Human Factors in Design, Engineering, and Computing, Vol. 238, 2026, 1358–1363
https://doi.org/10.54941/ahfe1008364

Emerging Technologies and AI in Aviation: Reshaping the Roles and Responsibilities of Human Factors

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ABSTRACT

Artificial intelligence (AI) is generating significant interest across the aviation industry, with applications such as aircraft design, operations, aviation data analysis, aviation maintenance and aircraft retirement. The Federal Aviation Administration (FAA), industry stakeholders, and researchers are actively exploring how these technologies can improve aviation safety, efficiency, operational capability, and potentially reduce human error. Historically, human error has accounted for over 80% of aviation accidents, yet the aviation industry is an ecosystem that involves humans at every level. However, before AI-enabled systems can be widely deployed in industry, they must demonstrate compliance with aviation's rigorous safety requirements. This paper examines how AI transforms human factors in the aviation ecosystem. It considers the implications of AI across different phases of aviation, from design, system safety, training, workload, decision-making, trust, explainability, regulatory oversight, and risks associated with it.

Keywords: Human factor, AI in aviation adoption, human error, Human-AI interface

INTRODUCTION

In the aviation ecosystem, human factors remain central across all aspects of operations. Human factors remain central to aviation safety because aviation systems depend on the interaction among people, aircraft, software, procedures, organizations, and operating environments. Historically, human factors accounted for nearly 80% of overall aviation accidents (Shappell et al., 2006). Traditionally, human-factors practice focused on reducing pilot error, improving cockpit design for operator comfort, managing fatigue, strengthening crew resource management, and supporting safe maintenance and air-traffic-control operations. Today, however, emerging technologies including artificial intelligence, machine learning, advanced automation, remotely piloted aircraft, decision-support systems, and increasing autonomous operations are changing both the nature of human work and the sources of safety risk in the aviation industry. Human-factors specialists must therefore move beyond error reduction and contribute to the design, certification, operation, monitoring, and governance of human–machine systems (Kirwan, 2025). This paper reviews the current adoption of AI uses across different aspects in aviation and discusses how the role of humans might change, and the risks and challenges associated with it.

Received October 17, 2026; Revised November 22, 2026; Accepted November 28, 2026; Available online December 1, 2026

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Overview of Current AI in the Aviation Ecosystem

The Federal Aviation Administration has published guiding principles for AI applications.

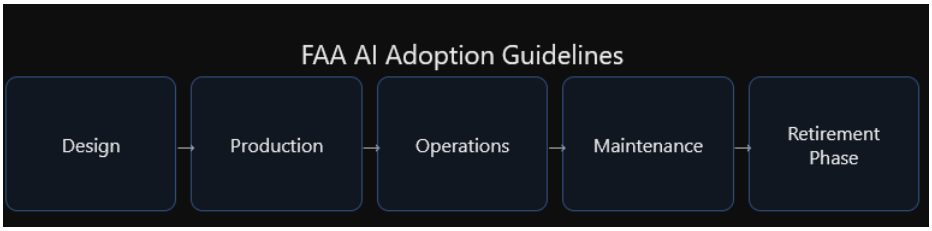


Figure 1: FAA AI adoption guidelines (adapted from FAA, 2024).

AI is currently being introduced across the many different aircraft life cycles (design, manufacture, operations, maintenance and retirement). The FAA identifies these as part of a broader effort to use AI safely and to improve the safety assurance of aviation (FAA, 2024).

AI can support model-based software development, data classification, requirements development, and certification documentation generation during the design phase (Mohaghegh & Mohaghegh, 2025). The designer can use statistical analysis of the input data to identify operational patterns and define system requirements (Karthikeyan et al., 2025). AI can also be used to develop or evaluate other AI models that are used within the aviation system.

In the production phase, AI is used to augment the existing robotic manufacturing and computer vision quality control systems. It can be used to analyze production faults, detect abnormal manufacturing patterns, detect FOD (Foreign Object Debris), detect line failures, and assess variations in component tolerances. This could lead to improved manufacturing consistency and the ability to find faults prior to the aircraft or components going into service (Kabashkin et al., 2024).

AI can be used in operations to assist with flight dispatch, pilot training, record-keeping and monitoring, flight simulators, scenario prediction, and safety risk management. It can also produce training manuals, operational procedures, and safety analyses. The benefits would be improved decision support and reduced human cognitive workload, which are traditionally managed by humans.

Aviation maintenance is a complicated system that involves humans, aircraft parts, tools, software, logistics and materials, and other related resources (Bohrey & Chatpalliwar, 2024). Because aviation maintenance requires extensive coordination among crew members, shifts, and different departments, AI can reduce the risk of miscommunication between shifts and support predictive maintenance and system-operation monitoring. This will foster overall more preventative maintenance cycles to identify latent threats, proactively identify hazards, and potentially increase overall aviation safety and reduce incidents and accidents.

AI also has potential in the retirement phase of the aircraft life cycle. This could be in the form of optimizing the decommissioning of aircraft, the recycling of components, asset management, analysis of historical flight data, supporting regulatory compliance and identifying lessons for future aircraft design. Retired aircraft and components could also be used to support AI powered pilot training simulators and aviation education.

AI adoption is clearly on the rise across the full system life cycle in aviation. The FAA has made it very clear that any AI applications will need to be introduced within the existing safety, certification and risk management. There is a particular need for scrutiny in the case of systems that are learning or adapting as they operate, as the traditional design methods may not be able to fully define their behavior. AI adoption will therefore need to be gradual, with ongoing monitoring, verification, validation and with clear human responsibility (FAA, 2024).

Human Factors Risks Associated With AI Adoption

Table 1: Human factors risks associated with each category.

	Human-Factors Risks	Potential Safety Concerns
Design	AI-generated requirements or certification documents may contain errors including slips, lapses, omissions, or inaccurate assumptions. Designers may develop over-reliance with AI outputs and reduce independent assessment for quality and safety assurance. AI output might also impose risks of misleading the reality between computer modelling simulations and practical application.	Inadequate requirements, performance optimization raised application risk, latent design faults, poor human operating environment design
Production	Personnel may become overly dependent on computer-vision inspections. False alarms, missed defects, poor interface design, and inadequate training may affect quality-control decisions. Production pressure may also encourage workers to accept AI results without sufficient review.	Defective aircraft parts, missed foreign-object debris, manufacturing inconsistencies, or incorrect and inconsistent geometrical tolerances may pass through the production system and affect aircraft reliability.
Operations	AI decision-support systems may create automation bias, complacency, loss of situation awareness, and lack of assertiveness for the human operators to challenge the AI decisions. Human operators may misunderstand AI limitations and the ethical consideration or be uncertain about who has final decision authority. AI-generated manuals and procedures may also contain inaccurate or outdated information.	Incorrect dispatch decisions, inappropriate flight-path recommendations due to the dynamic nature of the aviation ecosystem and delayed human intervention may occur.

(Continued)

Table 1: Continued.

	Human-Factors Risks	Potential Safety Concerns
Maintenance	AI-based predictive maintenance may produce false positives or false negatives. Maintenance personnel may lack sufficient understanding of computer output and some complicated aircraft parts might requires additional screening. Shift handovers may still be affected by poor communication, incomplete records, or a vague responsibility distribution between each shift and different sectors of the maintenance aspect.	Unnecessary maintenance, waste of time, resources, materials missed defects, delayed corrective action, incorrect part replacement, and latent maintenance hazards may contribute to incidents or accidents.
Retirement phase	AI may prioritize cost, efficiency, or asset value over safety and environmental considerations. Historical data may be skewed or biased, and personnel may have difficulty validating AI recommendations concerning aircraft retirement, component reuse, or recycling.	Unsafe reuse of components, incomplete records, loss of safety-critical knowledge, and poor regulatory compliance may result.

Common Challenges of the Role for Human Factors

Human Overreliance on AI: As AI-assisted decision-making platforms gain traction across nearly all aspects of operations, humans tend to rely heavily on AI-generated decisions or commands, regardless of their accuracy or ethical implications (Buçinca et al., 2021). Buçinca et al. (2021) suggested the important "to trust or to think" dilemma for humans when it comes to AI output. When the output from AI can be considered fast thinking and quick delivery, humans are likely to develop a sense of overreliance on AI output without proper training on how to use AI properly, in the sense that AI literacy and ethical output are considered.

Ambiguous accountability and lack of oversight: Schoenherr and Thomson (2024) suggest that, with current AI adoption, debate continues over who will ultimately take responsibility when AI-generated decisions and commands fail or cause safety-related accidents. Human decisions are often associated with some degree of cognitive bias, whether conscious or unconscious (Korteling & Toet, 2020). AI-enabled decision-making can avoid these flaws, unlike humans, because it analyzes conditions based on facts and data. Although 80% of historical aviation accidents are due to human error, adding a component like AI-assisted decision-making creates additional technical and psychological challenges for human operators (Schoenherr & Thomson, 2024). Currently, it is unclear what the overall oversight guidelines are for AI adoption in aviation, and whether operators are ultimately responsible for decisions made regardless of AI input, which could create issues between human operators and the rapid adoption of AI. The lack of current regulations and policies on AI adoption also shapes human operators' opinions about a potential increase in workload for overseeing AI output.

Training, user interface design, and competency issues: AI training is necessary for aviation personnel to adopt AI. Training should cover not only how to use the tool, but also how to evaluate the output, interpret the results, and revise them to produce the desired output (Maity, 2019). All human operators who regularly interact with the AI interface should have access to recurrent and regular training to develop the mindset that AI output can be incorrect at times and that all output still needs to be evaluated. Sundar et al. (2025) emphasize that ideal AI interface design must consider human factors to balance efficiency with empathy and foster effective communication as the foundation of AI interfaces. The goal of implementing AI should not be to impose additional workload on human operators.

DISCUSSION

AI and other emerging technologies can benefit the aviation industry by reducing workload, enabling complex data analysis, and supporting unbiased decision-making. Questions remain about who holds ultimate responsibility for decisions, commands, and actions that result in negative impacts. Humans' role might have to shift from an operating role to a supervising role, which might introduce latent, unidentified risks, increase mental workload, and impose psychological burdens.

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