INTERNATIONAL RESEARCH JOURNAL OF ADVANCED ENGINEERING AND TECHNOLOGY (IRJAET)

eISSN: 3087-4068

Volume. 02, Issue. 07, pp. 01-07, July 2025"

Frameworks and Techniques for Assessing Pilot Mental Workload in Advanced Aviation Systems

Dr. Gabriel T. Moreira
Department of Aeronautical Engineering, University of São Paulo, Brazil

Prof. Thiago R. Monteiro
Faculty of Mechanical and Aerospace Engineering, Federal University of Santa Catarina (UFSC), Brazil

Article received: 05/05/2025, Article Revised: 06/06/2025, Article Accepted: 01/07/2025
DOI: https://doi.org/10.55640/irjaet-v02i07-01

© 2025 Authors retain the copyright of their manuscripts, and all Open Access articles are disseminated under the terms of the Creative Commons Attribution License 4.0 (CC-BY), which licenses unrestricted use, distribution, and reproduction in any medium, provided that the original work is appropriately cited.

ABSTRACT

Pilot mental workload is a critical human factor in aviation safety and operational efficiency, profoundly impacting decision-making, performance, and overall system dependability within complex aviation-technological complexes. Excessive or insufficient workload can lead to errors, reduced situational awareness, and ultimately, aviation incidents and accidents [16]. This article presents a comprehensive overview of frameworks and techniques employed for modeling and assessing pilot mental workload. We categorize these methodologies into subjective, physiological, performance-based, and computational approaches, detailing their principles, applications, and inherent limitations. Drawing upon extensive literature, we synthesize insights into how these diverse methods contribute to understanding, predicting, and managing the cognitive demands placed on pilots. The discussion highlights the challenges associated with real-time, multi-modal workload assessment and emphasizes the necessity of integrated approaches for effective human-machine interface design, automation management, and flight safety [11]. The conceptualization of pilot mental load through robust modeling is crucial for optimizing the interaction between human operators and advanced aviation systems, thereby enhancing overall system reliability and safety.

KEYWORDS

Pilot mental workload, aviation systems, workload assessment, human factors, cognitive load, physiological monitoring, performance metrics, flight simulation, neuroergonomics, aviation safety.

INTRODUCTION

The modern aviation environment is characterized by an escalating degree of technological sophistication, with advanced avionics, automated systems, and intricate human-machine interfaces [15]. While these advancements significantly enhance aircraft capabilities, they simultaneously introduce new complexities for the human operator—the pilot. A paramount concern in this human-machine nexus is pilot mental workload, which refers to the cognitive demands imposed on an individual when interacting with a system to achieve specific goals [21, 22, 30, 36]. Effective management of pilot mental workload is unequivocally recognized as a cornerstone of aviation safety and operational effectiveness [4, 11, 16].

Mental workload is a multi-dimensional construct, encompassing aspects of attention, perception, decision-making, and memory [36]. Deviations from an optimal workload level—either excessively high or critically low—can lead to detrimental consequences. Overload can manifest as tunnel vision, missed cues, increased response times, and an elevated propensity for errors, jeopardizing flight safety [17, 37]. Conversely, underload, often associated with high levels of automation, can result in complacency, reduced vigilance, and a degradation of situational awareness, leaving pilots unprepared for unexpected events [31]. Therefore, accurately assessing, predicting, and modeling pilot mental workload is indispensable for designing effective human-machine systems, optimizing automation, developing training programs, and ensuring robust flight safety management [9, 11, 15].

The historical evolution of human factors research in aviation has consistently highlighted the importance of understanding cognitive processes and limitations [13]. Early models focused on information processing rates [17], while later developments considered the multi-resource theory of attention [36]. The increasing complexity of modern cockpits, where pilots must process vast amounts of information and manage multiple concurrent tasks, necessitates sophisticated methods for quantifying and predicting mental load [12, 13]. Understanding the interplay between the human-machine interface and avionics is vital for this [15].

This article provides a comprehensive exploration of the various methods employed for modeling and assessing pilot mental workload within the context of an aviation-technological complex. It aims to systematically review and categorize these approaches, from subjective self-reports to objective physiological measures and advanced computational models. By synthesizing insights from diverse research, we seek to elucidate the strengths and limitations of each methodology and underscore the necessity of a multi-modal, integrated approach to reliably capture the dynamic nature of pilot cognitive demands. The ultimate objective is to contribute to the ongoing efforts to optimize pilot performance, enhance cockpit design, and bolster the overall dependability of aviation systems.

METHODS

The conceptualization and evaluation of methods for modeling pilot mental workload necessitate a structured and comprehensive approach. Our methodology for this article involved a systematic review and synthesis of existing literature, categorizing the diverse techniques employed in human factors and aviation research. This process was driven by the need to provide a holistic understanding of mental workload assessment within the complex environment of aviation-technological complexes.

Systematic Literature Review

An extensive literature review was conducted to identify relevant studies, models, and techniques pertaining to pilot mental workload assessment. The search encompassed academic databases, conference proceedings, and technical reports focusing on human factors in aviation, cognitive psychology, ergonomics, and computational modeling. Keywords such as "pilot workload," "mental load," "human factors," "aviation safety," "cognitive modeling," "physiological measures," and "performance assessment" were utilized. The selected literature spans several decades, acknowledging the evolution of research in this domain, from foundational studies to recent advancements [13]. Emphasis was placed on studies that directly addressed the assessment or modeling of workload in pilots or similar high-stakes, multi-tasking environments [6, 7, 25, 34].

Categorization of Workload Assessment Methods

Based on the literature review, the identified methods for assessing pilot mental workload were categorized into four primary groups. This categorization provides a structured framework for understanding the diverse approaches:

- Subjective Methods: These rely on a pilot's self-assessment of their perceived workload.
- Physiological Methods: These measure biological responses indicative of cognitive effort.
- Performance-Based Methods: These evaluate changes in a pilot's task execution metrics.
- Computational/Modeling Methods: These involve mathematical or algorithmic representations of cognitive processes and workload.

Each category was then explored in detail, identifying common techniques, their underlying principles, typical applications in aviation contexts, and general strengths and limitations.

Integration of Aviation Context

Throughout the review and categorization, a particular focus was maintained on the applicability and relevance of each method to the unique demands of an aviation-technological complex. This involved considering:

- The dynamic and often high-stress nature of flight operations.
- The interaction with automated systems and complex human-machine interfaces [15].
- The critical importance of real-time assessment capabilities for in-flight decision-making.
- The need for non-intrusive and ecologically valid measures.
- The influence of environmental factors on pilot state [6, 42].

Studies specifically involving pilots, air traffic controllers, or simulator-based aviation tasks were prioritized to ensure contextual relevance [1, 7, 8, 25, 32, 34].

2.4 Synthesis and Framework Development

The final stage involved synthesizing the findings from the categorized methods to construct a conceptual understanding of how these approaches contribute to comprehensive mental workload modeling. This synthesis aimed to:

• Highlight the complementary nature of different methods.

• Identify the challenges in integrating data from various sources.

• Propose a holistic perspective on workload assessment that moves beyond single-measure reliance.

• Inform potential avenues for future research in enhancing pilot mental workload modeling capabilities.

The "results" section will therefore present a detailed exposition of these categorized methods, drawing directly from the identified literature, rather than presenting empirical data from a novel experiment.

RESULTS

This section details the various frameworks and techniques identified through the systematic literature review for modeling and assessing pilot mental workload within an aviation-technological complex. These methods are categorized to provide a structured understanding of their characteristics and applicability.

Subjective Methods

Subjective methods rely on self-reports or ratings provided by the pilot regarding their perceived mental workload. These methods are relatively easy to administer, inexpensive, and directly capture the individual's experience of workload.

• Rating Scales: The most common approach involves standardized questionnaires administered after a task or at specific intervals during a simulation.

o NASA Task Load Index (NASA TLX): This widely used multi-dimensional scale assesses workload across six subscales: Mental Demands, Physical Demands, Temporal Demands, Performance, Effort, and Frustration [1]. It has been extensively applied in aviation contexts, including for aircraft pilot workload analysis [1] and drone flight training simulators [7].

o Subjective Workload Assessment Technique (SWAT): Another prominent method that requires prior training to establish individual scaling factors.

• Applications and Limitations: Subjective methods are valuable for providing a global assessment of workload and are sensitive to individual differences [10]. They are often used as a primary measure due to their ease of use [20, 21]. However, their main limitation is their retrospective nature, making them unsuitable for real-time assessment. They are also prone to biases such as social desirability, memory effects, and individual interpretation of "workload" [20, 21].

Physiological Methods

Physiological measures capture the body's involuntary responses to cognitive demands, offering objective and continuous assessment. The premise is that increased mental effort elicits measurable changes in physiological parameters.

• Cardiovascular Measures:

o Heart Rate (HR) and Heart Rate Variability (HRV): Changes in heart rate and its variability are sensitive indicators of mental workload, reflecting autonomic nervous system activity [1, 10, 25, 30]. Increased mental load typically leads to increased heart rate and decreased HRV [1, 25]. Studies have used these to assess pilot workload [1, 10].

• Neurophysiological Measures:

o Electroencephalography (EEG): EEG measures brain electrical activity and can detect specific brainwave patterns (e.g., alpha, theta, frontal asymmetry) associated with different levels of cognitive load [26, 34]. Event-related potentials (ERPs) like the P300 component can also be used to assess cognitive demands [5]. Brain biomarkers derived from EEG can provide an assessment of cognitive workload in pilots under various task demands [8, 26]. A systematic review highlights the growing role of neurophysiology in aviation [33].

o Eye Movements (Oculometry): Measures such as blink rate, pupil diameter, and gaze patterns can indicate cognitive effort and attention allocation [37]. For instance, highway direction signs can affect a driver's mental workload and behavior as observed through eye movements and brain waves [37].

• Other Physiological Indicators:

o Electrodermal Activity (EDA): Skin conductance responses can reflect sympathetic nervous system arousal related to mental effort [6, 25].

o Electromyography (EMG): Muscle tension can be an indicator of stress or mental load [29].

• Applications and Limitations: Physiological measures offer objective, real-time assessment capabilities, making them valuable for dynamic environments like cockpits [25]. However, they can be influenced by non-workload factors (e.g., physical exertion, stress, individual differences) [6, 10, 25], require specialized equipment, and often need complex signal processing and interpretation.

Performance-Based Methods

These methods assess mental workload by analyzing a pilot's performance on a primary task or by introducing a secondary task that competes for cognitive resources.

• Primary Task Measures:

o Accuracy: The correctness of a pilot's actions (e.g., navigation precision, target hits).

o Response Time/Completion Time: The time taken to execute a task or respond to stimuli [13].

o Errors: The frequency and type of mistakes made during task execution [16].

o Task Specificity: These measures are direct and ecologically valid for the primary task but are often task-specific and may not generalize across different flight phases or scenarios.

• Secondary Task Measures:

o A common paradigm involves requiring the pilot to perform a secondary task (e.g., a simple reaction time task, memory task, or tracking task) concurrently with the primary flight task [12, 13, 20]. The assumption is that as primary task workload increases, performance on the secondary task will degrade as cognitive resources are diverted.

o Effective Indices: Studies have identified effective indices for monitoring mental load during performance of multiple tasks [12, 13].

• Applications and Limitations: Performance measures are objective and directly reflect task proficiency. They are valuable for identifying workload peaks or valleys associated with specific operational segments. However, they can interfere with primary task performance, and their sensitivity can vary. Moreover, they may not provide diagnostic information about why workload is high (e.g., specific cognitive processes affected).

Computational/Modeling Methods

Computational models aim to represent and predict human cognitive processes and workload through mathematical algorithms or simulation environments. These models offer predictive capabilities and can be used for system design and evaluation without requiring direct human testing.

• Analytical Models:

o These models use mathematical equations to describe the relationship between task characteristics and workload [2]. They can predict workload based on factors like information processing demands, decision complexity, and time constraints [2, 17].

• Human Performance Models:

o These are more elaborate computational simulations of human cognitive architecture and task execution [18, 23]. They simulate a human operator's interaction with a system, predicting performance and workload based on internal cognitive states and resource allocation [18, 38]. Examples include models that account for human operator behavior in human-machine systems, incorporating factors like light stimuli [3] or decision-making processes [9].

• Information Theory Models:

o These approaches quantify mental workload based on the amount of information processed by the pilot [38]. By analyzing the entropy and redundancy of task-related information, these models can estimate cognitive load [38].

• Expert Systems and AI Approaches:

o Intelligent systems can be developed to support pilots by assessing their state, including mental workload [14]. Machine learning techniques are increasingly being explored for distinguishing and predicting mental workload, especially in relation to cockpit display interfaces [34] and analyzing environmental factors [36, 42, 54].

• Applications and Limitations: Computational models are powerful for predictive analysis, aiding in the design of new systems and automation strategies [34]. They allow for "what-if" scenarios and can be integrated into broader system simulations. However, their accuracy is heavily dependent on the fidelity of the underlying human cognitive models and the availability of precise input data. They can be complex to develop and validate, and may not fully capture the subjective experience of workload.

Each of these categories offers unique advantages and contributes to a more comprehensive understanding of pilot mental workload. Their judicious combination often provides a more robust assessment than relying on a single method.

DISCUSSION

The diverse methodologies for assessing pilot mental workload, as detailed in the previous section, underscore the multifaceted nature of this critical human factor in aviation. No single method provides a complete picture, and each comes with its own set of strengths and limitations. The discussion that follows compares these approaches, highlights the challenges in their practical application, and outlines future directions for research in this vital domain.

Comparison of Workload Assessment Approaches

- Subjective methods (e.g., NASA TLX [1]) are valuable for their direct capture of the pilot's perceived experience of workload. They are easy to implement and provide qualitative insights often missed by objective measures [7, 20]. However, their retrospective nature means they cannot provide real-time feedback, and they are susceptible to individual biases and context effects [21]. They are best suited for post-flight analysis or simulator studies where immediate intervention based on workload is not required.

- Physiological methods offer objective, continuous, and real-time insights into cognitive effort [1, 8, 25]. Measures like HRV [1, 10] and EEG [8, 26, 34] can indicate autonomic and neural responses to stress and mental demand. The development of brain biomarkers holds promise for more precise assessment [8]. The primary challenge lies in their sensitivity to non-workload factors (e.g., emotional state, physical movement [6, 10]), the complexity of data interpretation, and the need for specialized equipment that may interfere with operational realism. Environmental factors, such as light stimuli, can also influence human operators [3].

- Performance-based methods provide objective data on how workload affects task execution [12, 13]. They are direct measures of the human-system interaction. Primary task measures offer ecological validity, while secondary tasks can provide diagnostic information about resource competition [20]. However, these methods can suffer from interference effects (especially secondary tasks) and may not always provide a clear diagnostic of why performance degraded (e.g., whether it's due to high cognitive load or poor skill). Their application in real operational flights can also be challenging due to safety and logistical constraints.

- Computational/Modeling methods are powerful for predictive analysis and system design [18, 34]. They allow for "what-if" scenarios without risking human pilots and can integrate various human factors principles into a coherent framework [18]. These models can range from simple analytical equations [2] to complex cognitive architectures that simulate human behavior [23]. The main drawback is their reliance on accurate and validated underlying human cognitive models, which can be difficult to develop and maintain, especially for novel tasks or environments. The complexity of human-machine interaction and avionics further complicates modeling efforts [15].

Challenges in Workload Modeling for Aviation-Technological Complexes

The unique demands of the aviation environment present several significant challenges for effective mental workload modeling:

- Real-time Assessment: The need for instantaneous workload feedback for adaptive automation and pilot assistance is paramount [31]. Most current methods, particularly subjective ones, fall short in this regard.

- Dynamic and Complex Environment: Workload fluctuates rapidly during different flight phases (e.g., take-off, cruising, landing, emergency situations). Modeling needs to account for this dynamism and the complex interplay of human, machine, and environmental factors [36, 42, 54].

- Multi-modal Integration: No single measure captures all facets of mental workload [36]. Integrating data from multiple sources (subjective, physiological, performance) is complex due to varying scales, temporal resolutions, and inherent noise [25]. Effective fusion techniques are required.

- Individual Differences: Pilots exhibit significant variability in cognitive capacity, coping strategies, and response to stress [10, 25]. A robust model must account for these individual differences rather than assuming a generic "average pilot."

- Ecological Validity vs. Control: Achieving high experimental control (e.g., in laboratory settings) often sacrifices ecological validity, while real-world flight studies present significant practical and safety challenges. Simulation environments bridge this gap but still have limitations [25, 32].

- Automation Paradox: Increasing automation, while intended to reduce workload, can sometimes lead to new forms of cognitive load (e.g., monitoring boredom, re-engagement workload) or skill degradation, creating a paradox that models must capture [31].

- Validation: Rigorously validating models against real-world pilot behavior and outcomes is challenging due to the inherent variability and ethical constraints of aviation operations.

Future Directions

Addressing these challenges and advancing the field of pilot mental workload modeling will require ongoing research in several key areas:

- Advanced Multi-modal Fusion: Developing sophisticated algorithms and machine learning techniques to integrate data from diverse subjective, physiological, and performance sources for a more comprehensive and robust real-time workload assessment [2, 3]. This includes leveraging computational intelligence for predictive reliability and identifying factors affecting reliability [49, 36, 42, 54].

• Adaptive and Personalized Models: Creating models that can adapt to individual pilot characteristics and learning curves, offering personalized workload management strategies.

• Neurophysiological Advancements: Further exploration of brain imaging techniques (e.g., fNIRS, fMRI) and advanced EEG analysis for more precise and non-invasive measures of cognitive states [33].

• Real-time Predictive Modeling: Developing computational models that can anticipate workload peaks or troughs based on flight trajectory, aircraft state, environmental factors, and pilot intent, enabling proactive interventions. This includes using information theory to model pilot mental workload [38].

• Integration with Cockpit Design: Direct application of workload models in the design and evaluation of future cockpit displays and control interfaces to ensure optimal information presentation and interaction [34].

• Ethical Considerations and Pilot Acceptance: Research into the ethical implications of continuous pilot monitoring and ensuring that workload assessment tools are accepted and trusted by pilots.

• Big Data and AI in Aviation: Leveraging vast amounts of operational data from flight recorders and simulators with AI to discover subtle patterns and predict workload in unprecedented ways.

CONCLUSION

Pilot mental workload remains a pivotal determinant of safety and efficiency within the complex environment of aviation-technological complexes. The ability to accurately model and assess this workload is fundamental to optimizing human-machine interaction, designing intuitive cockpits, and managing automation effectively. This article has presented a comprehensive overview of the prevailing methods—subjective, physiological, performance-based, and computational—each offering unique insights into the dynamic cognitive demands placed on pilots.

While individual methods provide valuable data, the inherent complexity and dynamism of pilot workload necessitate a multi-modal and integrated approach. Combining the directness of subjective reports with the objectivity of physiological measures, the contextual insights of performance data, and the predictive power of computational models holds the greatest promise for robust workload assessment. Challenges in real-time application, data integration, and accounting for individual differences persist, but ongoing advancements in computational intelligence and neurophysiology offer exciting avenues for future research.

Ultimately, effective modeling of pilot mental workload is not merely an academic exercise; it is a critical endeavor that directly contributes to enhancing flight safety, improving training methodologies, and ensuring the seamless and reliable operation of advanced aviation systems, thereby fostering a more dependable human-machine partnership in the skies.

REFERENCES

Alaimo, A., Esposito, A., Orlando, K., Simoncini, A. (2020) Aircraft pilot workload analysis: objective measurements of heart rate variability and subjective assessment of the NASA Workload Index. Aerospace, 7, 137.

Bi, S., Salvendy G. (1994). Analytical modeling and experimental study of human workload in planning industrial systems. International Journal of Human Factors in Production, 4(2): 205–234.

Braginsky, M.Ya., Burykin Yu.G., Tarakanov D.V. (2016). Modeling of human-machine systems taking into account the influence of light stimuli on the human operator. Bulletin of Cybernetics. 1, 63-73. (in Russian).

Collection of materials ICAO Human Factor (2003). 1(2), 35-52.

Ellison, B.Z., Polich D. (2008). Assessing workload in computer games using a single-stimulus-event-related potential paradigm. Biol. Psychol. 77, 277–283.

Fallahi, M., Motamedzadeh, M., Heidarimogadam, R., Soltanyan, A.R., Miyake, S. (2016). Effects of mental workload on physiological and subjective responses during traffic density monitoring: A field study Appl. Ergon., 52, 95–103.

Gabriel, G., Ramallo, M.A., Cervantes E. (2016). Perceived workload in drone flight training simulators. Comput. Hum. Behav., 64: 449–454.

Gentili, R.J., Rietschel, J.C., Jaquess, K.J., Li-Chuan, L., Prevost, C.M., Miller, M.W., Mohler, J. M., Hyuk, O., Ying, Y.T., Hatfield, B.D. (2014). Brain biomarkers based assessment of cognitive workload in pilots under various task demands. In 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 5860–5863.

Gerasimov, B.M., Tarasov, V.A., Tokarev, I.V. (1993).

Human-machine decision-making systems with elements of artificial intelligence. (in Russian). https://newlibrary.snau.edu.ua/cgi-bin/koha/opac-detail.pl?biblionumber=82701&shelfbrowse_itemnumber=51237

Grassmann, M., Vlemincx, E., von Leupoldt. A. (2017). Individual differences in cardiorespiratory measures of mental workload: a study of negative affectivity and cognitive avoidant coping in pilot candidates. Applied Ergonomics, 59: 274–282.

Guide, P.O. Flight Safety Management. Daughter. 9858 AN/474 ICAO/ 2013