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Assessment of New Competencies for Human - AI Teaming in Air Traffic Control

Hava Trafik Kontrolde İnsan- Yapay Zekâ Takım Çalışması Kapsamında Yeni Yetkinliklerin Değerlendirilmesi

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Abstract Artificial intelligence (AI) integration into aviation operations is progressively reshaping the professional landscape of air traffic management, thereby placing new demands on the human workforce. The aim of the study was to determine the priority weights assigned to eight specific AI competencies within the domain of air traffic control. The study was based on the framework of AI competencies applicable to the aviation sector established by the European Union Aviation Safety Agency (EASA). Data were collected from a purposive sample of 19 air traffic controllers. The data were analyzed using the Best–Worst Method (BWM), a multi-criteria decision-making technique. The findings indicate a substantial shift in the relative importance of different competencies during human-AI collaboration. Cognitive skills were assigned the highest priority weight, followed by data literacy, information technology competencies, and general AI knowledge. Communication and sensory competencies were assigned a secondary tier, while social and physical skills were allocated the lowest priority weights. These findings suggest that AI integration may transform the nature of the cognitive competencies required from air traffic controllers.

Öz Yapay zekânın havacılık operasyonlarına giderek artan entegrasyonu hava trafik yönetiminin profesyonel yapısını yeniden şekillendirmekte, insan iş gücünde yeni gereksinimler yaratmaktadır. Avrupa Birliği Havacılık Emniyeti Ajansı (EASA) tarafından belirlenen ve havacılık sektörü için geçerli olan yapay zekâ yetkinlik çerçevesi temel alınarak, bu çalışmada hava trafik kontrolü bağlamındaki sekiz spesifik yapay zekâ yetkinliğinin öncelik ağırlıklarının belirlenmesi amaçlanmıştır. Veriler amaçlı örnekleme yöntemiyle seçilen 19 hava trafik kontrolöründen toplanmıştır. Verilerin analizi çok kriterli karar verme tekniklerinden biri olan En İyi-En Kötü Yöntemi (Best-Worst Method- BWM) kullanılarak gerçekleştirilmiştir. Bulgular insan-yapay zekâ iş birliği sürecinde farklı yetkinliklerin önem derecelerinde belirgin bir değişim yaşandığını ortaya koymaktadır. Bilişsel beceriler en yüksek öncelik ağırlığını alırken bunu veri okuryazarlığı, bilgi teknolojileri yetkinlikleri ve genel yapay zekâ bilgisi takip etmiştir. İletişim ve duyusal yetkinlikler ikincil bir katmanda yer alırken, sosyal ve fiziksel beceriler en düşük öncelik ağırlıklarına sahip olmuştur. Bu bulgular, yapay zekâ entegrasyonunun hava trafik kontrolörlerinden beklenen bilişsel yetkinliklerin niteliğini dönüştürebileceğini göstermektedir.

Keywords Air traffic control · artificial intelligence competency · best--worst method · human--AI teaming · multi-criteria decision making

Anahtar Kelimeler Hava trafik kontrol · yapay zekâ yetkinliği · en iyi-kötü yöntemi · insan-yapay zekâ takımı · çok kriterli karar verme

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Assessment of New Competencies for Human - AI Teaming in Air Traffic Control

The global aviation sector is currently undergoing a period of sustained structural expansion, with no indication of a slowdown. According to data released by the Airports Council International (ACI) (2026), global passenger traffic is forecast to reach 10.2 billion in 2026, representing a 3.9% year-over-year increase. The long-term demand for air travel continues to exhibit robust resilience, with global passenger traffic projected to double by the year 2045, reaching 18.8 billion at a compound annual growth rate (CAGR) of 3.4%. This trajectory places the existing air traffic management infrastructure under sustained pressure to increase capacity, efficiency, and predictability without compromising the safety standards that define aviation's public trust.

The advent of AI has emerged as the predominant technological response to this structural challenge. The global AI in aviation market was valued at USD 7.45 billion in 2025 and is projected to grow from USD 8.83 billion in 2026 to USD 36.68 billion by 2034, exhibiting a CAGR of 19.48% (Fortune Business Insights, 2026). AI is being deployed in various capacities within the domain of air traffic management, including conflict detection and resolution, trajectory prediction, sector load management, and real-time decision support. This development signifies more than an increase in automation; it is indicative of a substantial transformation in the cognitive architecture of control operations. The European Union Aviation Safety Agency (EASA) has developed a dedicated AI roadmap and a framework of human competencies oriented toward the safe and effective integration of AI into aviation operations (EASA, 2023, 2024, 2025). This initiative is a response to the profound transformation that AI is bringing to the field of aviation. The implementation of AI in the aviation industry introduces a unique class of operational risks that differ from those associated with previous generations of automation. Single European Sky Air Traffic Management Research Joint Undertaking (SESAR JU) (2025) projects a gradual transition of European Air Traffic Management toward increasingly autonomous operational concepts, progressing from decision-support automation in the near term to highly automated human–machine collaborative environments by 2045. The conceptual framework for Level 4 automation entails the capacity for the system to autonomously formulate and implement operational decisions within predefined operational constraints, with human intervention being solicited solely in circumstances where conditions exceed the authorized scope of the system. Control would revert to a lower level of automation, thereby requiring greater human involvement in such circumstances. This paradigm shift has led to a redefinition of the role of air traffic controllers, who are now expected to transition from active tactical operators to the role of supervisory managers of increasingly autonomous systems. Conventional automation systems were designed to execute specific functions within clearly defined parameters, leaving the broader cognitive and decision-making architecture of air traffic control largely unaltered. Advanced AI systems, by contrast, exhibit a substantially wider range of functional domains, generate recommendations through opaque probabilistic processes, and manifest failure modes that may prove challenging to anticipate or detect in real time (Endsley, 2023a; Graydon et al., 2025). Controllers in a human-AI teaming context occupy a different operational role. Unlike previous operational paradigms, the human operator is no longer a passive recipient of systemic instructions; rather, advanced automation necessitates active supervisory engagement and timely tactical intervention to ensure continuous system integrity. The complexity of this new role is further compounded by the fact that the internal logic of AI may not be fully transparent, resulting in recommendations that are statistically valid rather than deterministically valid. This role transformation generates a specific and underappreciated set of competency demands. It is therefore essential that controllers possess sufficient data literacy to evaluate AI-generated outputs critically, rather than accept them unquestioningly as authoritative. Continuous cognitive engagement with airspace dynamics is paramount during extended

intervals of correct AI operation and minimal active stimulation. Professionals operating within this domain must also possess the capacity to discern the emergence of automation complacency in their own cognitive processes and implement metacognitive corrective strategies. Navigating these systems necessitates a foundational understanding of AI architecture and operational design domains to identify when a system is operating at the boundary of its reliable performance envelope (Kirwan, 2025; Stefani et al., 2024). The existing certification frameworks do not prioritize these demands uniformly, and the relative importance of these demands in relation to the full EASA-defined competency set has not been empirically established.

The academic literature concerning air traffic controller competencies is substantial and well-developed with respect to the traditional operational environment. Recent empirical studies support the notion that these fundamental skills are crucial and emphasize the need for ongoing adaptation. For example, Çınar and Tuncal (2024) point out that air traffic controllers regularly assess their abilities and place significant value on competency-based training. Additionally, it is emphasized that future research should explore the impact of technological advancements, particularly AI and machine learning, on air traffic control competencies. Despite the calls from practitioners for research in this area, the literature addressing the intersection of air traffic controller competencies and advanced AI integration is, by comparison, sparse, fragmented, and predominantly theoretical. Existing contributions tend to address discrete aspects of human-AI interaction, such as trust, design, ethics considerations, transparency, and transferability, without synthesizing these findings into a comprehensive, priority-weighted competency model that reflects practitioner judgments (Caldwell et al., 2022; Georganta & Ulfert, 2024a, 2024b; Hobbs & Li, 2023; Sharma, 2025). A further limitation of the extant literature concerns the methodological approaches employed to establish competency priorities. Multi-criteria decision-making techniques have been applied to evaluate the competencies of aviation personnel. For instance, Çeken and Beyhan Acar (2025) employed the Analytic Hierarchy Process (AHP) to evaluate the non-technical skills (NOTECHS) of airline pilot candidates. Similarly, Duan et al. (2023) used AHP within a hybrid evaluation approach, combining it with factor analysis and the entropy weight method, to quantify the core competencies of air traffic controllers across different operational posts. While these approaches provide valuable measurement frameworks, the Best-Worst Method (BWM) introduced by Rezaei (2015) is particularly appropriate for the current context. BWM is a highly promising approach, given its lower demand for pairwise comparisons in comparison to other methods, such as AHP. Its superior consistency performance and its demonstrated suitability for application by both individual and group decision-makers further substantiate its value (Rezaei, 2015, 2016). Despite the utility of the BWM across a broad range of priority-setting problems in healthcare, engineering, and logistics, its application to air traffic controller competency prioritization in human-AI teaming environments has not been documented in the published literature.

The study is guided by the profound shift from conventional operational skills to the novel paradigm of human-AI collaboration, thereby establishing a clear and pragmatic objective. The primary objective is to establish a framework prioritizing predefined AI competencies for air traffic controllers, highlighting the profession's shifting cognitive demands. Utilizing the BWM to determine these weights enables an assessment of the essential requirements for human operators in high-stakes algorithmic environments. The present study employs a prioritization process to contribute to the broader academic discourse on human-AI teaming in safety-critical systems. This work builds a necessary theoretical bridge between the established understanding of traditional air traffic control skills and the emerging requirements brought on by algorithmic integration. Methodologically, the study illustrates the application of BWM to the prioritization of competency dimensions in an aviation context. This approach presents a pragmatic alternative to conventional multi-criteria decision-making frameworks. The findings provide actionable insights for regu-

latory bodies, training academies, and operational organizations tasked with guiding the human workforce through the technological transition in air traffic management.

Literature Review and Theoretical Background

AI in Air Traffic Control

AI has emerged as a transformative technology across the transportation and aeronautics sectors (Abduljabbar et al., 2019). The integration of AI and big data analytics offers innovative solutions to enhance operational efficiency, reduce delays, and optimize resource utilization (Da Cruz, 2024). This digital transformation encompasses a range of applications, including aircraft manufacturing, maintenance, predictive analytics, and autonomous intelligent systems (Zaoui et al., 2024). The transition toward advanced automation necessitates a recalibration of the aviation industrial workforce, entailing the cultivation of novel professionals who are adept in the domains of AI and data-driven decision-making (Kabashkin et al., 2023). The integration of AI is instrumental in the development of autonomous air traffic management systems, thereby leading to a paradigm shift in conventional operational methodologies (Du et al., 2025).

The practical applications of AI in air traffic management encompass a wide range of critical tasks, including conflict detection, trajectory prediction, and traffic flow management (Degas et al., 2022). Machine learning models, including deep neural networks and reinforcement learning algorithms, are extensively utilized to process complex surveillance data and predict traffic patterns. For instance, AI-based decision support systems enable the early identification of potential mid-air conflicts and automatically recommend optimal resolution strategies, such as route offsets or altitude adjustments, thereby improving safety and operational fluidity (Du et al., 2025). Advanced flow management systems leverage predictive analytics to balance demand and capacity, adjust flight routes dynamically in response to adverse weather conditions, and minimize reactionary delays across the network (Da Cruz, 2024). The automation of routine tasks and the real-time processing of massive volumes of data have been demonstrated to enhance system-wide performance and reduce the cognitive burden on operators (Abdillah et al., 2024; Xia et al., 2026).

The implementation of highly automated AI systems in aviation is often hindered by the opaque nature of complex machine learning algorithms. The "black-box" characteristics of these models limit their interpretability, making it difficult for operators to verify the rationale behind specific algorithmic recommendations (Xie et al., 2021). To address these transparency issues, explainable AI (XAI) approaches have become crucial in safety-critical domains like air traffic management. XAI provides comprehensible and dependable insights into the system's reasoning processes, which is imperative for establishing technology trust and system acceptance among operators (Cartocci et al., 2026). The acceptance of these technologies is found to be strongly associated with perceived usefulness, adaptability, and the mitigation of perceived risks associated with automation failures (Schon et al., 2025). Recognizing these challenges, aviation regulatory bodies have established comprehensive guidelines and roadmaps to ensure that AI applications meet strict certification standards, ethical requirements, and robustness criteria before deployment (EASA, 2023).

SESAR initiative has been instrumental in modernizing European airspace by coordinating and validating AI-driven technological innovations (Bolić & Ravenhill, 2021). A systematic examination of SESAR projects highlights numerous projects that directly apply machine learning to enhance air traffic management infrastructure, focusing on areas such as network optimization, automated communication, and safety monitoring (Tuncal, 2025). Projects such as DIALOG and AWARE center on the development of digital assistants and sophisticated situational awareness tools that utilize speech recognition and predictive modeling to anticipate operational requirements. Similarly, initiatives such as ORCI aim to optimize runway centerline interception and approach sequencing, thereby increasing terminal area throughput during high-density

operations. Other projects, including ASTRA and DARWIN, target the prediction of tactical hotspots and the advancement of autonomous flight concepts through reliable machine reasoning platforms (Çeken, 2025). SESAR projects demonstrate the considerable potential of AI to transform air traffic management, provided that ethical governance, transparency, and comprehensive safety protocols remain fundamental to their development.

AI Competency

The rapid integration of AI across various sectors has necessitated a fundamental shift in the requisite skills for the modern workforce, particularly within the context of digital transformation and Industry 4.0 (Hernandez-de-Menendez et al., 2020). At the core of this transformation lies the critical distinction between AI literacy and AI competency. AI literacy is generally defined as the foundational knowledge and understanding of AI technologies, enabling individuals to critically evaluate these systems, recognize their ethical implications, and communicate effectively with them (Long & Magerko, 2020). As the literature indicates, AI literacy draws upon a multidisciplinary framework that encompasses mathematical, data, ethical, and computational literacies, focusing primarily on the cognitive acquisition of knowledge (Chiu, 2025). The current literacy levels prove inadequate to meet the demands of the modern era. To this end, there is a necessity to evolve from traditional literacy to AI competency. AI competency is defined by the capacity to apply AI in practical, effective, and ethical ways in real-world scenarios (Chiu et al., 2024; Ng et al., 2021). It encompasses an individual's confidence, human agency, and self-reflective mindset to utilize AI tools beneficially and responsibly (Chiu et al., 2024). The assessment of human competency in AI necessitates the evaluation of socio-technical interactions, in which both explicit knowledge and tacit experience play critical roles (Pinski & Benlian, 2023). The integration of these constructs constitutes the fundamental basis of AI fluency, thereby enabling individuals to make significant contributions and demonstrate continuous adaptability within an AI-driven societal context (Ruhi et al., 2025). The development of these fundamental AI competencies necessitates the implementation of dynamic educational frameworks and strategic workforce reskilling on a global scale (Ersanlı et al., 2025). Institutions of higher education must transition from a pedagogical approach that relies on the passive delivery of foundational AI literacy to an andragogical methodology (Ruhi et al., 2025). For instance, problem-based learning and human-AI collaborative environments have been demonstrated to substantially augment the cognitive competency essential for prospective leaders to formulate strategic decisions utilizing AI (Gupta & Jaiswal, 2024). Comprehensive frameworks emphasize the integration of AI pedagogy with a human-centered approach, ensuring that educators and students not only acquire proficiency in AI techniques but also adhere to ethical standards to promote inclusive and sustainable practices (United Nations Educational, Scientific and Cultural Organization [UNESCO], 2024). To implement these educational goals in a systematic manner, large language model (LLM)-driven methodologies have been utilized to formulate strategies that prioritize human-AI collaborative pedagogy and equity-centered protocols (Petrova, 2025). Generative AI literacy models have identified specific competencies, ranging from basic understanding to prompt engineering and legal awareness, which serve as a structured roadmap for embedding AI skills into lifelong learning initiatives (Annapureddy et al., 2025). Generative AI and automation are continuously redefining work processes, making the design of educational curricula for complementarity between human skills and machine intelligence a crucial priority (Hutson, 2025).

The aviation industry represents a particularly compelling case study in this regard, as it is a domain of significant complexity and critical safety implications. The sector is experiencing a profound technological paradigm shift driven by autonomous systems, multi-sensor data fusion, and advanced machine learning models designed to optimize operations, enhance predictive maintenance, and achieve environmental sustainability (Talib et al., 2025; Kabashkin et al., 2023). Specifically, in the domain of air traffic management,

the paradigm of human-AI teaming is progressing from a state of basic collaboration to a more profound level of integration, necessitating the harmonious sharing of situational awareness among human operators and digital systems, and the concurrent resolution of conflicts through synergistic means (Gerdes et al., 2025; Degas et al., 2022). It is therefore essential for aviation authorities and organizations to emphasize the need to equip the workforce with new competencies to prevent the risk of deskilling and to maintain clear legal liability and accountability channels in socio-technical systems (International Federation of Air Traffic Controllers' Associations [IFATCA], 2025). EASA has acknowledged these transformative impacts and has developed comprehensive AI roadmaps to guide the certification, safety risk mitigation, and ethical deployment of both machine learning and symbolic AI applications across the aviation life cycle (EASA, 2023). Thus, traditional aviation roles are being redefined, necessitating targeted training programs that bridge the gap between human expertise and sophisticated AI capabilities (Kabashkin et al., 2023).

To address these emerging workforce requirements in a systematic manner, EASA has outlined specific capabilities necessary for successful human-AI teaming. A comprehensive survey was conducted to evaluate the ethical and practical readiness of aviation professionals. This survey, which was carried out by EASA, identified eight core competencies required for the effective integration of AI into aviation systems (EASA, 2025). Firstly, professionals require advanced cognitive abilities to process complex thoughts, encompassing attention, memory, and reasoning. Secondly, data literacy is necessary to effectively understand, handle, and apply the vast amounts of information processed by AI. Thirdly, sensory competencies are vital for individuals to appropriately receive and interpret environmental stimuli, such as vision and sound. Fourthly, physical skills, including bodily capacities and fine motor skills, remain necessary for interacting with hardware and control systems. Fifthly, the ability to communicate effectively is paramount to facilitating clear verbal, non-verbal, and written exchanges in highly automated environments. Sixthly, social skills must be cultivated to ensure effective cooperation and understanding among human team members sharing an AI-augmented workspace. Seventhly, IT competencies are fundamental for operating computer networks and software tools seamlessly. Finally, general AI knowledge functions as the technological anchor, providing the workforce with a concrete understanding of machine learning principles and AI system capabilities (EASA, 2025). By proactively developing these eight competencies, the aviation industry can ensure that the integration of AI empowers its workforce, upholds rigorous safety standards, and bridges the gap between basic AI literacy and actionable, collaborative AI competency.

Human- AI Teaming

The integration of intelligent technologies into the modern workplace has catalyzed a fundamental paradigm shift from traditional human-automation interaction to the dynamic concept of human-AI teaming, where humans and AI operate interdependently toward shared objectives (Berretta et al., 2023; Caldwell et al., 2022; Cardon & Marshall, 2024; Hagos et al., 2024). Historically, the allocation of functions between humans and machines was dictated by rigid, rule-based frameworks. One such framework is the MABA-MABA (Men-Are-Better-At, Machines-Are-Better-At) list initially proposed by Fitts et al. (1951). The utilization of automation in these legacy systems was limited to a passive role, serving merely as a functional tool. Nevertheless, it has been observed that automation can inadvertently induce human complacency, result in a loss of situational awareness, or even leave operators entirely out of the loop (Endsley, 2023b; Hancock, 2007; Holford, 2022). Continuous technological progress has facilitated a profound co-evolution between human cognition and autonomous systems (Pedreschi et al., 2025). Modern AI surpasses conventional automation by engaging in cognitive tasks, adapting to complex environments, and functioning as an autonomous teammate rather than a mere decision-support mechanism (Endsley, 2023b; Hagemann et al., 2026; McNeese et al., 2018). In these hybrid configurations, the focus has shifted from backward, recommendation-centric

automation to forward, continuous support that augments human decision-making and fosters collective intelligence (Steyvers & Kumar, 2024; Zhang et al., 2024).

As this collaboration deepens, human factors such as mutual trust, perceived similarity, and shared mental models become critical, because the success of human-AI teaming heavily depends on whether human workers perceive the AI as a reliable and transparent collaborator rather than a disruptive interloper (Georganta & Ulfert, 2024a, 2024b). Effective human-AI teaming requires significant considerations regarding these human factors, demanding that systems maintain transparent communication and clear explainability to build an efficient partnership (Ali et al., 2025; Caldwell et al., 2022). Trust, in this context, is a dynamic and multi-dimensional construct that fundamentally dictates whether an operator will appropriately rely on or mistakenly reject an AI teammate during high-stakes scenarios (Hobbs & Li, 2023).

Within the aerospace sector, this transition toward human-AI teaming presents unprecedented opportunities to enhance operational safety, optimize flight paths, and address global pilot shortages by utilizing these foundational trust and teaming principles (Aditya, 2025; International Civil Aviation Organization [ICAO], 2025; Kabashkin et al., 2023). The modern flight deck has rapidly evolved from a reliance on conventional physical interfaces to integrating sophisticated human-machine interfaces, voice recognition, and gesture controls that enable highly automated and single-pilot operations (De Maria, 2016; Josh et al., 2022; Minaskan et al., 2022). The integration of AI functioning as a digital co-pilot requires a meticulous approach to ensure safe, ethical, and trusted use in critical flight scenarios where split-second decisions are paramount (Holley et al., 2024; Lorrig & Daw, 2024; Sharma, 2025). EASA has provided structured guidance delineating various levels of machine learning applications, explicitly distinguishing between basic cooperation (Level 2A), where AI completes predefined tasks under strict human authority, and advanced collaboration (Level 2B), where human and AI agents share situational awareness and dynamically reallocate tasks to achieve common objectives (EASA, 2024; Kilner et al., 2025). Practical implementations of these concepts are actively being explored in research initiatives such as the HAIKU project, which investigates the use of intelligent assistants for managing pilot startle responses, dynamically re-routing aircraft using operational intentions, and enhancing overall flight crew resilience (dos Reis et al., 2024; Haiku, 2025; Kirwan et al., 2024). Ultimately, realizing the full potential of these advanced cockpit applications requires comprehensive human factors assurance frameworks that address the unique cognitive demands of human-AI teaming, resolve authority-responsibility mismatches, and rigorously verify the safety boundaries of autonomous systems (Graydon et al., 2025; Kirwan, 2025).

In parallel with developments in the cockpit, the air traffic control domain is increasingly adopting human-AI hybrid (HAH) systems to manage the escalating volume and complexity of global airspace architectures (Degas et al., 2022; Xia et al., 2026). Air traffic management demands substantial cognitive resilience, necessitating that controllers possess the capacity to absorb shocks, swiftly adapt to anomalies, and continuously reorganize traffic flows without compromising safety (Torsi et al., 2025). To support controllers in these environments, digital partners such as the Digital Interactive Reliable Controller (DIRC) are being designed to facilitate Single Controller Operations (SCO) by autonomously performing routine tasks like conflict detection and resolution while maintaining transparent communication through smart interaction design (Tyburzy et al., 2024). To ensure the safe operation of these AI-based teammates, developers must establish strict operational design domains, which define the environmental and dynamic conditions within which the AI can reliably operate. When operational boundaries are exceeded, the AI automatically re-delegates tasks to human controllers (Stefani et al., 2024). However, the integration of such intelligent assistants into the air traffic control operations room necessitates the overcoming of significant user acceptance hurdles. Controllers often fear a loss of their authority and situational awareness if automation encroaches too far upon their roles (Schon et al., 2025; Stathis et al., 2025). Therefore, a human-centered approach that

fosters calibrated trust, provides explainable outputs, and maintains the adaptability of the joint cognitive system is required to support effective and sustainable human–AI collaboration in air traffic management (Stathis et al., 2025; Xia et al., 2026).

Best-Worst Method (BWM)

Multi-criteria decision-making is a fundamental branch of operations research that assists decision-makers in evaluating and selecting alternatives based on multiple, often conflicting, criteria. Within this domain, BWM has emerged as a highly effective and robust technique. Initially proposed by Rezaei (2015), the concept of BWM relies on a structured pairwise comparison approach that centers on two specific reference points. In this methodology, the decision-maker first identifies the best (most desirable or most important) and the worst (least desirable or least important) criteria among a predefined set. Following this identification, the preference of the best criterion over all other criteria is expressed using a scale from 1 to 9, creating a "Best-to-Others" vector. Subsequently, the preferences of all other criteria over the worst criterion are established, resulting in an "Others-to-Worst" vector. Finally, a minimax optimization problem is formulated and solved to determine the optimal weights of the criteria, minimizing the maximum absolute differences between the weight ratios and their corresponding pairwise comparisons (Rezaei, 2015).

When compared to traditional multi-criteria decision-making methods, particularly the Analytic Hierarchy Process (AHP), BWM presents several distinct differences and advantages. The most significant advantage is the substantial reduction in the amount of pairwise comparison data required. While AHP requires $n(n-1)/2$ pairwise comparisons for n criteria, BWM significantly streamlines this process by requiring only $2n-3$ comparisons (Malek & Desai, 2019; Wankhede & Vinodh, 2021). This reduction not only decreases the cognitive load and time demanded from decision-makers but also inherently leads to highly consistent comparisons and more reliable results (Ahmadi et al., 2017; Rezaei, 2015). The dual-reference approach of BWM mitigates the anchoring bias that often affects human judgment in single-direction pairwise comparisons, ensuring that the derived weights are logical and representative of real-world priorities (Choudhary et al., 2026).

Since its introduction, BWM has undergone various methodological advancements to adapt to different decision-making environments and address its initial limitations. For instance, while the original non-linear minimax model could result in multiple optimal solutions, Rezaei (2016) proposed a linear model for BWM that consistently yields a unique solution for criteria weights. To account for scenarios where experts might provide varying viewpoints due to incomplete information, Multi-Choice Best-Worst Method (MCBWM) was developed to handle multiple choices of preference relations (Hasan et al., 2022). Similarly, in real-world problems where several criteria might exert the exact same best or worst influence, an Improved-BWM was introduced to allow for the existence of more than one best or worst criterion, further increasing the model's flexibility (Pamučar et al., 2020). Moreover, to address uncertainties and ambiguities, BWM has been extensively integrated with fuzzy sets, rough sets, and grey systems, as well as combined with other analytical tools like TOPSIS, VIKOR, and MABAC (Peykani et al., 2026).

Due to its computational efficiency and robust consistency, BWM and its extensions have been widely applied across a multitude of academic and industrial fields. Over the past decade, it has been extensively utilized in supply chain management and transportation to evaluate sustainability performance, digitization enablers, and logistical resilience (Choudhary et al., 2026; Gupta et al., 2021). In the manufacturing sector, researchers have employed BWM to prioritize barriers to sustainable manufacturing and to analyze the complex challenges associated with Industry 4.0 adoption (Malek & Desai, 2019; Wankhede & Vinodh, 2021). The method has also been instrumental in identifying enablers of technological innovation for micro, small, and medium enterprises (Gupta & Barua, 2016). Beyond these domains, the method has successfully guided

decision-making in diverse areas such as renewable energy resource evaluation, banking, tourism, and agriculture (Pamučar et al., 2020; Peykani et al., 2026).

In addition to technical and operational fields, BWM has been effectively applied in the domain of human factors and human resource management. Evaluating human competencies and selecting personnel are inherently complex multi-criteria problems that involve both quantitative and qualitative human traits. For example, Li et al. (2020) applied a Bayesian BWM to conduct a multicriteria competency analysis of crowdsourcing delivery personnel, utilizing a framework based on knowledge, skills, abilities, and traits. Bayesian extension was particularly useful as it provided a probabilistic approach to aggregate the weights from a group of decision-makers. BWM has been successfully utilized in teacher selection processes. Telli and Ayçin (2021) employed BWM integrated with MABAC method to evaluate essential human-centric criteria for teachers, such as communication skills, empathy, professional passion, and positive personality traits. These applications strongly demonstrate that BWM is highly capable of prioritizing subjective, human-related criteria, thereby making it an invaluable tool for personnel selection and human factors evaluation.

Methodology

The study employs Best–Worst Method (BWM), a multi-criteria decision-making technique, to prioritize AI competencies for air traffic controllers. The methodological procedure involves defining the decision problem, establishing the evaluation criteria, collecting expert judgments through a structured BWM questionnaire, and calculating criteria weights using the linear BWM. The resulting weights are subsequently used to determine the relative importance and ranking of the identified competencies.

Decision Problem

The decision problem concerns the relative priority weights of the core competencies required for air traffic controllers to operate safely and efficiently in human–AI teaming environments.

Criteria Framework

The eight competencies used in this multi-criteria decision-making model were adopted directly from EASA (2025). The competencies are as follows:

- Cognitive Skills (C1) encompass the capacity of an individual to engage in mental processing involving functions such as attention, memory, and reasoning.
- Data Literacy (C2) involves the competency to handle, understand, and apply data while possessing the ability to assess confidence intervals and mitigate automation bias.
- Sensory Competencies (C3) denote the ability to perceive physical stimuli including light, heat, and sound.
- Physical Skills (C4) represent bodily capacities encompassing strength, balance, and fine motor skills.
- Communication Skills (C5) refer to the competency to interact effectively through verbal, non-verbal, and written methods.
- Social Skills (C6) constitute the ability to establish collaborative relations with others through understanding and cooperation.
- IT Competencies (C7) include the technical proficiency required for operating computers and utilizing software tools.
- General AI Knowledge (C8) encompasses an individual's comprehension of machine learning and AI-based systems.

Data Collection Process and Participants

The data were collected through a structured Best–Worst Method (BWM) questionnaire applied to a purposively selected sample of operational air traffic controllers. Purposive sampling was used to ensure that participants possessed substantial operational experience and domain-specific expertise, thereby enabling informed judgments regarding the relative importance of the evaluated competencies.

Initially, responses were obtained from 20 air traffic controllers. During the data screening and validation process, one response was excluded due to severe logical inconsistencies that violated the transitivity and consistency requirements underlying the BWM framework. Such inconsistencies resulted in preference structures that were incompatible with the mathematical assumptions of the method and prevented the generation of a valid optimization solution. The final sample comprised 19 participants. In BWM studies that rely on expert judgment, panel quality is generally more important than panel size. Participants should have relevant domain knowledge and professional experience. The consistency of their judgments should also be assessed. When population-level statistical generalization is not intended, a small, carefully selected panel may be appropriate (Khan et al., 2022; Tabatabaee et al., 2024). Accordingly, the purposively selected panel of experienced operational air traffic controllers provided an appropriate basis for deriving context-specific criteria weights.

BWM Application Steps

BWM procedure adopted in the study is presented in Table 1. To determine the relative importance of the criteria, the linear BWM approach proposed by Rezaei (2016) was employed using the BWM-Solver-6 computational package. The literature distinguishes between two widely recognized versions of BWM comprising the original non-linear model (Rezaei, 2015) and the linear model (Rezaei, 2016). Given its computational efficiency and ability to generate unique optimal solutions, the linear BWM formulation was selected for the study. The analysis followed the five-step procedure of the BWM framework, including the identification of decision criteria, selection of the best and worst criteria, elicitation of pairwise preference judgments, optimization of criteria weights, and assessment of consistency. The consistency of expert judgments was evaluated based on the consistency measurement approach proposed by Liang et al. (2020), thereby ensuring the reliability of the pairwise comparisons and the resulting weight estimates.

Table 1

BWM Application Steps

Step	Name	Description	Formula / output
1	Determine criteria	The decision-maker identifies *n* criteria $\{c_1, c_2, ..., c_n\}$ relevant to the decision.	$C = \{c_1, c_2, ..., c_n\}$
2	Identify best and worst criteria	Select the most desirable / most important criterion (Best, B) and the least desirable / least important criterion (Worst, W) from the set.	B = best criterion W = worst criterion
3	Best-to-Others (BO) vector	Compare the best criterion against all other criteria using integers 1–9. Captures how much B is preferred over each criterion j.	a_B = (a_B1, a_B2, ..., a_Bn) where a_Bj = preference of B over j and a_BB = 1
4	Others-to-Worst (OW) vector	Compare all criteria against the worst criterion using integers 1–9. Captures how much each criterion j is preferred over W.	$a_W = (a_{1W}, a_{2W}, ..., a_{nW})^T$ where a_jW = preference of j over W and a_WW = 1
5	Solve for optimal weights	Find weights $w^*_1, ..., w^*_n$ by minimizing the maximum absolute difference between each weight ratio and its corresponding pairwise comparison.	min max_j { |w_B/w_j − a_Bj|, |w_j/w_W − a_jW| } s.t. Σ w_j = 1, w_j ≥ 0

Step	Name	Description	Formula / output
			Equivalent LP form: min ξ s.t. |w_B − a_Bj·w_j |≤ ξ ∀j |w_j − a_jW·w_W |≤ ξ ∀j Σw_j = 1, w_j ≥ 0
Consistency check (post Step 5)			
CR	Consistency ratio	Evaluate how consistent the pairwise comparisons are.	

Ethical Approval

Ethical approval for the study was obtained from the Ethics Committee of International Science and Technology University (April 30, 2026, Approval No. 202604-01). Participation was voluntary, and all respondents provided electronic informed consent after being briefed about the purpose of the research, the confidentiality of their responses, and their right to withdraw from the study at any stage. No personally identifiable information was collected, and all data were analyzed in an aggregated form to ensure participant anonymity and confidentiality.

Findings

Demographic Profile

The demographic information of the 19 participants is shown in Table 2. Demographic data revealed that the air traffic controllers had a mean age of 39.10 years (*SD = 6.66*) with a mean professional experience of 13.89 years (*SD = 6.45*). Regarding their operational units; nearly half of the controllers were assigned to the Area Control Center (ACC; 47.4%, n = 9), while the remainder operated within the Approach Control Unit (APP; 36.8%, n = 7) and the Tower Control Unit (TWR; 15.8%, n = 3).

Table 2

Demographic Information of Participants

	Value
Number of participants	19
Age, mean	39.10
Age, SD	6.66
Experience, mean	13.89
Experience, SD	6.45
Tower Control Unit (TWR)	3 (15.8%)
Area Control Center (ACC)	9 (47.4%)
Approach Control Unit (APP)	7 (36.8%)

Weights and Prioritization

The resulting weights and rankings are presented in Table 3 and Table 4. Although some differences emerged across respondents, a consistent pattern can be observed in the overall distribution of weights. Competencies associated with cognitive processing, data utilization, and technological proficiency received greater emphasis than competencies related to physical or social attributes. The consistency ratios (CRs) reported for the included participants were within the adopted thresholds, indicating an acceptable level of coherence in their pairwise comparisons.

The arithmetic mean weights were used to represent the aggregated competency weights, while geometric means were additionally calculated to assess the robustness of the resulting priority structure. Both aggregation approaches produced the same ranking of the eight competencies. The aggregated results reveal that cognitive skills achieved the highest weight (0.203), making it the most important competency dimension for air traffic controllers operating in an AI-supported environment. This finding indicates that the air traffic controllers assigned the greatest relative importance to cognitive skills among the eight competencies evaluated. The high ranking of cognitive skills may reflect participants' expectations that controllers will need to monitor, evaluate, and manage AI-generated outputs. The prominence of data literacy (0.176), the second-highest ranked competency, further indicates that participants recognize the necessity of critically evaluating this information. The relatively high ranking of data literacy suggests that participants considered the evaluation of data and algorithmic outputs important for future air traffic operations.

The third and fourth positions were occupied by IT competencies (0.146) and general AI knowledge (0.136), respectively. The relatively high ranking of these dimensions reflects an expectation that future air traffic controllers will require a solid understanding of digital technologies and AI concepts. The findings suggest that participants expect future controllers to interact with increasingly sophisticated AI systems and to understand their capabilities and limitations. The top four competencies account for more than half of the total importance weight, highlighting the dominant role of cognitive and technology-oriented capabilities in the competency profile envisioned by the participants.

A second tier of competencies includes communication skills (0.108) and sensory competencies (0.108). Although these dimensions received lower weights than the leading competencies, they remain important components of professional performance. Communication continues to be a fundamental element of air traffic control due to the need for coordination among controllers, pilots, and other operational stakeholders. Similarly, sensory competencies retain relevance because controllers must continuously monitor complex operational environments and identify potentially critical changes in traffic situations. The lower relative importance assigned to these dimensions suggests that respondents perceive them as less directly affected by the growing integration of AI technologies than cognitive and technological competencies.

The lowest-ranked competencies were social skills (0.069) and physical skills (0.055). The relatively limited importance attributed to these dimensions may reflect the highly cognitive and technology-intensive nature of air traffic control work. While interpersonal effectiveness and physical capabilities remain relevant for professional performance, participants appear to view them as less critical for adapting to AI-supported operational environments than competencies related to reasoning, data interpretation, and technological interaction.

A descriptive analysis was conducted to explore the distribution of competency priorities across operational units. The mean weights calculated for tower (TWR), approach (APP), and area control center (ACC) controllers showed broadly similar descriptive patterns, with some variation across the three operational units. Among TWR controllers, cognitive skills received the highest weight (0.247), followed by data literacy (0.206) and IT competencies (0.137). In contrast, social skills (0.037) and physical skills (0.048) received the lowest weights. For ACC controllers, data literacy emerged as the highest-ranked competency (0.195), followed by cognitive skills (0.181) and general AI knowledge (0.157). Similar to the TWR group, physical skills (0.061) and social skills (0.072) received the lowest importance weights. Among APP controllers, cognitive skills ranked first (0.211), followed by IT competencies (0.187), data literacy (0.139), and general AI knowledge (0.116). Compared with the other operational units, APP controllers assigned relatively greater importance to IT competencies.

Table 3

Weights of AI Competencies

	C1	C2	C3	C4	C5	C6	C7	C8	CR
ATC1	0,215	0,357	0,086	0,054	0,086	0,032	0,086	0,086	0,222*
ATC2	0,289	0,119	0,071	0,051	0,289	0,060	0,089	0,032	0,214*
ATC3	0,236	0,142	0,057	0,040	0,031	0,021	0,236	0,236	0,167*
ATC4	0,306	0,252	0,053	0,027	0,074	0,041	0,123	0,123	0,361*
ATC5	0,093	0,354	0,035	0,066	0,066	0,077	0,154	0,154	0,361*
ATC6	0,306	0,197	0,079	0,079	0,131	0,031	0,079	0,098	0,310*
ATC7	0,079	0,095	0,302	0,032	0,095	0,159	0,119	0,119	0,214*
ATC8	0,167	0,083	0,167	0,167	0,083	0,028	0,222	0,083	0,125*
ATC9	0,340	0,226	0,151	0,025	0,065	0,065	0,065	0,065	0,125*
ATC10	0,081	0,081	0,042	0,072	0,072	0,072	0,072	0,510	0,125*
ATC11	0,113	0,113	0,113	0,043	0,278	0,113	0,113	0,113	0,071*
ATC12	0,146	0,350	0,087	0,037	0,062	0,062	0,109	0,146	0,262*
ATC13	0,195	0,130	0,027	0,130	0,097	0,049	0,097	0,275	0,286*
ATC14	0,107	0,107	0,401	0,033	0,089	0,089	0,107	0,067	0,304*
ATC15	0,091	0,151	0,065	0,030	0,091	0,091	0,332	0,151	0,304*
ATC16	0,237	0,237	0,042	0,015	0,167	0,167	0,067	0,067	0,222*
ATC17	0,088	0,124	0,103	0,069	0,077	0,031	0,431	0,077	0,304*
ATC18	0,312	0,127	0,095	0,027	0,127	0,047	0,190	0,076	0,222*
ATC19	0,451	0,100	0,075	0,038	0,075	0,075	0,086	0,100	0,304*
Mean	0,203	0,176	0,108	0,055	0,108	0,069	0,146	0,136	
Mean (TWR)	0,247	0,206	0,071	0,048	0,135	0,037	0,137	0,118	
Mean (ACC)	0,181	0,195	0,114	0,061	0,103	0,072	0,117	0,157	
Mean (APP)	0,211	0,139	0,115	0,049	0,103	0,078	0,187	0,116	
Geo_mean	0,175	0,156	0,084	0,046	0,094	0,059	0,125	0,111	

** Consistency level is acceptable*

Table 4

Priority of AI Competencies

	Weights (Mean)	Weights (Geo_mean)	Rank
C1 - Cognitive Skills	0.203	0.175	1
C2 - Data Literacy	0.176	0.156	2
C7 - IT Competencies	0.146	0.125	3
C8 - General AI Knowledge	0.136	0.111	4
C5 - Communication Skills	0.108	0.094	5
C3 - Sensory Competencies	0.108	0.084	6
C6 - Social Skills	0.069	0.059	7
C4 - Physical Skills	0.055	0.046	8

Note: Rankings were determined based on unrounded weight values.

Discussion

The primacy of cognitive skills in the findings is theoretically significant. Advanced automation does not reduce the cognitive demands placed on air traffic controllers. It restructures and intensifies them. As AI systems absorb routine surveillance tasks, the residual decision space delegated to controllers becomes disproportionately populated with ambiguous, high-stakes, and non-routine scenarios (Endsley, 2023b; Xia et al., 2026). Endsley's (1995) tripartite model of situation awareness remains instructive because it argues that effective perception, comprehension, and projection of dynamic environments are irreducibly human responsibilities regardless of the degree of technological mediation in the system. Bainbridge's (1983) ironies of automation offer a sharp lens for interpreting this result. Automation is applied precisely to tasks that are repetitive and tractable, reserving for the human operator the problems that are cognitively demanding, temporally compressed, and poorly defined. The air traffic controller, now cast primarily as a supervisory monitor, is paradoxically required to maintain a higher order of cognitive readiness than the systems being overseen. The present findings provide empirical support for this irony within the specific context of AI-supported air traffic control.

The dual-processing framework provides a complementary theoretical lens for interpreting these cognitive demands. Effective performance in highly automated air traffic management environments necessitates the dynamic integration of rapid, intuitive System 1 responses and deliberate, analytical System 2 reasoning, enabling controllers to reconfigure cognitive schemas when confronting anomalies that exceed AI operational parameters (Torsi et al., 2025; Zhang et al., 2024). Critically, as AI progressively assumes data-intensive tasks, the risk of the out-of-the-loop phenomenon intensifies; operators who are insufficiently engaged with real-time system states may lose the tactical awareness required to intervene effectively during automation failures (Endsley & Kiris, 1995). This phenomenon is compounded by automation complacency and the gradual atrophy of manual skills that accompanies sustained supervisory roles (Ali et al., 2025; Hancock, 2007; Holford, 2022; Minaskan et al., 2022). Cognitive vigilance therefore functions as the primary safeguard within the human-AI system, providing the contextual judgment and abductive reasoning that algorithmically bounded systems are structurally incapable of supplying (Hagos et al., 2024; Holley et al., 2024; Kirwan, 2025; Pedreschi et al., 2025).

Domain-specific analysis further refines this finding. The relatively high weight assigned to cognitive skills by the TWR controllers may be associated with the time-sensitive nature of tower operations, which requires the continuous integration of visual and digital information. The TWR environment generally requires timely transitions from perception to decision, which may explain the descriptive importance assigned to cognitive

skills by the participants in this group. These descriptive variations suggest that the perceived importance of cognitive competencies may differ according to operational context. However, the small subgroup sizes prevent firm conclusions about differences among operational units.

The secondary tier of findings, which includes data literacy, IT competencies, and general AI knowledge, corroborates the aerospace industry's accelerating transition toward algorithmic operational environments. This secondary tier also establishes a clear profile for the emergent air traffic controller role as an active human-AI collaborator rather than a passive system monitor (Kabashkin et al., 2023; Schon et al., 2025). In modern human-AI teaming architectures, the controller is expected to critically evaluate AI-generated outputs, including conflict resolution advisories and multi-dimensional trajectory predictions, rather than accepting them uncritically (Degas et al., 2022; Tyburzy et al., 2024). This evaluative function presupposes a level of technical literacy that traditional air traffic controller competency frameworks have not consistently demanded.

The centrality of data literacy in this competency model is most precisely understood through its operational adversary, which is defined as automation bias. As Skitka et al. (2000) demonstrated, automation bias describes the systematic human tendency to substitute automated cues for independent cognitive processing, generating errors of commission wherein operators follow erroneous automated directives without engaging contradictory informational sources. In an AI-supported air traffic control environment, where AI recommendations may be statistically reliable yet contextually inappropriate in specific edge-case scenarios, uncritical acceptance of algorithmic outputs poses a direct safety risk. Fluent data literacy equips controllers to assess AI confidence intervals, interrogate the provenance of recommendations, and apply calibrated skepticism that prevents heuristic replacement from compromising airspace safety (Caldwell et al., 2022; Georganta & Ulfert, 2024a, 2024b; Steyvers & Kumar, 2024).

The demand for general AI knowledge reflects an equally profound transformation in the operator's epistemic relationship with technological systems. Controllers must transition from passive end-users of automation to active members of joint cognitive systems, a transition that requires substantive understanding of AI limitations, operational design domains, and the potential for algorithmic or data biases to propagate through decision-support outputs (EASA, 2024; Graydon et al., 2025; ICAO, 2025; Kirwan, 2025). This knowledge domain is inseparable from the framework of XAI. As Lee and See (2004) established, trust in automated systems cannot be appropriately calibrated in the absence of transparency regarding the system's reasoning processes; blind trust and inappropriate distrust represent symmetrical failure modes with equivalent safety implications. XAI frameworks directly address this requirement by ensuring that automated recommendations are accompanied by interpretable explanations, thereby reducing cognitive workload, enhancing adoption willingness, and supporting the kind of calibrated reliance that safe human-AI collaboration requires (Bjurling et al., 2024; Cartocci et al., 2026; Kilner et al., 2025; Stathis et al., 2025). The descriptive results obtained from the ACC participants provide an initial indication of the potential importance of data literacy in area control operations. ACC controllers function across significantly longer time horizons than their TWR or APP counterparts, managing vast geographical sectors through predominantly data-driven processes. In increasingly automated environments, ACC controllers may assume a more strategic and supervisory role that involves evaluating predictive data outputs and monitoring system performance. This operational context may increase the importance of data literacy for ACC controllers. The ability to assess AI-generated sector predictions critically may become an important component of the ACC role as AI-supported tools are increasingly integrated into operations. APP controllers assigned relatively greater importance to IT competencies than the other groups. This descriptive result may reflect the role of technological systems and fallback procedures during the tactically demanding phases of aircraft sequencing.

The secondary ranking of communication skills and sensory competencies reflects a complex pattern of sustained relevance alongside substantive functional evolution. Communication has historically served as the foundational safety mechanism of aviation, ensuring effective coordination among distributed human stakeholders and aircrews through standardized phraseology and procedural protocols (Cardon & Marshall, 2024; Kirwan et al., 2024; Korentsides et al., 2024). The progressive integration of intelligent assistants and digital controllers into the operations room does not render this communicative infrastructure obsolete. Rather, it demands its extension into novel interactional domains. The role of air traffic controllers has evolved to necessitate the utilization of advanced multimodal interfaces, gesture controls, and synthetic voice communications. These technologies facilitate the establishment and maintenance of shared mental models among team members, thereby enhancing collaboration across the human-AI boundary.

This communicative expansion is theoretically significant. The prevailing communication paradigm in the context of air traffic control was initially developed with the assumption that all participants possessed a shared situational understanding and implicit contextual knowledge. This approach entailed the capacity for pragmatic inference, a phenomenon that is well-documented in the study of human interaction. Human-machine communication introduces different interactional constraints, demanding explicit, unambiguous, and structured communicative acts that may not always align with the informal adaptive communication characteristic of high-performing human teams (Haiku, 2025; Josh et al., 2022). The practical implication is that communication training within air traffic control must be expanded to encompass both interpersonal and human-machine communicative competencies, treating these as distinct but complementary skill sets rather than interchangeable expressions of a single underlying capacity.

Sensory competencies occupy an analogous position of retained yet reconfigured relevance. As automated subsystems assume the primary burden of routine conflict detection, the perceptual demands placed on air traffic controllers shift from continuous active surveillance toward selective, high-stakes monitoring of complex visual environments. Controllers must parse high-density human-machine interfaces to detect critical state changes and interpret multidimensional representations of airspace dynamics (De Maria, 2016; Lorrig & Daw, 2024; Sharma, 2025). Although automated systems may reduce some routine perceptual demands, failures to detect critical changes may still have important operational consequences. A defining feature of supervisory monitoring roles is the asymmetry between reduced perceptual frequency and heightened perceptual consequence. This imbalance directly dictates how training and human factors engineering must be designed for next-generation air traffic control environments.

Social and physical skills received the lowest competency rankings, although this finding requires careful interpretation in the context of the changing structure of aerospace operations. Physical skills appear to play a more limited role in modern air traffic control than cognitive and technology-related competencies. The contemporary air traffic control workspace is predominantly cognitive rather than manual, and the findings reflect this reality with predictable clarity. The physical demands of modern air traffic control, such as interface interaction and equipment manipulation, may represent basic requirements rather than distinguishing competencies.

The relative reprioritization of social skills is a more theoretically complex finding that requires careful contextualization. While interpersonal skills remain necessary in AI environments, findings show a strategic shift. Competency profiles are now heavily reweighted toward human-machine collaboration mechanics rather than focusing solely on interpersonal dynamics. This interpretation demands critical engagement with the established principles of Team Resource Management (TRM), which has functioned as a foundational safety management intervention in air traffic management by developing positive attitudes and effective behaviours related to teamwork, workload distribution, and communication under pressure

(Kirwan, 2025). TRM principles remain indispensable in degraded operational modes; in the event of sudden AI system failure, effective workload delegation and clear inter-human communication loops may constitute the sole remaining barrier against operational collapse. The relegation of social skills in the present findings may therefore reflect respondent perceptions of routine operational demands rather than a comprehensive assessment of the full competency envelope required across all operational conditions, including low-probability, high-consequence failure scenarios. The resolution of this tension indicates that a crucial direction for the field involves the evolution of TRM into frameworks capable of encompassing human-AI teaming dynamics. Traditional TRM models were conceptually grounded in assumptions of homogeneous human team membership, making them structurally ill-suited to hybrid teams in which one or more members are AI agents with different capabilities, failure modes, and communicative behaviours (Kirwan, 2025). Developing robust human-AI teaming models that preserve the safety-critical functions of TRM while accommodating the structural properties of AI team members is an urgent research and policy priority.

Implications

The aggregated findings carry substantive implications for the restructuring of air traffic controller training curricula, selection frameworks, and organizational design principles. Training academies must integrate rigorous instruction in data analytics, algorithmic logic, and AI system architecture, while simultaneously cultivating the metacognitive awareness required for controllers to recognize and counteract automation bias in real time. This curricular expansion must be accompanied by explicit training in XAI trust frameworks, enabling controllers to assess system transparency as a precondition for calibrated reliance rather than treating trust as a binary, context-independent disposition. The development of such metacognitive and evaluative capacities represents a qualitative departure from the procedural skill acquisition that has historically dominated air traffic controller training paradigms.

Selection processes must become correspondingly more granular in their assessment of cognitive profiles. The descriptive variations observed across TWR, APP, and ACC controllers indicate that future research should examine whether competency and selection criteria need to be adapted to different operational contexts. TWR and ACC environments involve different operational demands. Future studies with larger and more balanced samples could examine whether these differences are associated with distinct cognitive competency profiles. If these descriptive differences are confirmed in larger studies, selection and training frameworks could be refined to reflect the specific demands of different operational units.

Limitations

While this research provides a structured prioritization of essential skills, certain limitations must be acknowledged. The evaluation of future competencies relies inherently on the current expectations and perceptions of professionals regarding technologies that are still in developmental or early implementation phases. As AI architectures and operational design domains continue to mature, the actual demands placed on human operators may evolve in unforeseen ways, potentially altering the relative importance of the identified skills. Additionally, the findings reflect an aggregated perspective that may not fully capture the nuanced differences across varying levels of automation or specific regional airspace complexities. A primary methodological limitation pertains to the nature of expert elicitation inherent in multi-criteria decision-making frameworks. Although the BWM significantly reduces cognitive load and ensures high consistency through its linear formulation, the derived priority weights represent subjective expert judgments rather than empirically measured performance outcomes in fully realized human-AI hybrid systems.

Future Research Directions

The findings of the study establish a foundational priority structure for human-AI teaming competencies in air traffic control, yet they also illuminate critical pathways for future scholarly inquiry. First, as AI architectures transition from conceptual development to operational deployment, future research must pivot from anticipated competency requirements to empirical validation. High-fidelity simulator studies are needed to measure how the prioritization of cognitive skills and data literacy actively influences controller performance, workload, and stress-induced decision-making during simulated automation failures or "cognitive lockup" scenarios. Furthermore, from a methodological standpoint, future iterations of this research could integrate the current linear BWM framework with Fuzzy or Rough set theories to better capture the uncertainty and ambiguity inherent in subjective expert judgments regarding early-stage technologies. Additionally, to expand upon the aggregated perspective of the current findings, cross-sectional studies evaluating these competency priorities across varying levels of automation and specific regional airspace complexities would significantly enrich the global discourse on human-AI integration.

Conclusion

The findings show that the participating air traffic controllers assigned the highest relative importance to cognitive skills when evaluating competencies for human-AI teaming. As AI systems assume more routine surveillance tasks, controllers may increasingly be required to manage ambiguous, high-stakes, and non-routine situations. Supervising intelligent systems may require a competency profile that differs from that associated with conventional air traffic control operations.

Cognitive skills, data literacy, IT competencies, and general AI knowledge collectively define the critical competency tier for the AI-supported air traffic control environment. These dimensions may become increasingly important components of the air traffic controller competency profile as AI-supported systems are introduced. The ability to evaluate algorithmic outputs, recognize system limitations, and intervene when necessary is likely to become an important safety-related function of the human controller. Competency frameworks, training curricula, and selection instruments may therefore need to be reviewed as AI-supported systems become more widely integrated into air traffic control.

The descriptive unit-level findings suggest that perceptions of competency priorities may not be uniform across the profession. Tower, Approach, and Area Control Center environments involve different cognitive and technical demands. However, larger comparative studies are needed before recommending different competency standards for these operational contexts. Human resource strategies for AI-supported air traffic management may benefit from considering the operational characteristics of different control units.

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