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The Role of Workforce Planning in the Implementation of Human - Artificial Intelligence (AI) Teaming in Transportation

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ABSTRACT

The increasing adoption of Human–AI teaming across the transportation sector is reshaping operational roles, organisational structures, and future workforce competencies. As artificial intelligence systems evolve from decision-support tools to collaborative teammates capable of perception, prediction, and autonomous action, transportation organisations must fundamentally rethink how they design, train, allocate, and sustain their workforce. Workforce planning—traditionally centred on staffing levels, qualification pipelines, and operational forecasts—now plays a pivotal role in ensuring that human capabilities remain aligned with the cognitive, technical, and ethical demands of future human–AI teams. This paper examines the strategic function of workforce planning in supporting the safe and effective implementation of human–AI teaming across aviation, rail, maritime, and ground transportation environments. The analysis begins by outlining the systemic transformations introduced by AI-driven operations. In contrast to earlier waves of automation, contemporary AI systems introduce non-deterministic behaviour, dynamic adaptability, and shared decision-making responsibilities. These characteristics challenge legacy workforce models premised on stable task distributions and predictable human roles. Across transportation modes, the shift toward human–AI teaming requires workforce planners to anticipate emerging competencies such as AI oversight, interpretability skills, mixed-initiative collaboration, and algorithmic risk assessment. The alignment of these competencies with recruitment, selection, training, and career progression becomes essential to preventing skill gaps, cognitive overload, and mismatches between human capabilities and system demands. The paper further examines workforce planning as a human factors instrument that supports organisational readiness. Effective planning requires an integrated understanding of future task redesign, shifts in workload dynamics, and the redistribution of responsibilities between humans, AI agents, and remote support structures. Training and competency development are examined as critical components linking workforce planning to operational implementation. As human–AI teaming becomes central to safety-critical operations, organisations must develop training

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pathways that cultivate adaptive expertise, trust calibration, interpretability awareness, and resilience under automation. Workforce planning provides the structural basis for identifying training populations, sequencing AI-focused skills acquisition, and embedding competency-based training and assessment (CBTA/EBT) methods across the transportation ecosystem. The paper concludes by proposing a workforce planning model designed to support large-scale adoption of human–AI teaming in transportation. This model integrates technological forecasting, human factors analysis, competency mapping, and AI-focused resilience strategies. The findings emphasise that technological innovation alone is insufficient; the success of human–AI teaming depends on a strategically designed workforce that is cognitively, operationally, and organisationally prepared for the transport systems of the future.

Keywords: Workforce planning, Human–AI teaming, Transportation systems, Competency development, Adaptive automation, Human factors, Organisational readiness

INTRODUCTION

The progressive integration of artificial intelligence (AI) into transportation systems is redefining the structure of safety-critical work. Across aviation, rail, maritime, and ground transportation, AI systems are transitioning from deterministic automation and decision-support tools toward adaptive, learning-enabled teammates capable of perception, prediction, and semi-autonomous action. This evolution introduces a paradigm of Human–AI teaming that fundamentally alters task allocation, authority gradients, and responsibility structures within operational environments (Ziakkas, 2023; Hollnagel, 2014).

While technological readiness has received significant attention, comparatively less emphasis has been placed on the readiness of the workforce tasked with operating, supervising, and collaborating with AI-enabled systems. Workforce planning—traditionally focused on staffing levels, qualification pipelines, and capacity forecasting—now assumes a strategic human factors role. It becomes the primary mechanism through which organisations align human cognitive capabilities, competencies, and resilience with the emergent demands of human–AI teams.

This paper examines workforce planning as a foundational enabler for the safe and effective implementation of Human–AI teaming across transportation domains. It argues that without systematic workforce planning informed by human factors principles, organisations risk creating operationally certified but cognitively misaligned workforces, increasing vulnerability to automation bias, skill degradation, and system-level brittleness (Reason, 1997; Parasuraman et al., 2000). Recent empirical evidence from public transport sectors confirms this risk: Adio et al. (2025) found that AI integration in public transport workforces generates substantial challenges related to skills development and job displacement, with HR departments identified as critical mediators between technological capabilities and workforce readiness. Similarly, Muchipalli and Jain (2025) demonstrated that AI-driven talent management in metro rail corporations requires proactive competency mapping and predictive skill forecasting to prevent operational misalignment—reinforcing workforce planning as a human factors imperative rather than an administrative function.

CONCEPTUAL FOUNDATIONS OF HUMAN–AI TEAMING AND THE ROLE OF WORKFORCE PLANNING

Earlier generations of automation in transportation were designed around stable task substitution, with humans retaining ultimate authority and predictable monitoring roles. Contemporary AI systems diverge sharply from this model. Machine learning–based systems exhibit non-deterministic behaviour, adaptive responses to environmental variability, and context-sensitive decision-making, often operating as semi-autonomous collaborators rather than passive tools (Ziakkas & Vink, 2023).

In aviation, examples include AI-enabled decision-support systems for trajectory optimisation, fatigue prediction, and anomaly detection; in rail and maritime domains, autonomous navigation and predictive maintenance systems similarly reshape operator responsibilities. These systems introduce shared cognitive workspaces in which humans must interpret, supervise, and occasionally contest AI outputs under time pressure.

The emergence of Human–AI teaming disrupts legacy workforce models premised on stable role definitions and linear career progression. Tasks are redistributed dynamically between humans and AI agents, generating new cognitive demands related to oversight, sensemaking, trust calibration, and intervention timing. Workforce planners must therefore anticipate not only quantitative staffing needs but also qualitative shifts in expertise and workload distribution.

Failure to adapt workforce planning to these realities risks mismatches between human capabilities and system demands, increasing susceptibility to automation complacency, mode confusion, and erosion of manual and cognitive skills—phenomena extensively documented in aviation human factors literature (Parasuraman et al., 2000; Ziakkas, 2023).

METHODOLOGY

This study adopts a qualitative, integrative methodology combining human factors analysis, comparative domain review, and conceptual workforce modelling. The approach aligns with socio-technical systems theory, recognising workforce planning as an emergent property of interactions between technology, humans, organisational structures, and regulatory frameworks (Hollnagel, 2014).

The analysis draws on three primary sources:

1. Peer-reviewed human factors and automation literature across transportation domains;
2. Regulatory and policy documentation from aviation and multimodal transport authorities (EASA, ICAO,FAA);
3. Authorial synthesis informed by operational experience, safety management practice, and prior research on AI integration and human performance (Ziakkas, 2023).

The analytical framework integrates task analysis, workload modelling, and competency mapping to identify workforce planning implications across different levels of AI autonomy. Furthermore, the conceptual nature of the study limits direct empirical validation. However, the methodology is designed to support generalisability across transportation modes and provide a structured foundation for future empirical workforce planning studies (Table 1).

Table 1: Research methodology overview.

Method Element	Summary	Link to Findings
Analytical Framework	Qualitative socio-technical, human-centred approach	Positions Human–AI teaming as a system-level issue
Evidence Base	Literature, regulatory sources, prior research	Anchors findings in policy and established knowledge
Core Analysis	Task analysis and competency mapping	Identifies AI-driven role and skill redistribution
Validation & Limits	Conceptual triangulation; non-empirical	Frames findings and signals need for future studies

FINDINGS

The implementation of Human–AI teaming in transportation systems requires a fundamental redefinition of workforce planning as a core human factors function rather than a predominantly administrative or capacity-driven process. In safety-critical domains such as aviation, workforce planning directly shapes how human cognitive capabilities, limitations, and adaptive skills interact with increasingly autonomous and intelligent systems. Workforce planning in the Artificial Intelligence (AI) and Competency-Based Training and Assessment (CBTA) era must be understood as a strategic mechanism for sustaining human performance, organisational resilience, and system safety (Ziakkas et al., 2024). Traditional workforce planning approaches in transportation have been largely predicated on stable operational concepts, deterministic task allocation, and linear qualification pipelines. These approaches assumed relatively predictable human roles, incremental technological change, and time-based training models. However, the introduction of AI-enabled systems—particularly those based on machine learning, adaptive automation, and predictive analytics—has disrupted these assumptions. Human roles are no longer static, task boundaries are increasingly fluid, and responsibility is dynamically shared between humans and intelligent systems (Ziakkas et al., 2024).

From a human factors perspective, workforce planning now functions as a primary interface between technology design and human performance. AI systems alter workload profiles in non-linear ways: while routine tasks may be automated, cognitive demands associated with supervision, sensemaking, exception handling, and ethical judgement increase significantly. Ziakkas et al. (2024) emphasise that without proactive workforce planning informed by human factors analysis, organisations risk creating workforces that are technically qualified but cognitively misaligned with the realities of AI-supported operations. This misalignment has direct implications for error management, situation awareness, and operational decision-making under uncertainty.

A central contribution of the AI- and CBTA-driven workforce planning paradigm is the explicit shift from time-based qualification models toward competency-based frameworks. Competency-Based Training and Assessment prioritises demonstrable performance outcomes, adaptability, and contextual decision-making rather than accumulated hours or procedural familiarity alone. Workforce planning, when aligned with CBTA principles, enables organisations to identify emerging competency requirements early and to structure recruitment, training, and progression pathways accordingly (Ziakkas et al., 2024). AI-enabled workforce planning tools themselves exemplify this alignment: predictive analytics can now forecast skill requirements, reduce attrition risks, and enable real-time competency monitoring (Muchipalli & Jain, 2025). This creates a reflexive capability where AI supports the planning of AI-human collaboration—automated competency mapping and workforce scheduling optimize the very teams responsible for AI oversight, strengthening organizational resilience through data-driven workforce allocation. This alignment is particularly critical in Human–AI teaming environments, where competencies such as AI oversight, interpretability awareness, trust calibration, and mixed-initiative collaboration are essential yet poorly captured by legacy training metrics.

Workforce planning also plays a decisive role in shaping trust relationships between humans and AI systems. Trust calibration is influenced not only by interface design and training content but also by organisational decisions regarding role allocation, authority gradients, and workload distribution. Poorly planned workforce structures—such as assigning excessive supervisory responsibilities to a single operator or failing to provide adequate support layers—can foster automation overreliance or inappropriate distrust, both of which undermine safety and performance (Ziakkas et al., 2024; Parasuraman et al., 2000).

The relevance of workforce planning as a human factors instrument extends beyond aviation to other transportation domains. In rail and maritime systems, increasing levels of autonomy similarly reduce direct manual control while increasing the cognitive demands associated with monitoring, intervention timing, and anomaly detection.

Finally, workforce planning provides the organisational foundation upon which training systems, competency frameworks, and safety culture are built. Without a coherent planning strategy grounded in AI and CBTA principles, training initiatives risk becoming fragmented and misaligned with future operational needs. Conversely, when workforce planning is explicitly framed as a human factors instrument, it enables the systematic development of adaptive expertise, continuous learning, and sustainable human–AI collaboration across the transportation ecosystem (Ziakkas et al., 2024).

In summary, workforce planning in the Human–AI teaming era must be recognised as a strategic human factors capability. The success of AI integration in transportation will depend not only on technological maturity but on the deliberate design of a workforce that is cognitively prepared, competency-driven, and organisationally supported. Workforce planning thus becomes a decisive factor in determining whether Human–AI teaming enhances safety and resilience or introduces new systemic vulnerabilities.

Table 2 summarises the primary workforce competency shifts associated with Human–AI teaming across transportation modes.

Table 2: Workforce competency shifts in Human–AI teaming.

Domain	Traditional Core Competencies	Emerging Human–AI Teaming Competencies
Aviation	Manual flying, SOP adherence, checklist execution	AI supervision, trust calibration, intent interpretation, resilience under high automation
Rail	Signal interpretation, route management	Autonomous system oversight, anomaly sensemaking, human–machine coordination
Maritime	Navigation, watchkeeping	AI-assisted navigation monitoring, predictive decision-making, intervention timing
Ground Transport	Vehicle control, traffic compliance	Supervisory control, human–AI coordination, ethical decision oversight

DISCUSSION

The analysis of the findings confirms that workforce planning constitutes a primary safety enabler in the implementation of Human–AI teaming across transportation systems. As reflected in Table 3, workforce planning directly influences how human responsibilities, competencies, workload, authority, and training are structured in AI-supported operations. These dimensions align closely with regulatory expectations under Safety Management Systems (SMS) and Competency-Based Training and Assessment (CBTA) frameworks, reinforcing the view that Human–AI teaming must be addressed as an organisational design challenge rather than a purely technological transition.

Table 3: Workforce planning as a safety enabler for Human–AI teaming.

Workforce Planning Area	Regulatory-Aligned Finding	Operational Example
Role & Authority Design	Planning defines human roles, authority, and escalation in AI-supported operations	Shift from task execution to AI supervision with clear override pathways
Competency & Training Alignment	Planning enables competency-based qualification for AI environments	CBTA-based AI oversight and trust calibration training
Workload Management	Planning supports acceptable cognitive workload under automation	Anticipation of monitoring and intervention demands in reduced-crew operations
Safety & Resilience	Planning acts as a proactive safety and resilience control	Scenario-based planning addressing skill decay and vigilance loss

The framework's applicability extends beyond aviation: Bositkhanova and Dadaboyev (2025) identified convergent workforce planning challenges across industries implementing AI, including data privacy concerns, limited organizational readiness, and the need for evidence-based validation of AI-driven HR practices. Adenuga et al. (2020) demonstrated similar patterns in global logistics networks, where AI-driven workforce forecasting proved essential for peak demand resilience and disruption management. These cross-sectoral findings validate the generalizability of CBTA-aligned workforce planning as a universal human factors instrument for Human-AI teaming implementation.

Firstly, the research highlights the role of workforce planning in defining human responsibilities within AI-enabled operational concepts. Regulatory guidance consistently emphasises the need for clear role definition and accountability in safety-critical systems. In Human–AI teaming environments, workforce planning provides the mechanism through which responsibility shifts—from direct task execution to AI supervision, decision authority, and intervention—are formally specified. Without such planning, authority ambiguity emerges, increasing the likelihood of automation bias, delayed intervention, or inappropriate reliance on AI outputs.

Secondly, the findings underscore workforce planning as the structural foundation for competency-based qualification in AI environments. Legacy qualification models based on task exposure or time accumulation are insufficient to demonstrate readiness for AI-supported operations. Workforce planning aligned with CBTA principles enables organisations to define, assess, and sustain competencies such as AI oversight, trust calibration, and adaptive decision-making. From a regulatory perspective, this alignment supports evidence-based assurance of operator competence under evolving operational conditions. Recruitment strategies must adapt accordingly: Westover (2025) revealed that professionals with substantive AI capabilities outnumber those with explicit AI job titles by approximately 20-fold, suggesting transportation organizations focusing solely on traditional AI credentials may overlook substantial talent pools. Workforce planning informed by skill-based identification—rather than job title filtering—enables access to technically capable employees across diverse roles, accelerating internal AI capability development without exclusive reliance on external AI specialists.

Workload management emerges as a further critical dimension. Contrary to assumptions that automation reduces human workload, Human–AI teaming redistributes cognitive demands toward monitoring, anomaly detection, and intervention under time pressure. Workforce planning informed by human factors analysis allows organisations to anticipate these demands and maintain acceptable workload levels, particularly in reduced-crew or single-operator contexts. This anticipatory approach is consistent with regulatory expectations for fatigue management, human performance assurance, and operational resilience.

The research also reinforces the importance of workforce planning in structuring authority and trust relationships between humans and AI systems. Trust calibration is influenced not only by training and interface design but by organisational decisions regarding escalation, override authority, and supervisory support. Workforce planning operationalises these decisions by defining who monitors AI performance, who intervenes, and under what conditions authority transitions occur. Clear escalation pathways mitigate both automation over-reliance and unwarranted distrust, supporting stable Human–AI collaboration. Training alignment represents another regulatory-relevant outcome of effective workforce planning. As operational concepts evolve, workforce planning links future AI-enabled operations to training system design, ensuring that training pathways remain aligned with anticipated roles and responsibilities. Differentiated training for operators, supervisors, and instructors supports scalable implementation while maintaining compliance with CBTA and SMS principles.

Finally, the discussion positions workforce planning as a proactive safety control. By incorporating scenario-based forecasting of AI evolution, workforce planning enables organisations to identify latent risks such as skill degradation, vigilance loss, and supervisory overload before they manifest operationally. This function aligns workforce planning with proactive hazard identification and risk mitigation, reinforcing its role within contemporary safety management frameworks.

In summary, the research demonstrates that workforce planning operationalises regulatory principles within Human–AI teaming environments. It translates abstract requirements for competence, workload management, authority clarity, and resilience into concrete organisational structures. As AI integration accelerates, workforce planning will remain a decisive factor in determining whether Human–AI teaming enhances system safety or introduces new forms of operational risk.

CONCLUSION

This paper examined workforce planning as a key enabler for the implementation of Human–AI teaming across transportation systems. As artificial intelligence evolves from decision-support technology to an operational collaborator, the findings indicate that workforce planning must be treated as a strategic human factors function rather than a purely administrative activity. Human–AI teaming introduces dynamic task redistribution, shared decision authority, and non-deterministic system behaviour, which challenge traditional workforce models based on stable roles and time-based qualification pathways. Without deliberate workforce planning informed by human factors principles, organisations risk misalignment between human capabilities and the cognitive demands of AI-enabled operations.

The analysis further indicates that workforce planning provides the organisational mechanism for competency-based readiness, cognitive workload management, and trust calibration in Human–AI teams. Alignment with Competency-Based Training and Assessment (CBTA/EBT) principles supports the development of adaptive expertise and sustained human performance, particularly in reduced-crew and high-automation operational contexts. Overall, the findings suggest that the effectiveness of Human–AI teaming will depend not solely on technological capability, but on the extent to which workforce planning systematically aligns human performance, organisational structures, and evolving operational concepts. Workforce planning must also address ethical dimensions: Tarafdar (2025) emphasized that Human-AI collaboration frameworks require explicit preservation of worker autonomy and decision authority, while Okolo et al. (2023) highlighted cybersecurity workforce capacity as essential for protecting AI-enabled transport systems. These considerations reinforce that workforce planning extends beyond competency and workload—it encompasses ethical responsibility allocation, Just Culture principles under algorithmic decision-making, and the cultivation of a workforce capable of challenging AI outputs when safety or ethics are at stake.

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