Advancing Aviation Safety Through Machine Learning and Psychophysiological Data: A Systematic Review

Dr.Shashikala S V , Head of department , Dept of computer science and engineering, BGS Institute of Technology, Adhichunchanagiri university, BG Nagara, Karnataka
Mr .Amith D ,4th year ,8th sem , Dept of computer science and engineering , BGS Institute of Technology , Adhichunchanagiri university , BG Nagara , Karnataka

ABSTRACT

In the aviation industry, safety remains vital, often compromised by pilot errors attributed to factors such as workload, fatigue, stress, and emotional disturbances. To address these challenges, recent research has increasingly leveraged psychophysiological data and machine learning techniques, offering the potential to enhance safety by understanding pilot behavior. This systematic literature review rigorously follows a widely accepted methodology, scrutinizing 80 peer-reviewed studies out of 3352 studies from five key electronic databases. The paper focuses on behavioral aspects, data types, preprocessing techniques, machine learning models, and performance metrics used in existing studies. It reveals that the majority of research disproportionately concentrates on workload and fatigue, leaving behavioral aspects like emotional responses and attention dynamics less explored. Machine learning models such as tree-based and support vector machines are most commonly employed, but the utilization of advanced techniques like deep learning remains limited. Traditional preprocessing techniques dominate the landscape, urging the need for advanced methods. Data imbalance and its impact on model performance is identified as a critical, underresearched area. The review uncovers significant methodological gaps, including the unexplored influence of preprocessing on model efficacy, lack of diversification in data collection environments, and limited focus on model explainability. The paper concludes by advocating for targeted future research to address these gaps, thereby promoting both methodological innovation and a more comprehensive understanding of pilot behavior.

INTRODUCTION

As the global aviation industry undergoes transformative technological advancements, the role of pilots is concurrently evolving from simply operating machinery to making critical decisions in high-stakes, dynamic environments. In light of the complex nature of contemporary aviation operations, a comprehensive understanding of pilot behavior becomes paramount for enhancing aviation safety.

The industry facilitates the movement of millions of passengers and vast amounts of cargo annually, thereby serving as a linchpin in the global economy. Given this scale of operation, the imperative for ensuring aviation safety cannot be overstated; the consequences of failure are cataclysmic, both in terms of human life and economic impact
However, the achievement of optimal safety levels is a complex endeavor, influenced by a myriad of factors ranging from technological innovation to regulatory oversight. Advances in technology have undeniably contributed to enhanced safety mechanisms, from state-of-the-art air traffic control systems to predictive maintenance algorithms that preempt mechanical failures. Nonetheless, the industry is not immune to challenges Factors such as increasing air traffic, geopolitical tensions, and even natural disasters pose new kinds of risks that require continuous scrutiny and innovation in safety protocols .

Moreover, the stakes are not merely quantitative but also qualitative. A single aviation accident can have a ripple effect, undermining public confidence in air travel and triggering economic repercussions that extend far beyond the aviation sector. Regulatory bodies, therefore, are in a perpetual state of vigilance, working in tandem with airlines, aircraft manufacturers, and other stakeholders to formulate and implement safety guidelines that are both rigorous and adaptive to changing circumstances .

In summary, aviation safety is a multifaceted and everevolving concern that requires a holistic approach, embracing technological, human, and systemic factors. The high stakes involved, both in terms of human lives and economic implications, make it a subject of paramount importance that warrants ongoing research and continual improvement.

In the intricate system of aviation safety, the role of pilot behavior emerges as a focal point, governed by an intricate interplay of cognitive processes, emotional states, and physiological responses. Pilots, situated at the nexus of multifarious human-machine interactions, bear the colossal responsibility of safeguarding not just the aircraft and its passengers, but also the integrity of the entire aviation system. Their actions, or lack thereof, can have immediate and farreaching consequences that extend from the cockpit to the broader aviation ecosystem .

With the advent of increasingly automated flight systems, the role of pilots has evolved significantly. While automation has undeniably enhanced safety and efficiency, it has also engendered new forms of cognitive workload and psychological stress. Pilots are no longer solely vehicle operators but have become complex decision-makers tasked with managing an array of automated systems. They must maintain situational awareness and be prepared to intervene effectively in unexpected circumstances This shift has introduced challenges related to attention allocation, decision-making under pressure, and even ethical considerations, such as how to respond in unavoidable emergency situations.

Psychophysiological markers, such as EEG data, have emerged as invaluable tools for gaining insights into pilots' internal states, particularly during high-stakes scenarios like take-offs, landings, and emergency situations. These data types allow researchers to delve into the nuances of cognitive load, attentional focus, and emotional regulation, which are crucial for understanding how pilots make decisions under stress.

Moreover, the role of pilot behavior has systemic implications that ripple through the aviation safety ecosystem, influencing everything from regulatory frameworks to the design of new technologies For example, a nuanced understanding of how pilots handle attentional tunneling could inform the design of more intuitive cockpit interfaces. Similarly, insights into emotional and physiological responses to unexpected events could be invaluable for the development of realistic training simulations.

In summary, the multifaceted and systemic impact of pilot behavior necessitates its thorough investigation. Given its complexity and far-reaching implications, it warrants not just academic exploration, but also practical, real-world applications, ideally supported by advanced methodologies like ML and psychophysiological data analysis.

1.1 OBJECTIVES

1. **Identification of Relevant Studies**: The primary objective is to systematically identify and retrieve all relevant studies that investigate the application of machine learning techniques and psychophysiological data in advancing aviation safety. This includes studies published in peer-reviewed journals, conference proceedings, and relevant grey literature.

2.**Synthesis of Existing Literature**: To synthesize the existing literature on the utilization of machine learning algorithms in conjunction with psychophysiological data for predicting and mitigating safety risks in aviation operations. This involves summarizing key findings, methodologies, and outcomes across identified studies.

3.**Evaluation of Methodological Approaches**: To assess the methodological approaches employed in the identified studies, including the types of machine learning algorithms utilized, data collection techniques for psychophysiological data, and validation strategies adopted. This objective aims to provide insights into the strengths and limitations of existing methodologies in the field.

4.**Identification of Gaps and Future Directions**: To identify gaps and limitations in current research efforts and propose potential avenues for future research. This involves highlighting areas where further investigation is needed to enhance the effectiveness and applicability of machine learning techniques and psychophysiological data in aviation safety.

5.**Implications for Practice and Policy**: To discuss the practical implications of findings from the systematic review for aviation safety practitioners, policymakers, and other relevant stakeholders. This objective aims to provide actionable insights that can inform decision-making processes and contribute to the enhancement of safety protocols within the aviation industry.

SYSTEM ANALYSIS

2.1 EXISTING SYSTEM

As The current aviation safety framework employs a multifaceted approach, integrating traditional safety protocols with advancements in technology and data analysis. This system incorporates rigorous regulatory standards, comprehensive training programs, and real-time monitoring systems. Additionally, it leverages sophisticated aircraft design features and maintenance procedures to minimize risks. However, despite these efforts, challenges persist, including the need for more proactive risk prediction and mitigation strategies. Furthermore, the integration of machine learning algorithms and psychophysiological data holds promise for enhancing safety measures by enabling predictive analytics and personalized training interventions. Thus, there's a growing imperative to augment the existing system with these innovative approaches to further safeguard aviation operations.

2.1.1 Drawbacks of Existing System

The current aviation safety system faces several drawbacks. One significant challenge is its reactive nature, primarily relying on post-incident analysis to identify safety issues and implement corrective measures. This approach may lead to delays in addressing emerging risks and preventable incidents. Additionally, the complexity of aviation operations and the sheer volume of data generated pose challenges for manual analysis, potentially hindering timely identification of safety threats. Furthermore, human error remains a persistent concern despite extensive training and protocols. These limitations underscore the need for a more proactive and data-driven approach to safety management, highlighting the potential benefits of integrating advanced technologies like machine learning and psychophysiological data analysis into the existing system.

2.2 PROPOSED SYSTEM

The proposed system for advancing aviation safety entails a transformative integration of machine learning algorithms and psychophysiological data analysis into the existing framework. This innovative approach aims to revolutionize safety management by shifting from a reactive to a proactive paradigm, enabling real-time risk prediction and mitigation. At its core, the system harnesses the power of machine learning to analyze vast amounts of data, including flight data, maintenance records, and pilot physiological responses, to identify patterns and anomalies indicative of potential safety threats. By leveraging psychophysiological data, such as heart rate variability and cognitive workload, the system can assess pilot performance and mental state in real-time, facilitating early intervention in case of fatigue or stress-induced impairment.

Machine learning algorithms are deployed to analyze these diverse data sources, enabling the detection of patterns, anomalies, and early warning signs indicative of safety risks. By harnessing the power of predictive analytics, the system can forecast potential safety threats and recommend preemptive interventions to mitigate them effectively.

Moreover, the integration of psychophysiological data adds a human-centric dimension to safety management, allowing for personalized training programs tailored to individual pilot needs and stress levels

2.2.1 ADVANTAGES

➢ **Proactive Risk Mitigation**: By leveraging machine learning and psychophysiological data analysis, the system can identify potential safety risks in real-time, allowing for proactive intervention before incidents occur. This proactive approach minimizes the likelihood of accidents and enhances overall safety levels.

➢ **Personalized Training:** The integration of psychophysiological data allows for the customization of training programs based on individual pilot needs and stress levels. By tailoring training interventions to specific requirements, the system enhances pilot performance and resilience, ultimately contributing to safer flight operations.

➢ **Enhanced Situational Awareness:** Real-time monitoring of multiple data streams provides stakeholders with a comprehensive understanding of the aviation environment. This heightened situational awareness enables timely response to emerging safety concerns and facilitates more effective coordination among flight crew and ground personnel.

➢ **Optimized Resource Allocation:** By prioritizing safety-critical areas based on predictive analytics, the system enables optimized resource allocation and allocation, ensuring that interventions are targeted where they are most needed. This efficiency improves the effectiveness of safety measures while minimizing operational disruptions.

2.2.1 DISADVANTAGES

1. **Data Quality and Quantity**: One of the main challenges is obtaining high-quality and sufficient quantities of data for training machine learning algorithms. Aviation datasets may be limited in size, and ensuring the accuracy and reliability of the data can be challenging.

2. **Data Privacy and Security**: Aviation data, especially psychophysiological data from pilots, raises concerns about privacy and security. Ensuring that sensitive information is protected from unauthorized access or misuse is crucial but can be difficult to achieve, particularly when integrating data from multiple sources.

3. **Interpretability and Explainability**: Machine learning models, especially complex ones like deep learning algorithms, can lack interpretability, making it challenging to understand how they arrive at their decisions. This lack of transparency is a significant hurdle, especially in safety-critical domains like aviation, where understanding the reasoning behind decisions is essential.

4. **Generalization and Robustness**: Machine learning models trained on one set of data may not generalize well to new, unseen scenarios or environments. Ensuring that models are robust and reliable across various conditions, such as different weather patterns or aircraft types, is crucial for their effectiveness in real-world aviation applications.

5. **Regulatory Compliance**: Aviation safety is highly regulated, and any technology implemented in this domain must adhere to strict regulatory standards and guidelines. Ensuring compliance with regulations while also leveraging cutting-edge machine learning techniques can be a challenging balance to strike.

6. **Human-Machine Interaction**: Integrating machine learning systems into aviation operations requires careful consideration of human factors and human-machine interaction. Pilots and other aviation personnel must be able to trust and effectively interact with these systems, which may require additional training and support.

7. **Bias and Fairness**: Machine learning algorithms can perpetuate or even amplify biases present in the data used for training. In aviation, biases related to factors such as pilot demographics or geographic regions could impact the fairness and equity of safety systems, potentially leading to unintended consequences or disparities in safety outcomes.

IMPLEMENTATION

3.1 METHODOLOGY

The methodology of this systematic review serves as the architectural framework, designed to furnish robust, transparent, and reproducible outcomes. Adhering scrupulously to the guidelines this section delineates the meticulous steps taken to answer the posited research questions. It provides an exhaustive description of the protocols followed in the search, selection, and analysis of literature, in addition to quality assessment. Fig. 1 presents a graphical description of the procedure.

A. RESEARCH QUESTIONS

The present systematic review is directed by a set of carefully formulated research questions. These questions are designed not merely to clarify what is already known but to illuminate areas requiring further exploration. The principal research questions are:

- RQ1: What are the primary focus areas in the application of ML to psychophysiological data for understanding pilots' behavior?

◦ What behavioral and cognitive states are most studied?

- RQ2: How are preprocessing, data types, and feature extraction approached in existing studies on psychophysiological data for pilot behavior?

◦ Which psychophysiological data types are most used?
◦ What artifacts are commonly found in the psychophysiological data?
◦ What preprocessing techniques are prevalent?
◦ What features are commonly extracted?

- RQ 3 What are the types of models utilized to understand the pilot behavior?

◦ Which evaluation mechanism and metrics were utilized to assess the models?

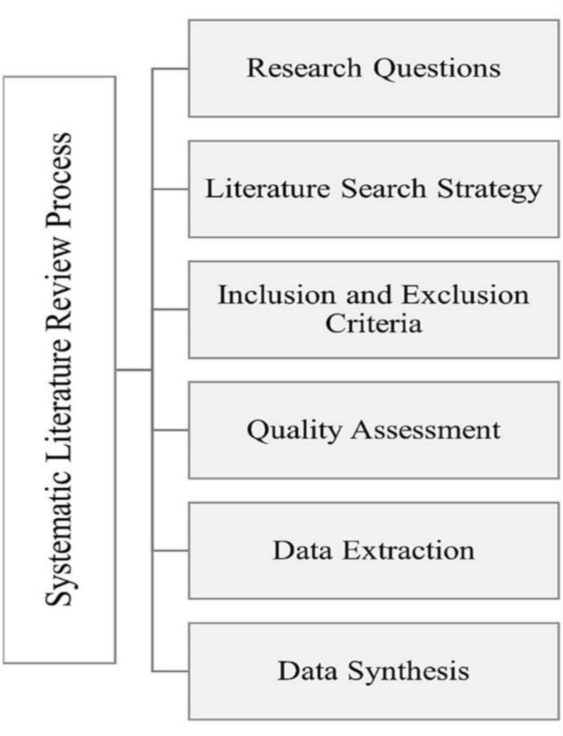

FIGURE 1. The adopted steps of the systematic review.

- RQ4: What is the comparative performance of various ML and DL models in predicting pilot behavior?

◦ What implications do these performance metrics hold?

- RQ5: What are the methodological limitations in existing studies?

◦ What future research directions are suggested by the methodological limitations?

B. LITERATURE SEARCH STRATEGY

The integrity of a systematic review is profoundly dependent on the comprehensiveness and rigor of its literature search strategy. To ensure a robust selection of studies pertinent to the research questions, this review adopted a multi-faceted search strategy, encompassing several academic databases and employing a sophisticated set of search queries.

1) SEARCH QUERIES

Keywords and Boolean operators were strategically aligned to construct queries that are both expansive and incisive. Search terms were primarily derived from the research questions. Subsequently, terms related to ML were incorporated based on authoritative sources such as [29]. Phrases such as "machine learning," "psychophysiological data," "EEG," and "pilot behavior" were intricately woven together through Boolean operators like "AND" and "OR," fashioning a search net designed for both breadth and precision.

2) ACADEMIC DATABASES

The review encompassed an exhaustive search across a selection of databases renowned for their scholarly contributions, namely IEEE Xplore, Scopus, PubMed, ScienceDirect, and Google Scholar. These databases were strategically chosen for their credibility and extensive coverage of academic articles in the fields of engineering, science, and technology. In Scopus and ScienceDirect, a comprehensive scan was conductedontitles,abstracts,andkeywordsforeachretrieved study. For IEEE Xplore, the focus was primarily on metadata. It is worth noting that PubMed was queried by scanning both titles and abstracts, while in Google Scholar, only titles were examined. Such differentiation in search strategies was necessitated by the unique syntax and capabilities of each database. Accordingly, modifications were made to the initial search string to suit the particular idiosyncrasies of each database.

3) TIME FRAME

The time frame selected for the search reflects a balance between historical depth and contemporary relevance. A window of the last fifteen years was delineated, allowing for an appraisal of seminal works while also encompassing the most recent advancements. This temporal scope ensures that the review remains at the cusp of contemporary scientific thought.

C. INCLUSION AND EXCLUSION CRITERIA

Theefficacyofasystematicreviewissubstantiallyinfluenced by the criteria governing the inclusion and exclusion of studies. These criteria act as sieves that sift through the amassed literature, retaining articles of relevance and discarding those that do not align with the objectives of the review. Inclusion Criteria:

1. Peer-Reviewed Journals and Conferences: Only articles published in peer-reviewed journals or conference proceedings were considered to ensure the research’s quality and credibility.
2. Pilot Behavior: Research specifically targeting pilot behavior, either in real-world or simulated environments, was included.
3. Machine Learning Models: Studies employing ML or deep learning (DL) algorithms for data analysis were considered.
4. Full-Text Availability: Studies were required to be fully accessible, either through open access or institutional subscriptions, for comprehensive analysis.

Exclusion Criteria:

1. Non-Peer-Reviewed Sources: Articles from non-peerreviewed sources, such as blogs, opinion pieces, or commercial publications, were excluded.
2. Non-Aviation Contexts: Research targeting sectors other than aviation, or general human behavior, was excluded.
3. Non-English Publications: Research published in languages other than English was not considered.
4. Unspecified or Ambiguous Methods: Studies lacking transparent methodology were excluded to ensure the integrity and reproducibility of the review.

3.2 SYSTEM ARCHITECTURE

This section serves as the empirical focal point of this systematic review, presenting a rigorous analysis of the data extracted from the 80 included studies. Adhering to the data extraction protocol delineated in the methodology section, this segment synthesizes the findings across multiple dimensions, including the types of ML models employed, their performance metrics, and the psychophysiological data types used for predicting pilot behavior. Furthermore, this section provides a granular breakdown of methodological choices in existing literature, including data preprocessing techniques, artifacts identified, and features extracted. The results presented herein aim to offer a comprehensive understanding of the current state of the art, serving as a foundational base for the subsequent discussion section where these findings will be interpreted, contextualized, and evaluated.

A. QUALIFIED STUDIES OVERVIEW: A SYSTEMATIC ENUMERATION OF EMPIRICAL INVESTIGATIONS

In order to provide a comprehensive overview of the empirical investigations qualified for inclusion in this review, multiple criteria have been considered for categorizing the studies. An initial enumeration of the studies is presented in Table 1, which lists each study by a unique Study ID, along with its citation and title. This table serves as a systematic reference, facilitating cross-referencing throughout this review.

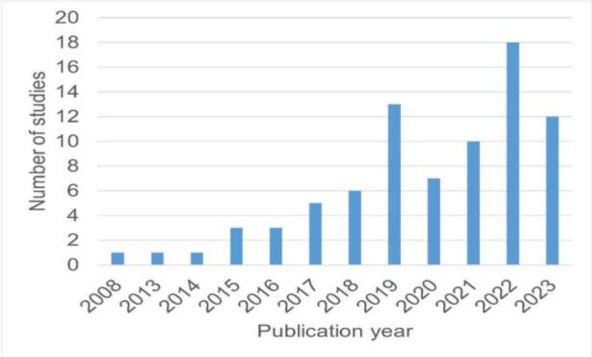

FIGURE 3. Study publication distribution using a yearly calendar.

In addition to tabulated data, Fig. 3 offers a temporal mapping of the studies, illustrating the number of publications per year. Upon examination of Fig. 3, it is evident that there has been a notable surge in the number of studies published from 2015 onwards, signaling an increased research focus on the subject matter. This could be attributed to various factors such as technological advancements, policy changes, or shifts in research priorities.

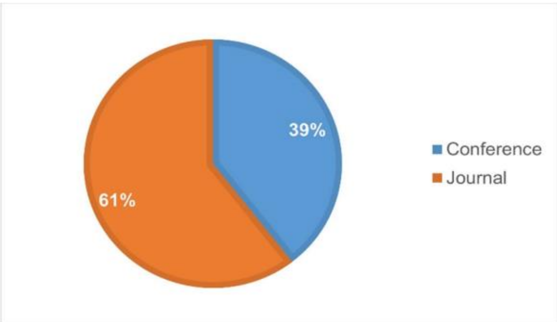

FIGURE 4. Publication type.

3.3 FLOWCHAT

To synthesize a collection of studies pertinent to the research aims, a rigorously formulated search query was executed across selected academic databases. This initial search yielded a total of 3352 potential studies for inclusion. Following this, a dedicated de-duplication process was undertaken, resulting in the removal of 2107 duplicate entries. This left 1245 studies for further examination.

Subsequently, a comprehensive screening process was carried out, wherein titles, abstracts, and keywords of these 1245 studies were meticulously evaluated against the inclusion and exclusion criteria. This narrowed down the list to 104 studies deemed potentially relevant. A subsequent full-text screening was conducted, further subjected to quality assessment protocols, leading to the exclusion of an additional 37 studies. At this juncture, the compilation stood at 67 studies.

Furthermore, to ensure a thorough and exhaustive review, the references cited in these 67 studies were also examined. This supplemental search led to the inclusion of an additional 13 studies that met the review's criteria.

Thus, the final pool of studies included in this systematic review totals 80. A visual representation of this sequential selection process is illustrated in Fig. 2.

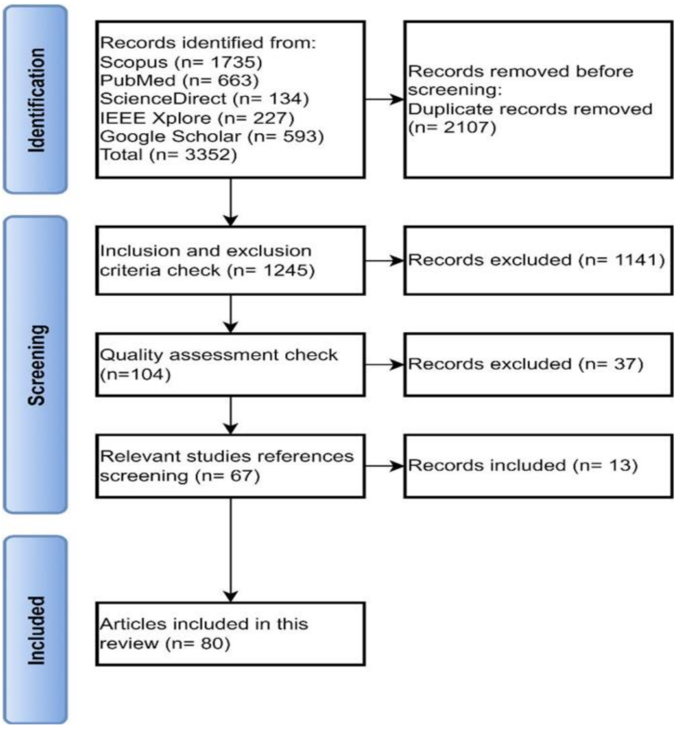

FIGURE 2. PRISMA flow diagram.

The data extraction process was designed to capture a rich set of information from each study, thereby enabling a nuanced analysis aligned with the research questions. For each study included in this systematic review, the following data were extracted:

1. **Article Title:** The title of the article was noted to provide a preliminary understanding of the study's focus and scope.
2. **Year of Publication:** The publication year was recorded to assess the temporal distribution of research efforts and to identify trends or shifts in research focus over time.
3. **Publication Venue:** The venue where the article was published.
4. **Behavioral Aspects:** Specific behavioral states or traits such as workload, fatigue, attention, and emotional states like stress or anxiety were identified and recorded.
5. **Model Type:** Information regarding the types of models employed, such as ML, DL, or Statistical Models, was extracted. This facilitated a comparative analysis of the methodologies adopted in the existing literature.
6. **Model Categories:** Within the ML models, specific categories such as tree-based models, SVM, and probabilistic models were noted to enrich the discussion on methodological diversity.
7. **Performance Metrics:** Metrics such as accuracy, recall, precision, and F1-score were extracted where available. This data aimed to provide a detailed account of the performance evaluations conducted in each study.
8. **Psychophysiological Data Types:** Types of psychophysiological data such as EEG, electrocardiogram (ECG), and galvanic skin response (GSR) were recorded to understand the range of data employed in assessing pilot behavior.
9. **Preprocessing Techniques:** Methods used for preprocessing, such as independent component analysis (ICA) or bandpass filtering, were also captured. This allowed for a comprehensive review of the techniques used to refine psychophysiological data before model training.

10. **Features Extracted:** The types of features extracted from the psychophysiological data, like power spectral density (PSD), wavelet coefficients (WC), or statistical measures, were noted. This contributed to the discussion on feature engineering practices in the existing literature.

Limitations and Future Work: An assessment of each study's limitations and suggestions for future research contribute to an understanding of gaps in the

APPLICATION

1. ****Predictive Maintenance**:** Machine learning algorithms can analyze data from aircraft sensors to predict when maintenance is required, helping to prevent unexpected failures and reduce downtime.

2. ****Flight Risk Assessment****: By analyzing historical flight data, weather conditions, and other relevant factors, machine learning models can assess the risk associated with specific flight routes or conditions, allowing airlines to make informed decisions about scheduling and operations.

3. ****Crew Resource Management**:** Psychophysiological data, such as heart rate variability or eye-tracking metrics, can provide insights into pilot workload, stress levels, and attentional focus. Machine learning algorithms can analyze this data in real-time to detect signs of fatigue or distraction, enabling interventions to maintain crew alertness and performance.

4. ****Anomaly Detection**:** Machine learning techniques can identify unusual patterns or deviations from normal behavior in aircraft systems or pilot performance, signaling potential safety hazards or security threats.

5. ****Air Traffic Management**:** By analyzing data from air traffic control systems, weather forecasts, and historical flight patterns, machine learning algorithms can optimize air traffic routes and scheduling to minimize congestion and improve efficiency while maintaining safety standards.

6. ****Training and Simulation**:** Machine learning can enhance flight simulators by creating more realistic scenarios and adaptive training programs that adjust to the individual learning needs of pilots.

7. ****Incident Investigation**:** Machine learning algorithms can assist in analyzing vast amounts of data from flight data recorders, cockpit voice recordings, and other sources to reconstruct the sequence of events leading up to aviation incidents or accidents, aiding in the investigation and prevention of future occurrences.

8. ****Cognitive State Monitoring**:** Psychophysiological data analysis can help monitor the cognitive state of pilots, air traffic controllers, and other aviation personnel, providing insights into factors such as attention, decision-making, and situational awareness.

9. **Safety Management Systems**: Machine learning can support safety management systems by analyzing incident reports, maintenance records, and other safety-related data to identify trends, patterns, and potential areas for improvement.

10. **Automated Decision Support**: Machine learning algorithms can provide real-time decision support to pilots and air traffic controllers by analyzing data from various sources and offering recommendations or warnings to mitigate safety risks.

CONCLUSION

This systematic literature review endeavors to offer a nuanced and comprehensive understanding of the current state of research that applies ML models for the interpretation of psychophysiological data, specifically focusing on the behavior of pilots. A multifaceted array of findings have emerged from this review, which span the gamut from the types of psychophysiological data employed to the specific ML methodologies and their corresponding performance metrics. Firstly, this review uncovers a pronounced heterogeneity in the types of psychophysiological data employed across studies, with EEG data standing out as the most commonly used. This prominence of EEG data could be indicative of the broader acceptance of its reliability and efficacy in capturing cognitive states, yet it also raises questions about the underutilization of other types of data like ECG, GSR, and eye-tracking metrics.
Significantly, the review has identified a substantial gap in the behavioral aspects studied, most notably the underrepresentation of emotional responses and attention dynamics in the existing literature. These areas, although critical to understanding human performance-limiting states, have been less explored compared to workload and fatigue. Emotional states and attention levels are not only crucial for aviation safety but also enrich the understanding of pilot behavior in a more holistic manner. The current methodological approaches oftencategorize theseaspects intobroader categories,thereby potentially missing nuanced interrelations between different behavioral and cognitive states. Therefore, a more balanced academic inquiry into these areas is warranted for a more comprehensive understanding of pilot behavior.

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