Agentic AI for Workforce Foresight: Enabling Intersectoral Competence Transfer in Engineering Consulting

Asmaa Abid-Baudin, Thibault Desbois, Karine Sacepe and Laurent Lefebvre
Capgemini Engineering, France

asmaa.abid-baudin@capgemini.com (Corresponding author)
thibault.desbois@capgemini.com
karine.sacepe@capgemini.com
laurent.a.lefebvre@capgemini.com

Abstract: Engineering consulting firms increasingly rely on artificial intelligence (AI) to identify, mobilize and develop talent across heterogeneous sectors such as aerospace, energy and mobility. While prior research has examined the effects of AI on knowledge work and decision support, its role in shaping intersectoral agility, that is the ability of consultants to transfer and recombine competencies across industries, and in reconfiguring staffing and workforce planning logics remains underexplored. This paper investigates how AI reshapes intersectoral agility and redefines staffing and workforce planning logics in engineering consulting firms. The study adopts abductive qualitative design conducted within a large international engineering consulting group. The empirical corpus comprises 24 semi-structured interviews and two focus groups involving 30 participants drawn from technical, managerial and support functions, complemented by documentary material and by projective scenario techniques used as elicitation devices. Data was analyzed through an iterative process of open, axial and selective coding combining AI-assisted identification of meaning units with systematic human validation, which generated 472 open codes. The findings, reported in structured form and compared with theoretical expectations, identify three core dimensions. First, transferability across domains is real but conditional upon a pre-existing knowledge base and human mediation. Second, hybrid competencies emerge as a situated capability articulating domain expertise, AI use, reflexivity and verification practices. Third, staffing practices are reconfigured by algorithmic support that participants accept only as a decision aid. Five cross-cutting conditions, namely governance and explicability, dignity and confidentiality, prudence, client trust and acculturation, delimit the acceptability of these transformations. The paper contributes by identifying the socio-organizational mechanisms through which AI reshapes competence transferability and staffing practices. It introduces conditional augmentation as a socio-organizational regime explaining why AI-enabled workforce foresight remains dependent upon human validation, organizational trust and contextual embedding. The findings further reveal four persistent tensions shaping augmented work: decision, transparency, agency and learning paradoxes. From a managerial perspective, transparency, human oversight and equity emerge as essential principles for reconciling efficiency with legitimacy and trust. The study calls for longitudinal and comparative research on the organizational consequences of AI-mediated workforce allocation systems.

Keywords: Artificial intelligence, Intersectoral agility, Hybrid competencies, Workforce planning, Algorithmic mediation, Engineering consulting

1. Introduction

Artificial intelligence (AI) is increasingly embedded in knowledge-intensive work, reshaping how information is accessed, processed and mobilized within organizations. Beyond operational efficiency, AI progressively redefines the conditions under which knowledge is constructed, evaluated and legitimized, prompting knowledge management scholars to revisit established models of knowledge creation and circulation (Böhm and Durst, 2025). In engineering consulting firms, where expertise, credibility and client trust are central, this transformation raises critical questions regarding the role of AI in supporting, augmenting or disrupting established knowledge practices (Vial et al, 2023).

A further shift is under way. Beyond generative assistance, agentic systems combine reasoning, memory and tool orchestration to plan and execute multi-step tasks with limited human prompting (Abou Ali, Dornaika and Charafeddine, 2026). In engineering settings, such architectures are progressively applied to competence mapping, profile matching and workforce forecasting, which makes them directly relevant to strategic foresight in learning organizations. Their technical potential is documented, yet their socio-organizational conditions of acceptability remain largely untested.

Existing research highlights the capacity of AI to enhance productivity and decision-making (Brynjolfsson, Li and Raymond, 2025), yet its integration into everyday practices remains situated and socially mediated. Generative AI introduces tensions between performance and legitimacy, automation and human judgement, standardization and contextualization. These tensions are especially salient where intersectoral mobility requires professionals to adapt continuously, transfer competencies across domains and navigate evolving organizational expectations (Institut de l'Entreprise and McKinsey, 2024; LaborIA, 2024).

AI cannot therefore be understood solely as a technological tool but as a socio-cognitive intermediary interacting with key processes of knowledge management. This article focuses on three interconnected dimensions through which AI contributes to the reconfiguration of knowledge practices: skills transferability across domains, understood as a form of boundary spanning; the emergence of hybrid competencies combining domain expertise and AI-assisted capabilities; and the transformation of staffing practices through algorithmic support systems. The research analyses how AI reshapes these dimensions in practice: under which conditions it facilitates or constrains the transferability of competencies, how hybrid skills are constructed and legitimized, and how AI-mediated staffing is perceived and appropriated by practitioners.

The article then presents the conceptual framework, methodology, results, discussion and conclusion.

2. Conceptual Framework

2.1 Boundary Spanning and Role Transitions

Boundary spanning designates the activity of individuals who connect distinct knowledge domains and transfer information across organizational frontiers (Tushman and Scanlan, 1981). Because knowledge is embedded in local practices, moving it across boundaries requires translation and transformation as well as transfer (Carlile, 2004). AI can be conceptualized as a cultural translator that provides rapid access to domain-specific knowledge, reduces lexical barriers and supports problem framing, which is consistent with the view that boundary spanning is interpretative as much as informational.

Boundary spanning cannot, however, be reduced to knowledge access. Research on role transitions shows that moving across roles or sectors involves adaptation characterized by uncertainty, cognitive load and identity reconfiguration (Louis, 1980; Ashforth, 2001). Ibarra (1999) introduces the concept of provisional selves, whereby individuals test alternative role behaviors and competence displays before stabilizing a new identity, through iterative adjustment based on feedback and social validation, and under the risk of perceived illegitimacy when prior competencies are not recognized. AI may therefore facilitate the early stages of boundary spanning and role exploration without eliminating the social and situated nature of identity validation.

2.2 Hybrid Competencies and Dynamic Capabilities

The growing importance of profiles combining domain expertise with advanced AI capabilities reflects the emergence of hybrid competencies (Wahlström et al, 2024). Such competencies go beyond tool usage and involve the ability to integrate heterogeneous knowledge sources, critically assess outputs and act in complex situations.

Competence-based and dynamic capability theories help interpret this evolution. Core competence theory emphasizes that performance derives from the ability to integrate and coordinate diverse knowledge assets rather than from isolated skills (Prahalad and Hamel, 1990). Dynamic capabilities theory conceptualizes how actors and organizations sense, seize and reconfigure resources in response to changing environments (Teece, Pisano and Shuen, 1997; Teece, 2007). Within this framework, AI may enhance sensing, by enabling rapid access to distributed knowledge and the identification of cross-domain opportunities, and may partially support seizing, while reconfiguring knowledge into actionable competence remains a matter of interpretation and judgement.

Competence approaches rooted in the notion of savoir agir (Le Boterf, 2010) add that competence lies not in the possession of knowledge but in the situated mobilization of resources in action. Hybrid competencies then correspond to a socio-technical capability combining domain expertise, AI-assisted reasoning, reflexivity, verification and contextual adaptation, which reconfigures the micro-foundations of competence rather than upgrading them.

2.3 Augmented Work and AI Paradoxes

The integration of AI is commonly framed through augmented work, in which intelligent systems enhance human performance by supporting cognitive and operational tasks, reshaping task allocation, expertise and decision-making (Brynjolfsson and McAfee, 2014; Davenport and Kirby, 2016; Daugherty and Wilson, 2018).

These transformations are neither linear nor unidirectional. They give rise to persistent tensions that paradox theory analyses as contradictory yet interdependent demands (Smith and Lewis, 2011): efficiency versus reliability, standardization versus contextualization, automation versus human autonomy. Rather than being resolved, such tensions must be continuously managed, balancing short-term performance gains against long-term legitimacy.

Practice-based perspectives on algorithmic work add that the organizational impact of AI depends on its embeddedness in everyday practices, governance structures and authority arrangements (Faraj, Pachidi and Sayegh, 2018). AI systems are not neutral tools but performative technologies that reshape how work is organized and how decisions are justified. Augmentation therefore operates under legitimacy constraints, its acceptance depending on explainability, accountability and the preservation of human judgement (Kovari, 2024), which redefines human actors as validators and interpreters rather than replacing them.

2.4 Organizational Socialization and Intersectoral Adaptation

Intersectoral mobility can finally be read through organizational socialization, the process through which individuals acquire the knowledge, norms, behaviors and relationships necessary to function effectively in each environment (Van Maanen and Schein, 1979). Socialization is multidimensional, combining cultural learning of values and expectations, technical learning of tools and domain knowledge, and relational embedding, and it is rooted in an organizational culture that shapes how individuals interpret situations and enact roles (Schein, 2010).

Intersectoral transitions make this process more demanding, since individuals must navigate unfamiliar cognitive and social frameworks. AI can support them by providing access to explicit knowledge, translating technical jargon and guiding initial learning trajectories, as documented for AI-assisted onboarding (Holstein et al, 2025) and intergenerational knowledge transfer (Falckenthal, Au Yong Oliveira and Figueiredo, 2025). Becoming fully operational nevertheless depends on social validation, experiential learning and integration into collective practices, which AI may accelerate but cannot replace.

3. Research Methodology

3.1 Research Design

The study adopts an abductive qualitative design, proceeding through iterative movements between empirical material and theoretical constructs to build plausible explanations of an emerging phenomenon, an approach appropriate because AI-mediated staffing is a recent practice for which established constructs are only partially applicable. The research was conducted within a large international engineering consulting group operating mainly in the industrial and aeronautical sectors, a setting in which consultants are routinely reallocated across client sectors and competence transfer is a strategic concern.

3.2 Data Collection and Sample

The empirical corpus combines 24 semi-structured interviews and two focus groups, involving 30 participants in total. Interviews lasted between 45 and 75 minutes and followed a guide covering individual trajectories and sector transitions, uses of AI in daily work, perceptions of competence and hybridization, and expectations regarding AI-supported staffing. The focus groups mobilized projective scenario techniques, participants reacting to visual artefacts depicting future allocation situations, to elicit anticipations that interviews capture less easily. Documentary material on competency frameworks, allocation policies and AI tool documentation provided complementary evidence. The sample combines sectoral coherence, all participants operating within the same organizational context, with functional diversity, since consultants being staffed and actors performing staffing are both represented (Table 1).

Table 1: Composition of the sample

Category of profile	Share of the sample	Typical roles represented
Technical and scientific	65 to 70 %	Engineers, developers, scientific experts, metrology specialists
Managerial and leadership	15 to 20 %	Delivery heads, engagement managers, practice leads
Support functions	10 to 15 %	Recruitment, staffing, PMO, ergonomics, finance
Junior or in training	Less than 10 %	Early-career engineers, trainees
Sectors and experience	Over 70 % industrial and aeronautical	Early career to over 20 years, complemented by consulting and research activities

3.3 AI-assisted Analytical Procedure

Analysis relied on an iterative coding process comprising open, axial and selective coding (Strauss and Corbin, 1998), combining AI-assisted identification of meaning units and themes with systematic human review. The approach draws on recent research on large language models in qualitative analysis while maintaining the interpretive authority of the researcher (Hayes, 2025; Kuckartz and Rädiker, 2024). AI was mobilized as a methodological support rather than a substitute for established analytical frameworks, its outputs being treated as reflexive inputs under continuous supervision. Rather than a single prompt, multiple exploration prompts were developed, compared and progressively stabilized through collective triangulation. Transcripts were anonymized and prepared through a controlled cleaning process preserving the meaning of participants' discourse. Consistent with recommendations on responsible AI use, AI was restricted to post-collection stages, namely data preparation and analysis, while data collection, interpretive arbitration and theorization remained under human control (Resnik and Hosseini, 2025). Table 2 summarizes the corpus and the analytical outputs.

Table 2: Empirical corpus and analytical outputs

Element	Volume	Analytical status
Semi-structured interviews	24	Primary material, transcribed and anonymised
Focus groups	2	Projective elicitation, collective sensemaking
Open codes generated	472	Progressive expansion of the codebook
Core thematic axes	3	High empirical density, saturation approached
Cross-cutting conditions	5	Recurrent across the three axes
Emerging themes	3	Exploratory, limited empirical support

3.4 Validation and Quality Criteria

The procedure is operationalized through an explicit validation framework. Beyond verifying task completion, the protocol assesses the reproducibility of outputs across repeated executions, their robustness under semantic reformulation, their sensitivity to input variations and their stability across prompt revisions, as well as potential cognitive or cultural biases and lexical robustness when confronted with domain-specific terminology.

The objective extends beyond technical reliability to methodological validity: fidelity to verbatim data, absence of hallucinated content and consistency under controlled variations. AI-generated coding were systematically compared with human analyses to evaluate convergence, divergence and interpretive coherence, in line with the criteria of credibility, transferability, dependability and confirmability (Lincoln and Guba, 1985) and with recommendations on demonstrating rigour in inductive research (Gioia, Corley and Hamilton, 2013).

4. Results

Three core thematic axes emerge as the most robust and densely documented dimensions, complemented by five cross-cutting conditions and three emerging themes with limited empirical support. The progressive expansion of the codebook indicates that saturation was approached on the core axes but not on the emerging themes, a point discussed in Section 6. Table 3 presents the thematic structure, the sub-dimensions attached to each axis, the empirical density observed and illustrative verbatims.

Table 3: Thematic structure of the results, empirical density and illustrative verbatims

Core axis	Sub-dimensions	Empirical density	Illustrative verbatim
Conditional transferability	Accelerated access to unfamiliar domains; prior knowledge base; expertise continuity; human mediation	High, converging across all profiles	"You need to already know something to be transferable. If you know nothing, you can't be transferable"

Core axis	Sub-dimensions	Empirical density	Illustrative verbatim
Hybrid competencies	Domain expertise; AI usage; reflexivity; adaptability; verification practices	High, notion itself contested	"With AI, we are always the author, the reviewer and the validator"
Transformation of staffing	Filtering of large volumes of profiles; multi-domain identification; improved matching; refusal of algorithmic decision	High, convergence on limits of automation	"Out of 100 CVs, it can filter them in five minutes"

4.1 AI as a Catalyst for Conditional Transferability

Across the corpus, AI is consistently described as an enabler of cross-domain exploration and accelerated learning, reducing the time required to access relevant information, supporting initial problem framing and accelerating entry into new tasks: "It allowed me to upskill much faster than if I had searched across multiple forums", and "AI can help you cross these boundaries, because it gives you a common foundation." AI thus contributes to a form of boundary spanning.

Transferability is nonetheless bounded and conditional. Movement between sectors or roles is not described as fully open but relies on a prior knowledge base and on the continuity of core professional expertise. Participants emphasize that anchoring matters more than breadth: "Changing sectors is possible, but keeping the same metrology expertise is essential." Transition across domains is further mediated by organisational and relational factors, particularly human support mechanisms such as mentoring, training or peer interaction: "You still need human support, training, mentoring to make that transition easier." AI facilitates exploration but does not substitute for situated learning and social validation. Transferability supported by AI therefore takes the form of an incremental and guided process rather than a disruptive shift.

4.2 The Emergence of Hybrid Competencies

The findings highlight hybrid competencies as a central transformation, combining domain-specific expertise, AI usage capabilities, reflexivity and critical thinking, and adaptability. Hybridization is strongly associated with efficiency gains, improved output quality and enhanced capacity to manage complex tasks. Participants describe AI as an ally that extends their capabilities: "With AI, I can produce 600 pages in 10 days."

A defining feature of hybrid competencies is the integration of verification practices. Individuals do not passively rely on AI outputs but assume the roles of author, reviewer and validator: "I know it's not 100 % reliable, so I always check afterwards." The ability to critically assess, refine and contextualize AI-generated content is a core component of hybrid competence.

The legitimacy of the notion is not universally accepted: some participants challenge the coherence of linking AI usage directly to professional competence, "I can't link AI with my job and my skills» or find it reductive. Synthetic hybridization scores are perceived as particularly problematic when they lack transparency or fail to capture the complexity of actual work. Hybrid competence consequently emerges less as a stable attribute than as a situated and dynamic capability, grounded in the articulation of multiple skills and in continuous reflexive engagement with AI.

4.3 The Transformation of STAFFING PRActices

The results indicate a significant transformation of staffing practices through the integration of AI-supported tools. These systems enable the rapid filtering of large volumes of candidate profiles, the identification of individuals combining diverse competencies, and improved matching between project requirements and available resources: "AI can quickly identify profiles that combine multiple domains." AI thus enhances the efficiency and scalability of staffing.

Despite these benefits, convergence regarding the limits of AI in decision-making is strong. Participants consistently assert that final decisions must remain human-driven, especially when they involve career trajectories, and position AI as a decision-support tool rather than a decision-maker. The findings also reveal tensions related to the acceptability of algorithmic mediation, which concern the risk of over-acceleration in decision processes, the reduction of individuals to profiles or scores, and the potential loss of individual agency. AI-supported staffing is consequently considered legitimate only when embedded within dialogical and contextualized practices, where human actors interpret, negotiate and validate recommendations.

4.4 Cross-cutting Conditions and Emerging Dynamics

Five transversal conditions refine the understanding of AI integration. Governance and explicability are critical conditions of acceptance, participants demanding transparency on the criteria and logic of calculation behind recommendations and treating human validation as a necessary principle. Dignity and confidentiality play a central role, resistance arising when AI is perceived as intruding into personal data or reducing individuals to quantifiable indicators. Prudence characterizes the relationship to AI outputs, which are systematically verified and cross-checked. Client trust constitutes an external constraint, since in confidential or high-stakes contexts it limits how far AI can be mobilized, independently of its technical capabilities. AI acculturation finally appears as a gradual and socially mediated process, relying on demonstration, experimentation and collective learning.

Three emerging and less densely documented themes point toward deeper transformations: the recombination of competencies, where skills are decomposed and reassembled for new purposes; deskilling risks, reflecting concerns about the erosion of expertise; and collective intelligence, where AI is sometimes perceived as less conducive to collaborative knowledge production. These themes remain exploratory but signal potential long-term shifts.

5. Discussion

Rather than a purely technological shift, AI appears as a socio-cognitive mediator reshaping competence articulation, role boundaries and organizational processes under specific conditions. Table 4 compares the expectations derived from each theoretical lens with empirical observations and states the resulting conceptual refinement.

Table 4: Comparative analysis of theoretical expectations and empirical findings

Theoretical lens	Expectation from the literature	Empirical observation	Conceptual refinement
Boundary spanning	AI lowers informational barriers and widens accessible domains	Transfer still requires prior knowledge, expertise continuity and human mediation	Bounded boundary spanning: boundaries displaced, not dissolved
Role transitions	AI accelerates the exploration of new professional roles	Transitions occur as micro-transitions within familiar frames, subject to social validation	Incremental rather than radical role change
Dynamic capabilities	AI strengthens sensing, seizing and reconfiguring	Sensing is clearly amplified, seizing partially, reconfiguring remains human	Augmented but incomplete capabilities requiring human orchestration
Hybrid competence	AI use adds a technical component to competence profiles	Hybridity operates as situated mobilization including verification; scoring it is contested	Hybridity as socio-technical capability, not a scored attribute
Paradox theory	AI generates tensions that organizations must manage	Four recurrent paradoxes structure practice: decision, transparency, agency, learning	Tensions are constitutive of augmentation, not transitional
Socialization	AI eases access to explicit organizational knowledge	Adoption depends on demonstration, peer interaction and identity work	AI as an object of socialization as much as an aid to it

5.1 Bounded Augmentation of Capabilities and Roles

The results confirm that AI extends boundary-spanning capacity, while showing that boundary spanning remains anchored in a prior knowledge base, in the continuity of core expertise and in human-mediated learning. AI does not eliminate boundaries but supports bounded boundary spanning, in which individuals explore adjacent domains without detaching from their professional identity, engaging in micro-transitions rather than radical role shifts. Read through the micro-foundations of dynamic capabilities, the same asymmetry appears : sensing is clearly amplified, seizing partially supported, whereas reconfiguring remains human and organizational, since integrating new knowledge into practice depends on reflexive validation and contextual decision-making. AI therefore does not constitute a dynamic capability but amplifies certain micro-foundations. The socialization lens completes this reading: adoption relies on demonstration, peer interaction and identity work, which makes AI an object of socialization as much as an aid to it, and explains why resistance emerges when it threatens professional autonomy, dignity or the meaning of work.

5.2 Four Paradoxes of Augmented Work

Efficiency gains are clear, namely accelerated knowledge production, improved matching and increased productivity, yet they are systematically accompanied by tensions. The decision paradox opposes augmentation and autonomy: while AI supports decision-making, it is simultaneously rejected as a decision-maker, "AI will never be the decision-maker", which indicates that increased computational capacity reinforces rather than replaces the need for human judgement. The transparency paradox opposes performance and explicability, since AI enhances analytical capacity while creating opacity, leading to strong demands for explanation, "Without knowing the calculation formula, it's difficult to assess." The agency paradox opposes efficiency and control, as accelerated processes may reduce the sense of individual choice, "You always need to leave the choice to employees." The learning paradox opposes capability and deskilling, since AI supports learning while raising concerns about skill erosion, "We are going to unlearn." Augmented work therefore does not simply enhance performance but creates tensional dynamics that must be actively managed.

5.3 Conditional Augmentation as Socio-organizational Regime

Across these lenses, a unifying interpretation emerges: AI integration is best understood as a socio-organizational regime of conditional augmentation. AI enhances boundary spanning, dynamic capabilities and work efficiency, but only where human validation remains central, criteria are explicable and contestable, learning processes are progressive and supported, and trust relations are preserved. Rather than displacing human actors, AI redefines their role as interpreters, validators and orchestrators of knowledge processes. This challenges deterministic views of AI and highlights the importance of organizational embedding, social mediation and reflexive use. It also delimits the conditions under which agentic architecture may credibly contribute to workforce foresight: anticipation based on competence data is accepted only where its criteria remain auditable and its recommendations revisable.

6. Conclusion

This study examines the role of artificial intelligence in knowledge-intensive contexts not only as a performance-enhancing tool but as a structuring mechanism for knowledge production and mobilization. The findings show that AI acts as a catalyst for competency transferability, enabling the articulation and recognition of hybrid skill sets across sectoral boundaries, while remaining dependent on prior expertise and human mediation. The results thus support a shift from declarative skill representations toward more dynamic, reflexive and evidence-based approaches to competence identification, with direct implications for staffing in contexts where consultants experience mismatches between their perceived potential and available missions.

Theoretically, the research contributes to discussions on boundary spanning and knowledge integration by positioning AI as an intermediary that enhances interpretability and comparability across domains and proposes conditional augmentation as an integrative framing of the observed tensions. It also extends qualitative methodologies by documenting how AI can support rather than replace interpretive processes, provided validation and triangulation mechanisms are implemented. Managerially, organizations can leverage AI not only to optimize resource allocation but also to foster more equitable and transparent skill recognition, which calls for reflexive tools helping consultants make their competencies visible, actionable and transferable.

Three limitations should be acknowledged. First, the study relies on a single organizational context, which limits generalizability and calls for comparative replication. Second, saturation was approached on the three core axes but not on the emerging themes, so results concerning recombination, deskilling and collective intelligence should be read as exploratory. Third, AI-assisted analysis introduces methodological variability, since output quality depends on prompt design, data structuring and validation protocols, which the present protocol documents but does not eliminate.

Future research could examine the longitudinal effects of AI-supported reflexive practices on career trajectories, compare settings with contrasting governance arrangements, and investigate when agentic systems enhance or constrain knowledge legitimacy in workforce foresight. Such research would contribute to a better understanding of the organizational conditions under which AI can be deployed while preserving trust, legitimacy and professional judgement.

Ethics Declaration: This study was conducted in accordance with ethical standards for research involving human participants. Participation was voluntary and based on informed consent. Participants were informed of the purpose of the study, of their rights including the right to withdraw at any time, and of the use of collected data. Data were anonymized and treated confidentially in compliance with the General Data Protection Regulation. Ethical review and approval were not required in accordance with institutional guidelines. The authors declare no conflict of interest.

AI Declaration: This research used generative AI tools in a limited support capacity. These tools supported the creation of projective visual artefacts used as elicitation material, aspects of data preparation including cleaning, anonymization and preliminary coding, and bibliographic exploration. These contributions were strictly limited to preparatory and supportive functions and did not replace analytical, interpretive or theoretical decision-making. All AI-generated outputs were reviewed, validated and refined through human oversight, including manual verification and methodological cross-checking. The authors retain full responsibility for the integrity, accuracy and scientific validity of the research presented in this paper.

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