informed by the literature on leadership theory, neuroplasticity, and AI adoption in construction, as well as cross-industry insights. The artifact is conceptual in nature, serving as a theoretical framework that guides practice.

To demonstrate and evaluate the utility of the KSLF, we applied it to illustrative scenarios in construction project management. The first case illustrates the consequences of over-reliance on AI scheduling tools, highlighting adaptability gaps when human expertise is underutilized. The second case illustrates how balanced human–AI engagement can improve both efficiency and resilience. Cross-industry analogies from healthcare, education, and transportation further validate the framework by showing similar risks of cognitive deskilling and successful mitigation strategies. While the evaluation is primarily conceptual and qualitative, it provides initial evidence that the KSLF artifact is both applicable and valuable in practice.

In line with DSR principles, this work contributes to both theory and practice. Theoretically, it extends leadership research by incorporating neuroplasticity as a design consideration in human–AI collaboration. Practically, it offers construction organizations a framework to guide leadership development and project management in an era of increasing automation.

The Kirk-Spock Leadership Paradigm for Human-AI Collaboration

The Kirk-Spock Leadership Framework (KSLF) provides an integrative framework that balances two contrasting yet complementary leadership approaches: Kirk's intuitive, emotion-driven leadership and Spock's analytical, data-driven leadership. This paradigm is particularly valuable in the context of human-AI collaboration, where the goal is to leverage the power of AI while ensuring that human leadership capabilities are maintained and enhanced.

Core principles of the KSLF

At the heart of the Kirk-Spock Leadership Paradigm are two core principles: the opposition between human intuition, creativity, and emotional intelligence (characterized by Kirk) and logical reasoning, precision, and analytical thinking (embodied by Spock). The metaphor originates from the Star Trek films and television series, where Kirk's bold, intuitive style often contrasts with Spock's rational and data-driven approach. The integration of these principles into leadership practices enables a more holistic approach, allowing leaders to adapt to both predictable and unpredictable challenges.

Kirk principle (Intuitive and emotional leadership)

The Kirk principle encourages leaders to engage with their teams through empathy, interpersonal connection, and decision-making based on experience, gut feelings, and a human-centered approach. Kirk's leadership is driven by vision, inspiration, and the ability to make fast decisions in high-pressure situations, without the luxury of data analysis. Leaders who follow the Kirk Principle are skilled at reading their team members' emotional states, building trust, and motivating others through challenging circumstances.

In the context of AI integration, the Kirk principle calls for leaders to remain engaged with their teams at an emotional and interpersonal level, using AI tools as augmentations rather than replacements. This ensures that the human aspects of leadership, such as empathy, collaboration, and intuitive decision-making, remain strong even when working alongside advanced technologies. Leaders are encouraged to rely on their emotional intelligence to make decisions, especially in ambiguous or high-stakes situations where AI may not yet provide clear guidance (Jordan & Troth, 2021).

Spock principle (Analytical and data-driven leadership)

The Spock principle emphasizes systematic problem-solving, relying on data, structured reasoning, and a thorough understanding of operational complexities. Spock's leadership style excels in situations that demand precision, clear thinking, and informed decision-making based on available information. Leaders who adopt the Spock Principle are adept at breaking down complex problems, evaluating multiple variables, and utilizing predictive models to optimize decisions and outcomes.

The Spock Principle aligns seamlessly with AI's strengths in data processing, optimization, and pattern recognition. In the human-AI collaboration context, Spock's approach emphasizes leveraging AI to provide insights, manage data streams, and predict outcomes with high accuracy. Leaders employing this principle ensure that AI tools are not only used for task automation but are actively involved in enhancing decision-making, forecasting, and resource allocation through data analysis (Raisch & Krakowski, 2021).

Human-AI collaboration: The integration of intuition and analysis

One of the unique aspects of the KSLF is its emphasis on balancing Kirk's intuitive leadership with Spock's analytical ability in human-AI collaboration. AI systems possess tremendous capabilities in handling large datasets and performing complex analyses; however, they often lack human judgment and emotional intelligence, which are crucial in many leadership contexts. By integrating both Kirk's and Spock's leadership styles, the KSLF offers a comprehensive approach to decision-making that maximizes the strengths of both human leaders and AI technologies.

The core idea behind KSLF is that AI should not replace human leadership but should complement and extend it. AI tools, when integrated effectively, enhance leaders' ability to make data-informed decisions, allowing them to use their analytical skills in tandem with intuitive judgments. For instance, while AI can suggest the best course of action based on historical data, human leaders can factor in qualitative inputs, ethical considerations, and emotional distinctions that AI may not fully comprehend.

KSLF advocates for active human-in-the-loop processes, where human leaders remain engaged in decision-making, critically evaluating and interpreting AI outputs rather than passively relying on them. This collaboration ensures that AI's recommendations are not accepted blindly but are scrutinized, adjusted, or enhanced based on human insights and values. For example, while AI systems can optimize project schedules and resource allocation, leaders must still consider human factors, such as team morale, communication challenges, and unforeseen contextual issues that AI may not account for.

KSLF also encourages a shift from hierarchical decision-making to a more collaborative approach, where AI systems and human leaders work as partners. By blending Kirk's interpersonal skills with Spock's analytical rigour, leaders can foster a more inclusive and adaptable decision-making process. This collaboration also nurtures a culture of innovation, as the integration of AI systems enables leaders to experiment with new ideas and solutions, leveraging AI's capabilities to test different scenarios and predict outcomes.

Neuroplasticity and leadership in the age of AI

A key element of the KSLF is its focus on neuroplasticity. The model emphasizes that to sustain effective leadership in an AI-augmented environment, leaders must continue to engage both their intuitive (Kirk) and analytical (Spock) faculties. Just as muscles atrophy from lack of use, so too do cognitive and emotional skills if they are not regularly exercised.

The KSLF encourages leaders to create time and space for practices that keep their cognitive and emotional faculties engaged, even in the presence of AI. This includes activities that promote intuition, creativity, and empathy, such as brainstorming sessions, team-building exercises, and scenario planning. These practices ensure that leaders continue to refine their decision-making abilities, preventing the cognitive disengagement that can result from over-reliance on AI tools.

In parallel, leaders are encouraged to regularly engage in activities that strengthen their emotional intelligence, such as training in interpersonal communication and conflict resolution. Even as AI takes over more tasks, leaders must retain the ability to understand and manage their own emotions, as well as those of their teams. By actively cultivating emotional intelligence, leaders can navigate complex social dynamics, manage stress effectively, and inspire their teams, ensuring that human values remain at the core of their leadership practices.

Practical Application of the KSLF in Construction Project Management

In the context of construction project management, the KSLF offers valuable guidance for leaders navigating the intersection of human leadership and AI. AI tools in construction management, including scheduling algorithms, risk management systems, and automated project monitoring tools, offer powerful support for informed decision-making. However, these tools require human oversight and interpretation to ensure that they align with the project's goals, the team's capabilities, and the organization's values.

A construction manager using AI-based project scheduling tools can rely on AI to optimize task sequences and resource allocation. However, the manager must use their intuition (Kirk) to consider variables not easily captured by AI, such as team members' well-being, potential weather-related delays, or unexpected supply chain disruptions. By balancing the analytical power of AI with human insight, the manager can adjust schedules to account for these human factors, ensuring the project stays on track while maintaining team morale.

Integrating Intuitive and Analytical Leadership

In construction project management, KSLF translates to encouraging leaders to harness both their experiential insights and data-driven analysis when confronting project challenges. Kirk-like intuition involves drawing on experience, trusting gut feelings, motivating teams through vision and charisma, and making timely decisions under uncertainty. Spock-like analysis involves methodical planning, scrutinizing data and evidence, objectively assessing risks, and applying scientific reasoning to problems. Rather than viewing these approaches as opposites, KSLF frames them as complementary halves of effective leadership. A leader or a leadership team operating under KSLF aims not to overemphasize one at the expense of the other. For example, during a construction project's design phase, a Kirk-oriented perspective might envision innovative design solutions or empathize with a client's unarticulated needs, while a Spock-oriented perspective would methodically evaluate the feasibility, cost, and safety of those ideas. By iterating between creative brainstorming and analytical range, the team can arrive at solutions that are both novel and viable.

This balanced paradigm aligns with the concept of dual-process thinking in psychology, where effective decision-makers toggle between a fast, intuitive mode (sometimes referred to as System 1 thinking) and a slow, deliberative mode (System 2 thinking). The Kirk mode (System 1) allows leaders to react quickly and tap into tacit knowledge in fast-moving situations, while the Spock mode (System 2) ensures that decisions are grounded in logic and facts. In the dynamic and uncertainty-prone context of construction projects, which often face sudden changes, unforeseen risks, and the need for on-the-fly problem solving, having the capacity to employ both modes is especially valuable.

The KSLF paradigm, incorporating these neuroplasticity-focused measures, can be visualized as a Venn diagram or an overlapping system, as shown in Figure 1. One circle represents intuitive/EI-driven practices (Kirk), another represents analytical/data-driven practices (Spock), and the overlap signifies integrated decision-making. Surrounding this overlap is a deliberate neuroplasticity support structure comprising ongoing activities and protocols (such as simulations, workshops, and human-in-the-loop reviews) that reinforce the use of both skill sets. AI tools are depicted not as a separate circle that overrides human circles, but rather as an outer layer of support that enhances what humans do, provided that humans remain actively engaged. In this way, the framework positions AI as a powerful ally that can expand a team's capabilities without supplanting the need for human judgment. By continuously flexing both their intuitive and analytical "muscles," leaders and teams cultivate a resilient cognitive flexibility that enables them to adapt even as technology evolves.

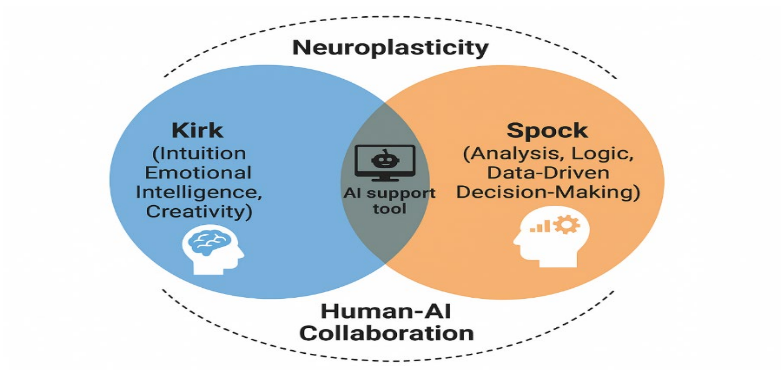

Figure 1. Balance between human intuition and creativity (Kirk) and AI-driven logic and analysis (Spock)

Illustrative Scenarios

The scenarios presented below are illustrative constructs developed to demonstrate how the Kirk-Spock Leadership Framework applies in practice. They are not empirical case studies drawn from fieldwork or primary data collection. Rather, they are designed to make the framework's principles concrete and to surface the contrasting outcomes that balanced versus imbalanced human-AI collaboration may produce. Findings emerging from these scenarios should be read as propositions and design insights, not as empirically validated results.

To concretely demonstrate the risks of imbalance and the benefits of the KSLF approach, we present two illustrative scenarios in the context of construction project management. The first case highlights a project that relied heavily on AI at the expense of human judgment, resulting in poor outcomes when unexpected events arose. The second case describes a project that struck a successful balance between AI assistance and human expertise, yielding both efficiency and robust problem-solving. While these cases are simplified for illustration, they reflect real concerns and practices observed in industry reports and expert analyses.

Scenario 1: Over-Reliance on AI in Scheduling Leads to Adaptability Gaps

Background: A large infrastructure construction project (e.g., a highway expansion) adopted an AI-driven scheduling and project controls system. This system used machine learning to integrate inputs from subcontractors, suppliers, and past project data, automatically generating and updating the project schedule. The project management office, impressed by the tool's capabilities, authorized it to fully automate the scheduling process. Human planners were instructed to follow the AI's schedule and updates closely and intervene only if necessary. Over time, the team developed great confidence in the AI's projections and stopped performing their independent analysis of the schedule or looking for potential issues; they assumed the system's forecasts were optimal.

Incident: Midway through the project, a critical supplier of steel components faced a sudden factory shutdown. This caused a significant delay in deliveries, a scenario that the AI system had not encountered in training data to the same extent, and thus its predictive model severely underestimated the impact on the schedule's critical path. The AI flagged a delay, but its suggested reallocation of resources was based on generic delay-propagation patterns. It did not account for several on-site realities (such as the limited storage space for materials and union work rules that constrained re-sequencing of tasks). The human project managers, having grown complacent, initially accepted the AI's recommendation, which proved flawed. As the weeks unfolded, it became clear that the mitigation plan did not contain the delay; in fact, conflicts in work crews and idle times increased. Under pressure, the project managers convened an emergency planning meeting to resolve the issues manually.

Outcome: In the emergency meeting, it became apparent that the team struggled to generate alternatives rapidly; many had not practiced manual scheduling or critical path method analysis in a long time. Some managers admitted they felt "out of their depth" when trying to perform tasks (such as resource levelling and network logic adjustments) that the software usually handled. Eventually, with help from a few senior engineers (who relied on their experience rather than the AI), the team crafted a revised schedule and recovery strategy. The project got back on track, but not before incurring significant cost overruns and stakeholder frustration. A post-mortem review identified the root cause as overreliance on the AI system, which led to the erosion of the team's adaptive planning skills. In essence, the project suffered from a lack of "Kirk-style" intuition and on-the-spot problem-solving when it was most needed because those muscles had atrophied during months of routine automation. This case underscores that even a highly capable AI can leave an organization vulnerable if human leaders are not ready to step in with creativity and expertise when facing novel crises.

Scenario 2: Balanced Use of AI with Ongoing Human Cognitive Engagement

Background: A commercial building project implemented a suite of AI tools, including software for risk analysis and a decision-support system for selecting subcontractors based on past performance data. However, in this project, the project director fostered a culture that valued human insight alongside AI input. The team established a practice of weekly "analog sessions," during which all AI tools were turned off for a portion of the meeting. In these sessions, the project team (project manager, schedulers, engineers, and site supervisors) would review the week's progress and upcoming tasks using whiteboards and paper printouts. They engaged in face-to-face discussions to identify risks or coordination issues, deliberately trying to anticipate problems without relying on the software's risk flags. They would ask questions like "If we had no software, what do our instincts and experience tell us about this schedule?" In parallel, the AI systems were still used outside of these sessions to crunch numbers and provide detailed analyses; the difference was that the team did not treat the AI's outputs as fact. Every recommendation from the AI (such as a predicted delay or an optimal subcontractor choice) was debated in team meetings, with team members bringing in their ground-level knowledge or intuition before final decisions were made.

Incident: During the foundation phase, the AI risk model highlighted a moderate risk of delay due to expected bad weather. In contrast, some team members in the analog session voiced a different concern based on their gut feeling: the recent high on-site labor turnover. They intuitively felt that losing several experienced crew members might pose a coordination problem that the AI, which focused on weather and technical risks, had not given much weight to. Acting on this human insight, the project manager added an extra safety buffer to the schedule and initiated cross-training for the remaining crew to cover critical skills, even though the AI's analysis did not specifically recommend it. Indeed, over the next month, productivity dipped due to reliance on less experienced replacements, but proactive measures kept the project on schedule. Later, when a genuine weather delay did occur, the team used both the AI's contingency suggestions and their brainstorming to minimize downtime. They had previously discussed backup tasks that could be advanced during rain, something the AI was not programmed to do.

Outcome: The project was completed on time and within budget. In the post-project review, stakeholders praised the team's adaptability. The project director attributed their success to maintaining a balance between data-driven planning and human judgment. The weekly analog sessions were credited for keeping the team's problem-solving and communication skills sharp. Team members reported feeling more confident in making decisions with the help of AI, rather than simply deferring to it. This case exemplifies how the KSLF approach, which encourages both Kirk-like intuition (e.g., hunches about team morale and skills) and Spock-like analysis (e.g., using AI-driven data insights), may lead to more resilient project execution. The human and AI elements worked in tandem, and because the humans remained mentally engaged, they were ready to handle surprises that the AI did not foresee. The organization's deliberate practice of human-in-the-loop decision-making prevented the loss of expertise and, in fact, enhanced team learning, as junior members learned from senior mentors during the analog problem-solving exercises.

Cross-Industry Perspectives

The contrasting outcomes of the two cases above are not unique to the construction industry; they reflect broader patterns observed in other industries that deal with automation. In healthcare, for example, the integration of AI diagnostic tools has improved accuracy in radiology and pathology, yet experts caution that young clinicians must still learn traditional diagnostic reasoning. If a doctor always trusts an AI's reading of an MRI or lab result without forming their own assessment, their diagnostic insight may decline over time. Paranjape et al. (2019) note that medical training programs are beginning to incorporate AI and emphasize the importance of maintaining clinicians' fundamental reasoning abilities to avoid overdependence. In education, technology is widely used in learning environments, and studies have found that students who rely exclusively on calculators or educational software may exhibit weaker mental calculation and problem-solving skills. An OECD report (2015) highlighted that while digital tools can enhance learning, they are most effective when complementing, not replacing, the practice of core skills; for instance, students still need to practice manual arithmetic to develop number sense, otherwise the calculator becomes a crutch. In transportation, the aviation and automotive sectors provide cautionary tales: airline pilots in highly automated cockpits can experience skill degradation in manual flying, and drivers of cars with advanced driver-assistance systems can lose the habit of diligent road scanning. Endsley (2017) documents how increased automation in driving can reduce situational awareness; drivers may overlook hazards when they assume the automated system will handle everything, a situation that has led to accidents when the technology hands back control to an unprepared human. These examples from medicine, education, and transportation all echo the same underlying principle as our construction scenarios: human expertise is perishable if not exercised, especially in the presence of capable machines that can think or observe for us.

The cross-industry evidence thus reinforces the importance of strategies like the KSLF paradigm. Whether you are a project manager, a doctor, a student, or a driver, maintaining an active role in your interaction with AI systems is crucial. The human mind remains versatile and creative in ways machines are not, especially when facing novel situations or ethical dilemmas, but that versatility is maintained only through continual use. Just as the healthcare field advocates for “explainable AI” that doctors can interpret and learn from, rather than blindly following, the construction field can advocate for AI-assisted leadership, where managers continuously hone their judgment and skills in tandem with AI outputs.

Discussion

The foregoing analysis suggests that integrating AI into project management need not come at the expense of human cognitive development. On the contrary, if approached deliberately, it can serve as a form of regenerative leadership development, whereby AI challenges human leaders to elevate their skills. The Kirk-Spock Leadership Paradigm, augmented with neuroplasticity principles, serves as a roadmap for achieving this balance. Several key implications and insights emerge:

The ability of leaders to adapt, learn, and reframe problems, essentially becoming neuroplastically rich, is increasingly valuable in the fast-changing construction industry. By consistently engaging both intuitive and analytical thinking, leaders keep their brains flexible and ready to acquire new competencies. This cognitive agility enables better handling of unexpected events and opportunities for innovation. The KSLF approach ensures that adopting AI does not dilute this asset. Instead of leaders becoming one-dimensional (either overly intuitive without rigor, or overly analytical without creativity), they remain well-rounded. Our case studies aimed to demonstrate that a neuroplastically engaged team could outperform a complacent team in the face of unexpected challenges. In the long run, organizations that foster such adaptable minds may find that their teams can more readily adopt new technologies and processes, precisely because their leaders possess the mental resilience to learn continually. Thus, safeguarding neuroplasticity is not just about avoiding negatives (skill loss); it is about actively creating positive capacity for change and complexity. Future-oriented construction firms may even consider incorporating neuroplasticity metrics into their leadership development programs, for example, encouraging job rotations, cross-functional teamwork, and complex problem-solving projects that challenge cognitive abilities.

If the balance advocated here is not achieved, there is a genuine risk of cultivating a workforce that is hyper-efficient but fragile, one that performs well under normal conditions with AI support but breaks down when encountering unanticipated scenarios or when the technology malfunctions. This risk can be characterized as cognitive deskilling or even a form of learned helplessness in the face of technology. The negative case study and cross-industry examples highlight how competency can erode silently. From a strategic perspective, this undermines succession planning and organizational knowledge retention. For instance, if mid-level managers never learn to make decisions independently of AI, they may struggle to step into senior roles that require more judgment and oversight. There are also safety and ethical implications. An over-dependence on algorithms might cause leaders to overlook ethical considerations (e.g., an AI’s recommendation might be efficient but inhumane, something only a human conscience might catch) or could reduce caution in safety-critical monitoring. Over time, an organization can lose its culture of expertise, meaning that instead of people being valued for their skills and insights, they are valued only for their ability to operate the systems. This scenario is antithetical to the spirit of craftsmanship and problem-solving that has long defined the construction profession. It also poses a risk at the industry level: widespread deskilling could make the industry less attractive to new talent who seek creative and engaging work, not just button-pushing. Therefore, it is in the enlightened self-interest of both companies and the construction sector to avoid the path of least resistance (letting AI do everything) and instead choose the path of continuous human development alongside AI.

Achieving the Kirk-Spock balance with neuroplasticity in mind will likely require intentional changes in organizational culture and policies. Leaders at the top must communicate that the goal of adopting AI is to augment human capabilities, not to replace or diminish them. This can be translated into concrete practices: for example, companies can mandate that, for certain types of decisions, an alternative analysis by a human team be conducted even if an AI has provided an answer. They can celebrate examples where employees caught or improved upon an AI insight, to reinforce that human contributions are valued. Training programs, as mentioned, should be redesigned to cover both new technology and the underlying skills. Another idea is to incorporate mentorship and knowledge transfer into AI deployment, pairing less experienced staff with veterans to solve problems together and using the AI as a tool, so that tacit knowledge is passed on and enriched with AI-based knowledge. Moreover, organizations could invest in periodic workshops or hackathons where teams are given unfamiliar problems or scenarios (possibly outside their usual domain) to solve without relying on their standard tools, purely to exercise creativity and teamwork. Such practices align with the concept of a “learning organization” and will help keep employees’ minds sharp. In performance evaluations, management might include criteria related to innovation, critical thinking, and team communication, indirect signals that merely following algorithms is not enough to be a high performer. Over time, these measures can cultivate a culture where human–AI collaboration is dynamic, with employees confidently contributing their unique human insights.

On a broader level, industry associations and professional bodies in construction management could develop guidelines for the balanced use of AI. This might include recommended limits on automation for certain types of decisions, or checklists to ensure human review of AI outputs. The concept of “neuroplasticity audits,” introduced in the framework, can be expanded into an industry practice: organizations could periodically assess the impact of digital tools on their workforce capabilities. If a specific critical skill (for example, cost estimation or contract negotiation) is found to be under practiced because a tool handles it, the audit would flag it and suggest corrective action (such as rotational assignments or refresher training in that skill). Additionally, accreditation bodies may encourage construction management curricula that integrate AI literacy with strong foundational training in management principles, so that graduates enter the field with a mindset to use AI responsibly. Finally, researchers and policymakers should collaborate to collect longitudinal data on how AI adoption affects managerial skills in the construction industry. Such data can inform future regulations or standards, ensuring that modernization does not lead to inadvertent deskilling of professionals.

Limitation and Future Research

While the Kirk-Spock Leadership Framework offers a theoretically grounded and practically oriented response to the challenge of human-AI collaboration in construction project management, several limitations must be acknowledged. First, the framework is conceptual. Its development follows Design Science Research principles, and the illustrative scenarios presented are constructed to demonstrate applicability rather than to provide empirical evidence of effectiveness. The framework's validity in practice remains to be tested through rigorous field studies. Second, the cross-industry analogies drawn from healthcare, education, and transportation, while instructive, are not direct equivalents of construction project management contexts. The organizational structures, risk profiles, and regulatory environments differ substantially, and analogical reasoning carries inherent limits. Third, the paper relies on a selective synthesis of the neuroplasticity literature rather than on primary cognitive research conducted in construction settings. While the neuroscientific evidence cited is well established, its translation into leadership practice entails interpretive steps that future empirical work should examine more directly.

Looking ahead, the construction industry's adoption of Lean Construction methods provides a particularly fertile environment for testing and refining the KSLF. Several specific directions are worth pursuing. The Last Planner System® represents an ideal research site: LPS implementation involves regular cycles of collaborative planning, commitment-making, and variance analysis, processes in which the tension between human judgment and AI-assisted forecasting is immediately observable. Future studies could examine whether AI-automated lookahead planning and constraint analysis enhance or erode the collaborative reasoning skills that make LPS effective. Similarly, the PPC metric and the accompanying variance analysis workflows could be studied to determine whether automating tracking and flagging reduces practitioners' engagement with the underlying causes of plan failures, a direct form of cognitive deskilling within a Lean process.

Make-ready planning, which requires foremen and planners to exercise anticipatory judgment about constraints, resources, and sequencing, represents another natural testing ground for the Kirk-Spock balance. Research could explore how AI-assisted constraint identification interacts with planners' own make-ready reasoning, and whether over-reliance on algorithmic constraint flagging diminishes planners' independent foresight over time. Lean learning environments, including pull planning workshops, retrospectives, and after-action reviews, may themselves serve as built-in safeguards for neuroplasticity, and future work could assess whether teams that engage regularly in these practices demonstrate greater cognitive resilience when AI tools are unavailable or produce erroneous outputs.

Finally, longitudinal studies tracking cognitive skill retention in project teams using AI-assisted Lean tools versus those practicing conventional LPS would provide the empirical foundation that this conceptual paper cannot. Such studies could incorporate cognitive assessments, structured interviews, and project performance data to build a more complete picture of how balanced human-AI collaboration unfolds over time in real construction environments. Collaboration between researchers in construction engineering, cognitive science, and organizational behavior will be essential to advancing this agenda.

Conclusion

Artificial intelligence is transforming the landscape of construction project management, providing powerful tools to manage complexity and uncertainty. However, the human brain, with its remarkable adaptability and depth of understanding, remains an irreplaceable asset in leadership. This paper has argued that sustaining this human asset in the AI era requires a conscious balancing act. Using the Kirk-Spock Leadership Paradigm as a metaphor and framework, we proposed how combining intuitive ability, analytical rigor, and mindful AI collaboration may lead to better outcomes than leaning on any one element alone. A key contribution of this work is highlighting neuroplasticity as a focal concern: the long-term cognitive health and growth of leaders and teams should be treated as a critical success factor, on par with project schedules and budgets. By incorporating practices that keep leaders' minds engaged, such as scenario drills, manual problem-solving sessions, and human-in-the-loop decision protocols, organizations can enjoy the efficiency of AI while also cultivating leadership capabilities that grow stronger with experience.

The examples and cases discussed suggest that the dangers of cognitive complacency in the face of AI are real but may be avoidable. A culture of balanced human–AI partnership not only averts skill atrophy but can create a virtuous cycle where AI tools push humans to learn faster and humans push AI to be used more creatively. For the construction industry, which stands at the tip of digital transformation, the timing is ripe to embed these principles into practice. Leaders who champion the Kirk-Spock approach may find that their teams are more adaptable, innovative, and resilient in the face of disruptions. Moreover, by valuing human intuition and empathy alongside machine intelligence, construction projects can maintain a human-centered orientation, which is crucial for safety, ethics, and stakeholder satisfaction.

In conclusion, we advocate for further research into the impact of AI integration on leadership development and team performance in the construction industry. Empirical studies could, for instance, examine how alternating between AI-assisted and manual decision-making tasks affects managers' cognitive skills over time, or how project outcomes correlate with the level of human–AI balance in decision-making processes. It would also be valuable to explore neuroplastic changes through cognitive testing among professionals who frequently use AI, enabling direct observation of the brain's responses. By deepening our understanding of these phenomena, the industry can formulate more precise guidelines to harness AI's benefits without compromising the growth and adaptability of its human practitioners. In the journey toward more innovative construction projects, maintaining the brain fitness of our human leaders will ensure that technology truly serves as a tool for progress, not a substitute for the rich problem-solving capabilities that have built the world around us.

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