

The Human-Centric Intelligence Framework: Integrating Human Intelligence, Knowledge Management and Artificial Intelligence for Engineering Organizations

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Abstract

Artificial intelligence is becoming embedded in engineering organizations at remarkable speed. Yet much of the current discussion still treats intelligence mainly in computational terms: model capability, automation, prediction and generation. That view is useful, but it is incomplete for knowledge-intensive and high-consequence engineering environments. Engineering performance depends on analytical cognition, but it also depends on experience, tacit know-how, context, relationships, creativity, practical judgment, adaptability, systems thinking, ethics and collective learning. This paper proposes the Human-Centric Intelligence Framework (HCIF), a conceptual framework that places these interdependent forms of human intelligence at the foundation of knowledge management (KM) and artificial intelligence (AI). Drawing on knowledge-creation theory, particularly tacit-explicit knowledge conversion and the SECI model, and extending assistive human-centric approaches to AI, HCIF conceptualizes organizational intelligence as a layered socio-technical system. KM captures, structures, validates and circulates human knowledge; AI retrieves, synthesizes, analyzes and augments that knowledge; and people retain responsibility for contextual interpretation, ethical judgment and accountable action. The framework is especially relevant to engineering design, project management, asset operations and other settings in which a technically plausible output may still be unsafe, unconstructable, commercially inappropriate or contextually wrong. The paper develops the framework, proposes an operating architecture and research propositions, and outlines an agenda for empirical validation. Its central argument is that the strategic objective of enterprise AI should not be maximum automation, but stronger human and organizational intelligence i.e. People + Knowledge + Intelligence + AI.

Keywords: human-centric intelligence; knowledge management; artificial intelligence; tacit knowledge; engineering organizations; human-AI collaboration; organizational intelligence; SECI; judgment; assistive AI

I. Introduction

Artificial intelligence has moved rapidly from experimentation into mainstream organizational use. Stanford's 2026 AI Index reports that 88% of surveyed organizations used AI in at least one business function in 2025, while generative AI was used in at least one function by 70% of organizations (Stanford Institute for Human-Centered AI, 2026). As adoption expands, the managerial question is changing. The issue is no longer simply whether organizations will use AI, but how AI should be embedded in work, decision-making and organizational knowledge systems.

For engineering organizations, this is not an abstract question. Engineering decisions are rarely reducible to information retrieval or computational optimization. A design may satisfy the calculation and still be difficult to construct. A project schedule may be mathematically feasible yet unrealistic when local logistics, stakeholder constraints or regulatory requirements are considered. An equipment selection may meet a technical specification while creating avoidable maintainability or lifecycle problems. Experienced professionals make these distinctions by combining formal knowledge with accumulated experience, contextual awareness, intuition, professional ethics and judgment.

The growing capability of generative and agentic AI makes it increasingly important not to equate machine capability with the full range of intelligence required for engineering work. AI is exceptionally useful for pattern recognition, information synthesis, prediction, optimization and content generation. However, engineering performance emerges from a wider intelligence ecology. People contribute forms of intelligence that are experiential, relational, contextual and normative, while knowledge management provides the organizational mechanisms through which much of that intelligence can be shared, retained, challenged and reused.

This paper develops the Human-Centric Intelligence Framework (HCIF) as an extension of an assistive, human-centric approach to AI-enabled knowledge management. Its central proposition is that enterprise AI adoption is, in important respects, a knowledge-management challenge before it is an automation challenge. The aim should therefore be to design systems that augment human capability and organizational intelligence, rather

than to pursue automation wherever automation is technically possible. HCIF is organized around the sequence People → Knowledge → Intelligence → AI, with human accountability remaining the governing principle.

The paper makes four conceptual contributions. First, it develops a taxonomy of human-centric intelligence relevant to engineering organizations. Second, it connects these intelligence forms to tacit and explicit knowledge and to organizational knowledge-creation processes. Third, it proposes an integrated operating architecture linking human experts, knowledge infrastructure, AI augmentation and governance. Fourth, it develops testable research propositions and an empirical agenda for examining the framework in engineering design and project environments.

II. Theoretical Background

2.1 Knowledge as the substrate of organizational intelligence

Knowledge management distinguishes between information that can be codified and knowledge that remains embedded in human experience, practice and social interaction. Polanyi's observation that people can know more than they can tell remains fundamental to engineering practice. Experienced engineers often recognize patterns, anomalies and risks without being able to reduce the entire reasoning process to a procedure. Such tacit knowledge is not inferior to formal knowledge; in many high-skill environments it is precisely what differentiates competent execution from expert performance.

Nonaka and Takeuchi's knowledge-creation theory provides a useful bridge between individual and organizational intelligence. The SECI model describes knowledge creation through Socialization, Externalization, Combination and Internalization. Socialization transfers tacit knowledge through shared experience; externalization articulates tacit knowledge into concepts or representations; combination reorganizes explicit knowledge; and internalization embeds explicit knowledge into practice. For AI-enabled organizations, SECI is important because AI systems are strongest where knowledge has been made accessible in machine-readable or retrievable form, while much of the organization's highest-value expertise may remain tacit.

Accordingly, knowledge infrastructure should be understood as more than repositories. It includes connected architecture, taxonomies and ontologies, validated content, lessons learned, expert networks, governance, knowledge ownership, retrieval mechanisms, organizational memory and processes for capturing experience. AI deployed without this substrate may amplify fragmentation or provide fluent answers unsupported by authoritative organizational knowledge.

2.2 Human-centric AI and Industry 5.0

Human-centric approaches to technology challenge the assumption that technological progress should be measured primarily by automation. The European Commission's Industry 5.0 vision places worker wellbeing, skills and empowerment at the center of production systems and emphasizes human-centricity, sustainability and resilience (Breque, De Nul, & Petridis, 2021). This perspective is compatible with engineering knowledge management because engineering organizations depend on expertise communities and socio-technical systems rather than technology in isolation.

Trustworthy AI frameworks similarly emphasize governance and risk management. The NIST AI Risk Management Framework is intended to help organizations manage risks to individuals, organizations and society while enabling beneficial AI use (Tabassi, 2023). The significance for HCIF is that human oversight cannot be treated as a ceremonial approval step. Oversight requires capable humans with access to relevant organizational knowledge, sufficient contextual understanding, and clearly assigned decision rights.

Recent knowledge management research is beginning to formalize the complementarity between humans and AI. Dittmar and Sposato (2026), for example, propose the Trust-Complementarity Model of Collective Intelligence, in which calibrated trust, complementary capability utilization and feedback loops contribute to stronger human-AI decision performance. HCIF extends this line of inquiry by asking a prior question: which forms of human intelligence should engineering organizations deliberately preserve, develop and combine with AI?

III. Research Gap and Conceptual Problem

Existing AI frameworks commonly emphasize model capability, responsible use, human-in-the-loop controls, explainability and task allocation. Knowledge-management frameworks, by contrast, tend to emphasize knowledge creation, storage, sharing and application. These bodies of literature increasingly intersect, but the idea of 'human intelligence' often remains underspecified. The human participant is frequently represented simply as a reviewer, expert or decision-maker, without sufficient attention to the distinct and interacting capabilities that make expert judgment possible.

That abstraction has practical consequences. If an organization cannot identify what people contribute to a decision, it becomes difficult to decide what should be automated, what should be augmented, what knowledge should be captured and where human authority is indispensable. Engineering organizations may naturally

privilege analytical intelligence because it is easier to formalize and measure, while underestimating contextual, practical, relational or ethical intelligence. The result may be a system that improves a narrow measure of efficiency while weakening decision quality at the level of the project or organization.

The research problem can therefore be stated as follows: How can engineering organizations conceptualize, manage and augment the multiple forms of human intelligence that underpin expert judgment, and how can knowledge management and AI be configured to transform those capabilities into sustainable organizational intelligence?

IV. Methodology: Conceptual Framework Development

This study adopts a conceptual theory-building approach. It does not attempt to test a single causal relationship. Instead, it brings together constructs from knowledge management, human intelligence, organizational learning, human-AI collaboration, responsible AI and engineering decision-making to develop an integrative framework. This approach is appropriate because the phenomenon is socio-technical: the relevant unit of analysis is not the AI model in isolation, but the interaction among people, knowledge assets, organizational processes, technological systems and governance arrangements.

Framework development followed four conceptual steps: (1) identifying forms of human intelligence that materially influence knowledge-intensive engineering work; (2) mapping these forms to tacit and explicit knowledge processes; (3) defining complementary roles for KM and AI; and (4) specifying governance mechanisms and outcomes relevant to engineering organizations. HCIF is therefore presented as a theory-informed conceptual framework and a basis for subsequent empirical testing, not as an already validated causal model.

V. The Human-Centric Intelligence Taxonomy

HCIF defines human-centric intelligence as the integrated capacity of individuals and groups to understand, interpret, create, relate, adapt, judge and act responsibly within real-world contexts. The concept is intentionally broader than psychometric intelligence. Its concern is not intelligence as a test score, but the combination of human capabilities through which knowledge becomes sound organizational action.

Human-centric intelligence	Organizational meaning	Primary KM/AI implication
Cognitive and analytical intelligence	Logical reasoning, decomposition, quantitative analysis, diagnosis and structured problem-solving. In engineering, it supports calculations, option evaluation, root-cause analysis and technical verification. AI can strongly augment this layer through computation, search, simulation and pattern recognition.	KM should curate authoritative technical knowledge, calculations, standards and decision records. AI can strongly augment computation, retrieval, simulation, comparison and pattern recognition, while human experts verify assumptions and engineering significance.
Experiential intelligence	Capability accumulated through repeated exposure to situations and consequences. It enables experts to recognize what tends to work, what fails in practice and which weak signals deserve attention. KM can preserve elements of this intelligence through lessons learned, case histories and expert debriefs.	KM should capture experience through lessons learned, after-action reviews, case histories and expert debriefs. AI can retrieve and synthesize analogous past cases, but experienced professionals should judge whether prior experience is transferable to the present situation.
Tacit intelligence	Embodied know-how that is difficult to fully articulate. It includes craft knowledge, professional instinct and practice-based pattern recognition. It is particularly vulnerable to retirement, turnover and organizational silos, making externalization a strategic KM priority.	KM should prioritize externalization through mentoring, knowledge cafes, communities of practice, structured knowledge elicitation and expert knowledge capture. AI can assist transcription, elicitation and retrieval, but should not be assumed to reproduce embodied know-how that has not been adequately articulated.
Emotional intelligence	Capacity to perceive, understand and regulate emotion in oneself and others. Engineering leadership, negotiation, safety culture, conflict resolution and change management depend on it. AI may support communication but cannot assume the moral and relational accountability attached to human interaction.	KM should preserve knowledge about team dynamics, change experience and stakeholder interactions through reflective practice and leadership learning. AI may support communication analysis, coaching and sentiment cues, but empathy, relational judgment and accountability should remain human responsibilities.

Human-centric intelligence	Organizational meaning	Primary KM/AI implication
Social and relational intelligence	Understanding networks, influence, trust, power, collaboration and stakeholder relationships. Major projects often succeed or fail through interfaces among clients, contractors, regulators, communities and disciplines, not through technical analysis alone.	KM should map expert networks, communities, stakeholder histories and relationship-dependent knowledge. AI can support expert location, network analysis and stakeholder-information synthesis, while humans retain responsibility for trust-building, influence, negotiation and relationship management.
Contextual intelligence	Ability to interpret knowledge relative to place, timing, culture, constraints, history and organizational reality. Context determines whether a technically valid recommendation is appropriate. Retrieval-augmented AI can improve context access, but humans remain essential in deciding which context is material.	KM should preserve the conditions, assumptions, provenance and circumstances surrounding knowledge rather than storing content in isolation. Context-aware and retrieval-augmented AI can surface relevant project information, but humans must determine which contextual factors are material to the decision.
Creative intelligence	Capacity to imagine alternatives, reframe problems and generate useful novelty. AI can expand ideation spaces, while human purpose, constraints and evaluation determine which ideas are meaningful and responsible.	KM should make diverse knowledge, prior solutions and cross-disciplinary insights accessible for recombination. Generative AI can broaden the option space and support ideation, while humans define purpose, constraints, novelty, feasibility and the value of proposed solutions.
Practical intelligence	Ability to convert abstract knowledge into workable action under imperfect conditions. It asks not merely 'is this correct?' but 'will this work here, with these people, resources and constraints?'	KM should capture implementation knowledge, field constraints, workarounds and constructability or operability lessons. AI can compare options and retrieve practical precedents, but experienced practitioners should determine whether a recommendation can work under actual resource and operating conditions.
Ethical and moral intelligence	Capacity to evaluate what ought to be done, including fairness, safety, duty, professional responsibility and societal consequences. This layer establishes boundaries on optimization and automation.	KM should codify professional obligations, safety requirements, ethical principles, regulatory constraints and decision precedents. AI can flag conflicts, risks and compliance considerations, but value judgments, duty of care and accountability for consequential decisions must remain human-governed.
Cultural intelligence	Ability to understand and operate across cultural norms, institutional settings and diverse teams. It is increasingly important in multinational engineering projects and global supply chains.	KM should capture locally relevant practices, institutional knowledge and lessons from multicultural teams and projects. AI can support translation and access to cultural information, but human interpretation is required to avoid stereotyping and to navigate norms, sensitivities and institutional realities.
Adaptive intelligence	Capacity to learn, revise assumptions and respond to uncertainty. It converts feedback into changed behavior and is central to resilience in volatile project environments.	KM should create rapid feedback loops that capture changing conditions, corrections, near misses and emerging lessons. AI can detect shifts, anomalies and new patterns and support scenario analysis, while humans revise assumptions, priorities and actions as circumstances evolve.
Intuitive intelligence	Rapid, often non-conscious judgment based on accumulated pattern recognition. Intuition should not be romanticized: it can contain bias. Within HCIF it is treated as a valuable signal that should be tested against evidence, peer challenge and explicit knowledge.	KM should create mechanisms for experts to articulate intuitive concerns and connect them to evidence, cases and peer challenge. AI can test intuitive signals against historical data and explicit knowledge, helping distinguish useful pattern recognition from bias or unsupported confidence.
Systems intelligence	Ability to see interdependencies, feedback loops, second-order effects and lifecycle consequences. It prevents local optimization from undermining overall system performance.	KM should connect knowledge across disciplines, lifecycle stages and organizational boundaries through integrated repositories, ontologies and knowledge graphs. AI can model dependencies, detect interactions and support scenario analysis, while humans assess second-order effects and system-level trade-offs.

Human-centric intelligence	Organizational meaning	Primary KM/AI implication
Collective intelligence	Capability that emerges when diverse people combine complementary knowledge and perspectives through effective interaction. KM and AI can both amplify collective intelligence by improving knowledge accessibility, coordination and synthesis.	KM should enable knowledge sharing, communities of practice, cross-disciplinary collaboration and organizational memory. AI can improve discovery, synthesis and coordination across distributed expertise, provided that governance preserves diverse viewpoints and avoids replacing deliberation with a single machine-generated answer.
Judgment and wisdom	The integrative layer that combines evidence, experience, context, values, uncertainty and consequences to choose an appropriate course of action. Wisdom is not simply more information. It includes restraint, proportionality and awareness of what is not known.	KM should provide decision-makers with validated evidence, context, precedents, lessons and access to relevant expertise. AI can synthesize options, uncertainties and consequences, but final judgment—especially under ambiguity, competing values or high consequence—should remain with accountable human professionals.

VI. The Human-Centric Intelligence Framework (HCIF)

HCIF is organized around five nested layers: Human Intelligence, Knowledge Conversion, Knowledge Infrastructure, AI Augmentation and Human-Governed Organizational Action. These layers should not be read as a simple technology stack. They form a learning system: action produces experience; experience produces knowledge; governed knowledge improves AI-supported analysis; and the resulting insight returns to people who interpret, decide and act.

Layer 1 - Human intelligence assets. The organization begins with people rather than technology. Individuals and teams possess the intelligence forms identified above. These capabilities are distributed unevenly across disciplines, experience levels, locations and communities of practice.

Layer 2 - Knowledge conversion. Through socialization and externalization, experience and tacit knowledge become shareable. Through combination, explicit knowledge from standards, procedures, calculations, project records, lessons and external evidence is integrated. Through internalization, validated knowledge returns to practice and becomes part of professional capability.

Layer 3 - Knowledge infrastructure. Knowledge must be governed, discoverable and connected. This layer includes repositories, taxonomies, ontologies, metadata, expert directories, lessons-learned systems, document controls, validation workflows, access controls, knowledge ownership and provenance. It creates an authoritative organizational memory from which both people and AI can work.

Layer 4 - AI augmentation. AI performs high-volume cognitive work: retrieval, summarization, classification, comparison, pattern detection, prediction, scenario generation, simulation support and workflow execution. Generative AI is particularly useful for synthesizing explicit knowledge; agentic systems may execute bounded tasks. Neither role implies transfer of ultimate engineering accountability.

Layer 5 - Human-governed action and learning. Humans interpret outputs in context, challenge assumptions, resolve ambiguity, apply ethical and professional standards, make accountable decisions and observe consequences. Outcomes are then captured as new knowledge, closing the learning loop.

6.1 The core HCIF equation

People + Knowledge + Intelligence + AI → Augmented Organizational Intelligence

The order is intentional. People create, interpret and apply knowledge. KM turns dispersed knowledge into an organizational resource. Multiple forms of human intelligence give that knowledge context, meaning and judgment. AI can then augment these capabilities at scale. Starting with AI and attempting to retrofit people and knowledge around it creates a greater risk of fragmented adoption, weak trust and automation that is technically impressive but organizationally low-value.

6.2 A decision-rights principle

HCIF proposes that task allocation should be based on the kind of intelligence a task requires, not simply on whether the task can be automated. Activities dominated by retrieval, comparison, computation and pattern recognition may support relatively high levels of AI autonomy. As ambiguity, consequence severity, competing values, safety implications, stakeholder legitimacy or professional accountability increase, human authority should become progressively stronger. HCIF therefore proposes an 'augmentation gradient' rather than a binary choice between human and machine.

VII. Relationship Between HCIF and Knowledge Management

Knowledge management is the connective tissue of HCIF. Without it, valuable human intelligence remains concentrated in individuals and local teams, AI draws from fragmented information rather than validated organizational knowledge, and lessons are repeatedly lost between projects. Within the framework, KM performs six closely related functions: capture, codification, contextualization, validation, distribution and institutionalization.

Capture converts experience into retrievable organizational memory. Codification gives structure to documents, lessons and concepts. Contextualization preserves the circumstances under which knowledge was generated. Validation establishes authority and provenance. Distribution ensures that relevant knowledge reaches the point of work. Institutionalization embeds lessons into standards, workflows, training and decision routines.

This interpretation moves KM beyond the idea of a repository and treats it as an intelligence-enablement function. The strategic question is no longer only, 'How do we store what we know?' It becomes, 'How do we convert human intelligence into reusable organizational capability without removing the context that gives knowledge its meaning?' AI makes this question more urgent because machine retrieval can scale poor knowledge just as efficiently as it can scale good knowledge.

The SECI model becomes operational within HCIF. Socialization strengthens experiential, tacit, social and cultural intelligence. Externalization makes elements of tacit, intuitive and practical intelligence available to others. Combination allows AI and humans to integrate explicit knowledge across projects and disciplines. Internalization transforms validated insight into improved human capability. The cycle is then accelerated by AI, but it remains grounded in human practice.

VIII. Application to Engineering Organizations

8.1 Engineering design

Engineering design combines codified technical knowledge with expert interpretation. AI can search standards, compare specifications, identify inconsistencies, generate alternatives and support calculations. Yet experienced engineers also bring constructability, operability, maintainability, safety and lifecycle judgment. Under HCIF, design-assist systems would draw not only on formal standards but also on approved lessons learned, prior design decisions, failure histories and expert commentary, while ensuring that high-consequence recommendations remain subject to accountable professional review.

8.2 Project management and project controls

Project controls are an obvious area for AI because schedules, costs, risks and progress data can be analyzed at scale. But projects are not driven by data alone. Outcomes are shaped by behavior, interfaces, contractor capability, local conditions, stakeholder relationships and weak signals that may not be fully represented in a dataset. An AI system may identify a schedule variance; an experienced project manager must still judge whether the variance is recoverable, whether reported progress is credible and which intervention is operationally and organizationally feasible. HCIF therefore combines AI's analytical strength with the contextual, relational, experiential and practical intelligence of project professionals.

8.3 Operations, maintenance and asset integrity

Asset environments contain decades of work orders, inspection records, operating procedures and incident data. AI can connect these records and detect patterns that humans may miss. Nevertheless, field technicians and engineers possess embodied knowledge about equipment behavior, abnormal sounds, recurring failure modes and practical maintenance constraints. Capturing this knowledge through structured debriefs, communities of practice and AI-assisted knowledge elicitation can reduce knowledge loss while preserving human verification for safety-critical decisions.

8.4 Safety and high-consequence decisions

Safety illustrates why human-centricity must mean more than ease of use. A recommendation can optimize cost or production and still increase latent risk. Ethical intelligence, systems intelligence and professional judgment are therefore part of the governance architecture, not optional additions. In HCIF, high-consequence AI use should be bounded by traceability, validated knowledge sources, explicit communication of uncertainty, escalation rules and named human accountability. This is consistent with the risk-management orientation of the NIST AI RMF and related critical-infrastructure guidance.

IX. Governance Architecture for HCIF

Governance determines whether HCIF functions as a genuinely human-centered system or becomes little more than a human-centered label attached to automation. Five governance domains are proposed.

First, knowledge governance: ownership, validation status, provenance, retention, classification and lifecycle controls for knowledge assets. Second, AI governance: model selection, use-case approval, risk classification, evaluation, monitoring and change control. Third, decision governance: explicit allocation of recommendation rights, approval rights, escalation thresholds and professional accountability. Fourth, human capability governance: competency standards, AI literacy, critical-thinking skills, knowledge-sharing expectations and protection against deskilling. Fifth, learning governance: mechanisms for capturing outcomes, near misses, corrections and user feedback and reintegrating them into both knowledge bases and AI evaluation.

Trust in AI should be calibrated rather than maximized. Excessive trust can create automation bias, while insufficient trust can prevent useful adoption. Explainability, provenance and visible uncertainty can help professionals decide when reliance is warranted. Just as importantly, organizations should preserve the professional right and practical ability to challenge an AI recommendation when contextual knowledge, experience or engineering judgment indicates that something is wrong.

X. Research Propositions

P1: Engineering organizations with stronger knowledge infrastructure will achieve higher decision quality from enterprise AI than organizations with comparable AI capability but weaker knowledge infrastructure.

P2: The positive effect of AI capability on engineering decision performance will be mediated by the accessibility, quality and contextual richness of organizational knowledge.

P3: Human-AI decision performance will be higher when task allocation reflects complementary intelligence capabilities rather than maximum technical automation.

P4: Tacit-knowledge externalization will positively influence the usefulness and trustworthiness of AI-supported engineering decisions.

P5: Human judgment will have a stronger moderating effect on AI-supported performance as decision ambiguity, consequence severity and contextual dependence increase.

P6: Calibrated trust will produce better human-AI decision outcomes than either generalized high trust or generalized low trust.

P7: Organizations that institutionalize AI-supported lessons through SECI processes will demonstrate stronger organizational learning and lower recurrence of project errors.

P8: Human-centric AI governance will reduce professional deskilling when it explicitly preserves learning, challenge and decision responsibilities for human experts.

P9: Collective intelligence will increase when AI improves cross-disciplinary knowledge access while decision processes preserve diverse human perspectives.

P10: HCIF maturity will be positively associated with safety, project predictability, knowledge retention, innovation and organizational resilience.

XI. Proposed Empirical Validation

A mixed-method research design is proposed for empirical validation. Phase 1 would use expert interviews across engineering design, project management, construction, operations, maintenance and HSE to assess the relevance and completeness of the intelligence taxonomy and identify sector-specific manifestations. Critical-incident interviews would be particularly useful because they can reveal how experts draw on tacit, experiential and contextual knowledge when making consequential decisions.

Phase 2 should develop a survey instrument measuring HCIF constructs: knowledge infrastructure maturity, tacit-knowledge capture, AI augmentation intensity, human oversight quality, calibrated trust, contextual intelligence utilization, collective intelligence and decision outcomes. Structural equation modeling could test the proposed mediation and moderation relationships across a sufficiently large sample of engineering professionals.

Phase 3 should conduct comparative case studies or field experiments. Teams could perform realistic engineering or project-control tasks under three conditions: conventional work, AI-only/AI-dominant assistance, and HCIF-configured assistance using governed organizational knowledge and explicit human decision rights. Outcomes should include accuracy, decision time, error detection, explanation quality, confidence calibration and expert-rated contextual appropriateness.

Longitudinal validation is also important. Some HCIF outcomes—knowledge retention, deskilling prevention, organizational learning and resilience—cannot be adequately measured in short experiments. Multi-project studies could examine whether lessons captured through AI-enabled KM are actually reused and whether recurrence of known errors declines over time.

XII. Discussion

HCIF reframes the enterprise AI debate by shifting the unit of analysis away from a contest between human and artificial intelligence. For engineering organizations, the more useful unit of analysis is the combined socio-technical system: human intelligence + organizational knowledge + artificial intelligence. This framing

avoids two unhelpful extremes: assuming that automation is inherently superior, and treating AI as inherently incompatible with professional expertise.

The framework also explains why knowledge management becomes more, not less, important in the AI era. Generative AI makes answers easier to produce, but producing an answer is not the same as organizational knowing. Engineering organizations still require authoritative sources, context, provenance, lessons learned, expert networks and mechanisms for correction. As AI capability grows, so does the value of a trustworthy knowledge substrate.

A second implication concerns professional capability. Human-centricity should not mean placing a person in a workflow merely to approve a machine-generated output. Meaningful human control requires competence. If AI progressively performs the analytical work through which junior professionals develop first-principles understanding, an organization may preserve nominal human oversight while gradually losing the expertise required to exercise it. HCIF therefore treats capability development and knowledge internalization as governance requirements.

Third, HCIF provides a basis for distinguishing generative, assistive and agentic roles. Generative AI can synthesize and create candidate content. Assistive AI can enhance professional cognition and decision-making. Agentic AI can execute bounded tasks and workflows. The appropriate level of autonomy should depend on consequence, reversibility, knowledge quality and the human intelligence dimensions required. High analytical load with low consequence may support extensive automation; high contextual or ethical load with severe consequence should remain strongly human-governed.

Finally, HCIF suggests a broader definition of organizational intelligence. An intelligent engineering organization is not necessarily the one with the most AI. It is the one that can bring together the right expertise, trusted knowledge, appropriate technology and sound judgment at the point of decision; learn from outcomes; and preserve accountability. In that sense, AI is a multiplier of organizational intelligence rather than its definition.

XIII. Managerial Implications

Engineering leaders can begin by mapping critical decisions and identifying the forms of intelligence each decision requires. This is a more useful starting point than compiling a catalogue of AI tools. For each decision, leaders should ask: What explicit knowledge is required? What tacit knowledge is normally applied? Which contextual factors matter? What are the consequences of error? Who remains professionally accountable? Which activities can AI accelerate, and which still require human interpretation and judgment?

Organizations should also invest in knowledge infrastructure alongside model capability. Practical priorities include validated enterprise search, controlled engineering repositories, lessons-learned taxonomies, expert-location systems, project knowledge graphs, knowledge provenance, communities of practice and structured capture of expert experience. AI interfaces should surface source material and uncertainty rather than only polished answers.

Performance measures should extend beyond productivity. Relevant indicators include decision quality, error recurrence, time to locate authoritative knowledge, reuse of lessons, expert participation, trust calibration, near-miss detection, knowledge retention, learning velocity, safety performance and the ability of staff to independently challenge AI outputs.

XIV. Limitations and Future Research

HCIF is a conceptual framework and should not be interpreted as empirically established. The proposed intelligence categories overlap and may not behave as independent constructs. Their relative importance may also vary across sectors, cultures and types of engineering work. Future research should refine measurement scales, test the taxonomy across engineering disciplines, compare novice and expert users, examine how sustained AI use affects the development of tacit knowledge, and establish appropriate autonomy thresholds for different risk classes. Comparative studies across regions, including African engineering organizations, would be particularly valuable because contextual intelligence, institutional conditions and infrastructure constraints may produce different human-AI configurations from those found in highly digitized economies.

XV. Conclusion

The next phase of enterprise AI is likely to depend less on access to models alone than on the quality of the socio-technical systems within which those models operate. Engineering organizations possess an intelligence resource that extends well beyond formal technical knowledge. It includes cognitive, experiential, tacit, emotional, social, contextual, creative, practical, ethical, cultural, adaptive, intuitive, systems and collective intelligence, integrated through judgment and wisdom.

HCIF places these human capabilities at the foundation of AI-enabled organizational performance. Knowledge management converts dispersed human knowing into accessible, contextualized and governed organizational memory. AI augments retrieval, synthesis, analysis and bounded execution. People contribute

purpose, context, professional responsibility, ethical interpretation and accountable judgment. The desired outcome is therefore not artificial intelligence in isolation, but augmented organizational intelligence.

For engineering organizations, the principle is straightforward: technology should amplify expertise without eroding the human capacities that make expertise trustworthy. The strategic sequence is People → Knowledge → Intelligence → AI. When that sequence is respected, AI can serve not as a substitute for engineering judgment, but as an infrastructure for making human and collective intelligence more accessible, scalable and effective.

Declarations

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Appendix A. HCIF Diagnostic Questions for Engineering Organizations

- People: Which decisions depend on experienced human judgment, and where is that expertise located?
- Knowledge: What authoritative explicit and tacit knowledge supports each critical decision?
- Context: Does the knowledge retain information about project conditions, assumptions, geography, stakeholders and consequences?
- AI: Which cognitive activities can AI augment safely, and what evidence is available to validate its outputs?
- Decision rights: Who may recommend, approve, override and escalate AI-supported decisions?
- Learning: How are corrections, outcomes and near misses captured and fed back into organizational memory?
- Capability: Are professionals still developing the expertise required to challenge AI outputs?
- Governance: Can every high-consequence AI-supported decision be traced to sources, assumptions and accountable human authority?