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Application of Artificial Intelligence, Machine Learning and Deep Learning in Piloted Aircraft Operations: Systematic Review

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ABSTRACT

Aviation research on artificial intelligence (AI), machine learning (ML), and deep learning (DL) has seen significant growth as these emerging technologies hold immense potential for supporting both human-centered and technology-centered aspects of civil aircraft operations. This systematic review, following the guidelines of Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020, was registered on the Open Science Framework (DOI 10.17605/OSF.IO/ZR7A3) and focused specifically on the use of AI, ML, and DL in human-centric flight operations. The review conducted a comprehensive search of databases including Scopus, Web of Science, IEEE Xplore, as well as online repositories (ResearchGate and Aerospace Research Central) to identify relevant articles published between 2013 and 2023. In total, 32 studies were included, which explored various applications of AI, ML, and DL in aircraft pilots and flight operations. The studies were categorized into four main areas: (i) assessment and management of human factors risks, including AI-assisted data analysis of pilot performance, crew resource management, and ML-based support for pilots' cognitive workload monitoring, (ii) detection of human errors, with support systems based on ML-based approaches for real-time monitoring and DL models for biometric monitoring of cockpit pilots were identified for the detection of human errors in flight safety, (iii) reduction and prediction of human errors, categorized into AI-assisted predictive analytics in flight accidents, and ML-based pattern recognition to predict unstable approaches, and (iv) prevention of human errors in aviation through ML utilization for pilot training enhancement, and AI-supporting flight automation and decision support systems for flight operation. Analysis of the included studies revealed a rising trend in the publication of articles after 2020, albeit at a slow rate. It is worth noting that the majority of studies focused on conceptual applications, with fewer studies involving empirical testing. The findings of this review highlight the potential for future research in developing and testing improved human factors risk assessment (HRA) models assisted by computational intelligence in piloted aircraft operations, with the ultimate aim of enhancing flight safety.

Keywords: Artificial intelligence, Machine learning, Deep learning, Flight operation, Aircraft pilot, Human errors, Human factors

INTRODUCTION

Pilot errors continue to pose a significant challenge within the general aviation sector, contributing to a majority of accidents. Data from the International Civil Aviation Organization's (ICAO) integrated Safety Trend Analysis and Reporting System, covering the period from 2013 to 2022, reveals that out of 815 reviewed and validated general aviation accidents, 70.6% are attributed to human errors (ICAO Accident Statistics 2013-2022, ICAO Safety Report 2023). These errors predominantly stem from pilot-related mistakes during flight operations, encompassing factors such as misjudgements of abnormal flight operations, pilot fatigue, diminished situational awareness, and suboptimal decision-making.

Artificial Intelligence (AI) encompasses the creation of computer systems with the ability to carry out tasks that traditionally demand human intelligence. Machine Learning (ML) involves the crafting of algorithms or systems that learn from specific training data to automate analytical model construction and address related tasks. Deep Learning (DL), a subset of machine learning, relies on artificial neural networks characterised by multiple layers (Janiesch, Zschech, and Heinrich, 2021).

According to a number of reviews, the research related to AI, ML and DL has expanded significantly. The expansion is attributed to the significant potential these emerging technologies hold in enhancing various aspects of civil aircraft operations, encompassing both human-centric and technology-centric domains. However, little is known about how AI can be utilized to improve different aspects of pilot safety. AI applications can provide decision-making support, real-time monitoring, and analyzing large datasets to identify patterns and potential risks. ML algorithms can be trained on various datasets such as historical flight data and human performance metrics to detect patterns related to potential hazards, errors, or critical situations. DL can be applied to analyze complex data sources, such as physiological signals or cockpit images, to identify subtle patterns that may indicate potential safety issues.

Hence, this review aims to systematically examine the current status of research on the application of AI, ML and DL in piloted aircraft operations for flight safety. The results of this review provide insights for practitioners and researchers on AI's theoretical and practical uses of AI applications in aviation safety, highlighting areas for improvement like training, procedures, and equipment design. The study was categorized into four main areas: (i) assessment and management of human factors risks, (ii) detection of human errors, (iii) reduction and prediction of human errors, and (iv) prevention of human errors to enhance flight operation safety.

METHODS

This systematic review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines and was registered on the Open Science Framework (DOI 10.17605/OSF.IO/ZR7A3). A comprehensive database search of Scopus, Web of Science, IEEE Xplore, and two online repositories (ResearchGate and Aerospace Research Central) was conducted to find all articles relevant to the topic. See Table 1 for the search strategy. The search was performed on 20 September 2023 and included two sets of keywords. The first set of keywords were "artificial intelligence," "machine learning" and "deep learning". The second set of keywords included "aircraft cockpit," "flight operation," "aircraft operation," "aircraft pilot," "airline pilot" and "flight crew". This PRIMSA-based review comprised articles published between January 2013 and September 2023.

Table 1. Search strategy and search results.

Scientific database (2013–2023 September)	Search String	# of titles and abstracts
Scopus	Article title, Abstract, Keywords ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") AND Article title, Abstract, Keywords ("aircraft cockpit" OR "flight operation" OR "aircraft operation" OR "aircraft pilot" OR "airline pilot" OR "flight crew")	363
Web of Science	#1 TI= ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") OR AB= ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") #2 TI= ("aircraft cockpit" OR "flight operation" OR "aircraft operation" OR "aircraft pilot" OR "airline pilot" OR "flight crew") OR AB= ("aircraft cockpit" OR "flight operation" OR "aircraft operation" OR "aircraft pilot" OR "airline pilot" OR "flight crew") #1 AND #2	2465
IEEE Xplore	((Document Title: Artificial Intelligence OR Document Title: Machine Learning OR Document Title: Deep Learning) OR (Abstract: Artificial Intelligence OR Abstract: Machine Learning OR Abstract: Deep Learning)) AND ((Document Title: aircraft cockpit OR Document Title: flight operation OR Document Title: aircraft operation OR Document Title: aircraft pilot OR Document Title: airline pilot OR Document Title: flight crew) OR (Abstract: aircraft cockpit OR Abstract: flight operation OR Abstract: aircraft operation OR Abstract: aircraft pilot OR Abstract: airline pilot OR Abstract: flight crew))	129
ResearchGate		23
Aerospace Research Central		15

Total abstracts and titles reviewed: 2986.
Total abstracts and titles reviewed minus duplicates: 2552.
First selection of studies (after title and abstract review): 669.
Second selection of manuscripts/studies (after full text review): 32.

This study screened titles and abstracts based on the following criteria: (a) usage of AI systems and/or ML algorithms and/or DL models in human-piloted aircraft; (b) AI, ML and DL assisting in human operations to identify, analyze, and prevent human errors related to flight operations and (c) being published in English language peer-reviewed articles or conference proceedings. The exclusion criteria were as follows: (a) introduction of any AI, ML and/or DL application in aviation, even including aircraft operations; (b) analysis using AI, ML and/or DL for Human-Machine Interface (HMI) to optimize pilot-aircraft interaction alone; (c) using AI, ML and/or DL to develop cockpit aids for fully autonomous flight; (d) case studies, textbooks, and dissertations and (e) full article not available in electronic document.

The search results were imported into EndNote 21, and duplicates were eliminated. The authors then checked each record based on the title and abstract, following the inclusion and exclusion criteria. Any records that did not meet the criteria were removed using the Covidence systematic review software. The remaining records were subjected to full-text screening, and any excluded records were provided with reasons. Two authors independently screened the records to identify relevant articles, and any disagreements were resolved through group discussion with a third reviewer.

Data were extracted according to a predetermined format that included authors, publication year, study purpose, methods, framework or model for computational intelligence, outcomes, techniques, domains, and results. Additionally, the selected articles were analyzed based on the themes of the studied fields and were classified into four main areas related to human factors for pilots: (i) human factors risk assessment and management, (ii) human error detection, (iii) human error reduction and prediction, and (iv) human error prevention.

RESULTS

Search Results

A total of 2948 records were retrieved from searching three databases: Scopus (n = 363), Web of Science (n = 2465), and IEEE Xplore (n = 129). After removing 396 duplicates, 2559 records were left for title and abstract screening. 1908 records were excluded after screening the titles and abstracts. Out of the remaining 644 records, 616 were removed because they focused on AI/ML/DL application in aviation only (n = 179), AI/ML/DL for Human-Machine Interface (HMI) (n = 164), used AI/ML/DL for fully autonomous flight and unmanned flight operation (n = 265), were case studies, textbooks, dissertations (n = 5), or had no full-text available (n = 3).

In addition, 38 records were found in two online repositories, ResearchGate (n = 23) and Aerospace Research Central (n = 15). Out of these records, 21 were excluded due to duplicates (n = 7), the introduction of AI/ML/DL application in aviation (n = 2), AI/ML/DL for Human-Machine Interface (HMI) (n = 6), using AI/ML/DL for fully autonomous flight and unmanned flight operation (n = 4), case studies, textbooks, and dissertations (n = 1), and full article not available (n = 1). Finally, 32 papers were deemed relevant to the systematic review (Figure 1). Figure 1 shows the PRISMA process of literature search and selection.

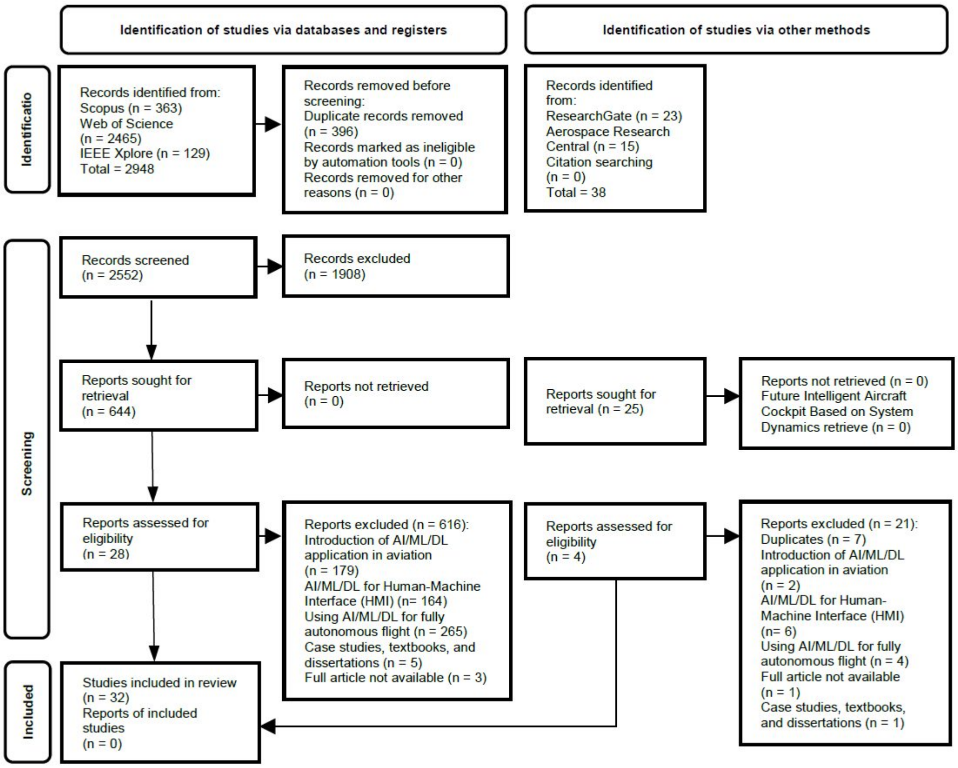

Figure 1: PRISMA process used to identify and select relevant studies.

ASSESSMENT AND MANAGEMENT OF HUMAN FACTORS RISKS

Seven articles focused on the assessment and management of human factors risks in aviation, covering diverse facets such as AI-assisted data analysis (n = 3), crew resource management (n = 1), and cognitive workload monitoring (n = 3). In the realm of AI-assisted data analysis, Jiang et al. (2021) employ a multi-dimensional data fusion approach and an LSTM model with an attention mechanism to achieve a remarkable 94% detection accuracy for pilots' mental workload. Paces and Insaurralde (2021) contribute by introducing an AI-based system for manual pilot performance assessment, emphasizing its potential in pilot training and underscoring the need for ongoing considerations in AI-assisted evaluation. Lounis, Peysakhovich, and Causse (2021) explore the influence of pilot expertise on visual scanning strategies through a flight simulator study, revealing insights into expert pilots' superior perceptual efficiency and distribution of attention, with implications for aviation training and safety. In the realm of crew resources management, Piera et al. (2022) introduce a socio-technical simulation model to enhance pilot performance in single-pilot cockpits, emphasizing the model's achievements in understanding Pilot-AI interaction, the impact of extra cognitive tasks, and effective simulation of abnormal flight scenarios.

For cognitive workload monitoring, Ji et al. (2022) investigate EEG patterns during critical flight phases, highlighting the significance of β-wave changes and the potential applications of their findings in pilot workload management and aviation safety. Mohanavelu et al. (2022) contribute with an ML-based approach to identify pilots' mental workload, emphasizing the effectiveness of HRV and EEG features and the importance of subject-independent classification in real-time systems. Finally, Taheri Gorji et al. (2023) focus on discriminating cognitive workload levels in pilots using EEG and ML, achieving high accuracy and suggesting future research directions for refining the discrimination of cognitive workload levels. In conclusion, this review provides valuable insights into recent advancements in assessing and managing human factors risks in aviation. The collective findings underscore the pivotal role of AI, ML, and advanced technologies in enhancing pilot performance, improving safety measures, and optimizing cockpit design. The holistic approach showcased in these studies, which integrates technical, social, and cognitive aspects, contributes significantly to the evolving landscape of human factors research in aviation.

DETECTION OF HUMAN ERRORS

Eight articles, including AI-supporting real-time monitoring (n = 3) and biometric monitoring (n = 5), were identified for the detection of human errors in flight safety. AI-powered systems for real-time monitoring track various parameters, enabling the detection of unusual patterns or deviations. Binias, Myszor, and Cyran (2018) contribute a study utilizing EEG signals to detect pilots' reactions to unexpected events, aiming to enhance cognitive cockpit performance. The study provides insights into cognitive responses to unforeseen situations, utilizing ML methods such as Common Spatial Pattern and various classification algorithms. Wu et al. (2019) introduce a novel approach integrating spherical Haar wavelet transform and DLfor tracking a pilot's attention, demonstrating its potential for improving pupil center detection. Wang et al. (2020) decode pilot behavior consciousness through a multimodal approach incorporating EEG, ECG, and eye movements, analyzing various physiological characteristics using SVM.

AI and DL analyze pilots' biometric data to detect signs of fatigue, stress, or other conditions contributing to human errors. Lee et al. (2020) propose an MFB-CNN for classifying four pilot mental states based on EEG signals. Deng et al. (2020) emphasize the importance of precisely detecting pilot fatigue using a DL network and EEG signals. The study introduces a novel model, DCSAEN-SoftMax, for fatigue identification, achieving high recognition rates. Han, Kwak, Oh, and Lee (2020) developed a robust system for detecting pilots' mental states using multimodal biosignals and a multimodal deep-learning network. The proposed method achieves the highest accuracy, emphasizing the significance of considering multiple modalities for understanding and predicting pilots' mental conditions. Li et al. (2023) focus on detecting pilot stress through physiological signals, employing a Transformer-based DL model. The proposed model demonstrates high accuracy in identifying stress based on various physiological signals. Lee et al.

(2023) introduce MentalNet, a hybrid deep neural network for continuous monitoring and analysis of pilots' mental states using EEG signals. The model exhibits superior accuracy compared to conventional models, successfully classifying seven mental states across all subjects.

REDUCTION AND PREDICTION OF HUMAN ERRORS

Seven articles were identified for the reduction and prediction of human errors in aviation, categorized into AI-assisted predictive analytics (n = 5) and pattern recognition (n = 2). In the realm of predictive analytics, studies demonstrate the potential of AI in analyzing large datasets to predict and mitigate human errors. Notably, Jain, Misra, and Truong (2022) leverage DL techniques to predict unstable approaches for general aviation aircraft, employing a recurrent neural network (RNN) model. Cantero et al. (2022) concentrate on predicting go-arounds in non-stabilized approach scenarios, using a ML regression model trained from pilots' expertise. Odisho, Truong, and Joslin (2022) contribute a comprehensive study on runway safety improvement, developing predictive models to identify and mitigate factors leading to runway excursions, including Unstable Approaches and Rejected Landings. Additionally, Dhief et al.'s (2022) investigation into a predictive model for go-around events using ML within pilot-in-the-loop simulations demonstrates the potential for real-time support. D. Gil et al. (2021) introduce the E-pilot system, a predictive model designed to forecast hard landings during the approach phase of commercial flights, employing advanced ML techniques. Madeira et al. (2021) explore the application of ML and natural language processing (NLP) techniques to predict human factors in aviation incident reports, enhancing safety by identifying and categorizing human factors contributing to incidents.

For pattern recognition, Rajendran et al. (2021) focus on predicting situational awareness in pilots using electrocardiogram (ECG) signals, developing a predictive model based on physiological data collected in a flight simulator. Baomar and Bentley (2016) introduce an Intelligent Autopilot System (IAS) that utilizes ML and artificial neural networks to learn piloting skills from human pilots through imitation, aiming to enhance autopilot capabilities and reduce crew dependence. These articles collectively showcase the diverse applications of AI in analyzing large datasets, identifying patterns, and predicting potential errors in aviation. From predicting unstable approaches to enhancing runway safety and predicting human factors, these studies contribute valuable insights and tools to improve aviation safety by proactively addressing and mitigating human errors.

PREVENTION OF HUMAN ERRORS

This review identified ten articles on the prevention of human errors in aviation. The articles can be categorized into two main themes: training enhancement (n = 3), automation and decision support systems (n = 6). In the realm of training enhancement, AI-based training programs are explored as a proactive measure to prevent errors. Bach et al. (2021) introduce a novel hierarchical structure of finite state machines (FSMs) for interactive pilot training, emphasizing the creation of dynamic and realistic scenarios. The study focuses on the preflight procedure for a Boeing 737 captain, employing dynamic hyperlinks to simulate realistic scenarios. The analysis of hypertext arrangements and user traversals helps determine threshold values for dynamic hyperlinks, contributing to adaptive learning experiences. Källström et al. (2022) explore the integration of ML agents into pilot training simulations. Intelligent agents capable of learning and adapting within scenarios enhance training effectiveness. Experiments compare teams with synthetic agents to those with mixed human and synthetic agents. Human pilots find value in situation awareness maps, but concerns are raised about synthetic agents' behavior in conflicts. The study concludes by emphasizing the importance of designing learning agents with architectures that generalize across various environments. Mao, Ren, and Zhao (2022) propose an off-axis flight vision display system using ML. The system, designed for take-off and landing, utilizes a deep neural network to predict free-form surface models, streamlining the design process. The ML approach demonstrates effectiveness in predicting surface coefficients, saving design time and improving efficiency in optical engineering.

Automation and decision support systems are explored as tools to reduce human errors. Lyu, Nandiganahalli, and Hwang (2018) address mode confusion detection in the flight deck using a Generalized Fuzzy Hidden Markov Model (GFHMM), providing successful detection and proposing enhancements. Álvarez, González, and Gracia (2020) delve into the integration of automation in flight procedures, introducing the Cockpit Automation Procedures System (CAPS) to address safety challenges. Würfel, Djartov, Papenfuß, and Wies (2023) present the Intelligent Pilot Advisory System (IPAS), an AI-based decision support system aiming to enhance decision-making on airline flight decks. Ramos et al. (2023) discuss the conceptual design of the Integrated Flight Advisory System (IFAS), emphasizing improved decision-making, situational awareness, reduced workload, and increased safety. Watkins, Gallardo, and Chau (2018) introduce a Pilot Support System employing ML for real-time decision support and pattern recognition to enhance pilot decision-making. Zhang, Sun, and Zhang (2021) employ a system dynamics approach to investigate the evolutionary game and collaboration mechanism in future intelligent aircraft cockpits. Pitchammal and Sadda (2013) discuss the application of AI techniques in the critical mission computer (MC) of fighter aircraft, outlining the development of an Intelligent Mission Computer (IMC) to reduce pilot workload and enhance decision-making. Together, these articles contribute significantly to advancing aviation safety through innovative training methodologies, AI integration in decision support, and automation technologies in the flight deck, emphasizing a holistic approach targeting human factors and real-time adaptability.

Table 2. Studies of AI, ML, and DL applications in piloted aircraft operations (n = 32).

Author (Publication year)	Application (AI/ML/DL)	Domain	Results
I. Assessment and management of human factors risks			
AI-assisted data analysis (n = 3)			
Jiang et al. (2021)	DL (LSTM)	Assessment of pilots' mental workload using Electroencephalogram (EEG) data	LSTM model integrated with an attention mechanism achieved a 94% detection accuracy for 2-second EEG data.
Paces & Insaurralde (2021)	AI	Assessment of manual pilot performance during flight training	The effectiveness of the AI algorithms in evaluating pilots' behaviour and progress during runway approaches was validated.
Lounis, Peysakhovich & Causse (2021)	ML (Cosine KNN)	Investigation of the influence of pilot expertise on visual scanning strategies in the cockpit.	Professional pilots, compared to novices, exhibit superior perceptual efficiency, better attention distribution, and more complex scanning patterns. Flight performance data support expertise in better flying performance. ML achieves 93% accuracy in classifying expertise.
Crew resource management (n = 1)			
Piera et al. (2022)	AI	Enhancement of pilot performance in the future single-pilot cockpit through the development of a socio-technical simulation model.	Socio-technical simulation model proves effective in reducing the negative effects of interruptions and improving overall performance in demanding flight scenarios, with implications for designing new Pilot-AI interactions.
Cognitive workload monitoring (n = 3)			
Ji et al. (2022)	ML	Investigation of Electroencephalogram (EEG) patterns of pilots during critical phases of take-off and landing.	A substantial increase in the proportion of β-wave during critical phases of take-off and landing.

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Table 2. Continued

(Publication year)	Application (AI/ML/DL)	Domain	Results
Mohanavelu et al. (2022)	ML	Assess and classify the mental workload of pilots during flight operations, with a specific focus on fighter pilots engaged in air-to-air combat.	There is effective differentiation between low and high mental workload conditions, with HRV features excelling in takeoff and landing, and EEG features performing better during cruise.
Taheri Gorji et al. (2023)	ML	Utilizing ML method and Electroencephalography (EEG) to discern and discriminate cognitive workload levels in aircraft pilots during flight.	Combining power spectral density (PSD) and log energy entropy, achieved an accuracy of 91.67%, precision of 93.89%, recall of 91.67%, and an F-score of 91.22%, which effectively discriminate between low, medium, and high cognitive workload states in pilots during flight.
II. Detection of human errors AI-supporting real-time monitoring (n = 3)			
Binias, Myszor, and Cyran (2018)	ML (LDA, k-NN, SVM, RFs, ANNs)	Employing the ML approach to detect a pilot's reaction to unexpected events using Electroencephalographic (EEG) signals	The study compared different classification algorithms and found that the Neural Network classifier achieved the best mean accuracy, outperforming Linear Discriminant Analysis (LDA) and other classifiers by almost 5% and 8%, respectively.
Wu et al. (2019)	DL (SVM, DAEN-SVM, DSAEN-SVM, DCAEN-FSVM, DCAEN-FGSVM, DHCAEN-FGSVM.)	Development of a novel approach for tracking a pilot's attention by the method integrates spherical Haar wavelet transform and DL techniques.	The proposed DHCAEN-FGSVM presents a detection accuracy of 94.8% with SOHO wavelet input features, demonstrating effectiveness through experiments on public and actual datasets.

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Table 2. Continued

(Publication year)	Application (AI/ML/DL)	Domain	Results
Wang et al. (2020)	ML (SVM)	Decoding of pilot behaviour consciousness by a multimodal approach that incorporated Electroencephalography (EEG), Electrocardiogram (ECG), and eye movements.	The identified physiological characteristics affected by different pilot behaviors include the power spectra of the θ waves of EEG, the standard deviation of normal-to-normal intervals in ECG, root mean square of standard deviation, and average gaze duration.
Biometric monitoring (n = 5)			
Lee et al. (2020)	DL (MFB-CNN)	Using a multiple-feature block-based convolutional neural network (MFB-CNN) with temporal-spatial EEG filters, and classify four pilot mental states including fatigue, workload, distraction, and normal.	The classification accuracy was 0.75 (±0.04). The pseudo-online analysis showed detection accuracies of 0.72 (±0.20), 0.72 (±0.27), and 0.61 (±0.18) for fatigue, workload, and distraction, respectively.
Deng et al. (2020)	DL (DCSAEN)	Detection of pilot fatigue for aviation safety using DL networks, DCSAEN-SoftMax model and EEG signals.	Experimental setups employing FIR filters extract δ, θ, α, and β waves, establishing their correlation with fatigue. DCSAEN-SoftMax utilizes a contractive loss function and sparse penalty term, significantly enhancing micro fatigue identification.
Han, Kwak, Oh, and Lee (2020)	DL (MDL-CNN, LSTM)	Development of a robust system for detecting pilots' mental states (distraction, workload, fatigue, normal) using multimodal biosignals, including EEG, ECG, respiration, and EDA, and a multimodal deep learning (MDL) network.	The proposed method achieved the highest accuracy (85.2%), surpassing baseline methods significantly. The model demonstrated consistent and robust performance for most subjects, ranging from 78.5% to 90.6%.
Li et al. (2023)	DL (TNN-CNN)	Detecting pilot stress using physiological signals through a multi-modal Transformer-based DL model that integrates position information from a transformer network and a convolutional neural network (CNN).	The study evaluates the model using physiological data from 14 pilots under various stress states, including electrocardiography (ECG), electromyography (EMG), electrodermal (EDA), respiration (RESP), and skin temperature (SKT). The model demonstrates high accuracy, achieving 93.28%, 88.75%, and 84.85% for 2-class, 3-class, and 4-class classification tasks, respectively.

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Table 2. Continued

(Publication year)	Application (AI/ML/DL)	Domain	Results
Lee et al. (2023)	DL (CNN-LSTM)	Monitoring and analyzing pilots' mental states through the creation and assessment of MentalNet, a hybrid deep neural network. Employing electroencephalography (EEG) signals, the model categorizes diverse abnormal mental states (AbSs), encompassing low fatigue, high fatigue, low workload, high workload, low distraction, and high distraction.	The model demonstrated a grand-average accuracy of 68.04% (± 5.26%), classifying seven mental states, including low fatigue, high fatigue, low workload, high workload, low distraction, and high distraction, across all subjects. This accuracy was noted to be at least 6.55% higher compared to other conventional models used in the study.
Author (Publication year)	**Application (AI/ML/DL)**	**Domain**	**Results**
III. Reduction and prediction of human errors			
AI-assisted predictive analytics (n = 6)			
Jain, Misra, and Truong (2022)	DL (RNN)	Recurrent neural networks (RNNs), utilizing DL techniques to predict unstable approaches. The RNN model acts as a risk mitigation tool, offering real-time assessments of flight parameters and implementing a predictive warning system for pilots.	The model achieved an accuracy of 84% in predicting unstabilized approaches for a light multi-engine general aviation aircraft. The study utilized a dataset of approximately 42,000 landings to train and validate the model. The vertical speed of the aircraft was identified as the most significant predictor of an unstabilized approach.
Cantero et al. (2022)	ML	Prediction of go-arounds in non-stabilized approach scenarios using a ML regression model trained from pilots' expertise, provides real-time support by announcing parameter deviations and suggesting corrective actions to enhance decision-making during non-stabilized approaches.	The performance of classification models achieved results with an average precision of 0.96, sensitivity of 0.84, and an F1-score of 0.88. The high values of precision, sensitivity, and F1-score suggest that the model performs well in predicting instances where a go-around might be necessary during non-stabilized approaches.

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Table 2. Continued

(Publication year)	Application (AI/ML/DL)	Domain	Results
Odisho, Truong, and Joslin (2022)	ML	Development of predictive models using various algorithms such as decision tree, neural network, logistic regression, support vector machine, random forest, and gradient boost machine, addresses pilot decision-making lapses and predicts Unstable Approach Risk Misperception (UARM) and Rejected Landings for runway safety.	The study indicates that the Decision Tree (DT) model exhibited a high predictive power of 96%, accurately forecasting Unstable Approach Risk Misperception (UARM) with 98% accuracy. The research contributes significant insights to enhance pilot training, risk perception, and anomaly detection in large flight data, ultimately bolstering overall aviation safety through data-driven approaches and predictive modelling.
Dhief et al. (2022)	ML	Development of a predictive model for go-around events in aviation through the application of ML techniques within pilot-in-the-loop simulations, showcasing promising results in terms of precision, sensitivity, and F1-score.	The probability of a go-around exceeding 93%, when the pilot decides to initiate it for almost 50% of the flights in the test set. The model proposed is capable of identifying successful landings, as it shows low probabilities of go-around once the aircraft has landed. The probability of a go-around when the plane touches down is below 35% and 10% for KPHL and KVNY airports respectively.
D. Gil et al. (2021)	ML (LSTM)	Development of the E-pilot system, a predictive model by advanced ML techniques designed to analyze diverse flight parameters for predicting and preventing hard landings, with a focus on enhancing aircraft safety.	After analyzing a large dataset containing 58177 commercial flights, the approach has shown an average sensitivity of 85% and an average specificity of 74% at the go-around point. The proposed cockpit-deployable recommendation system outperforms existing approaches.
Madeira et al. (2021)	ML (LS, SVM, NLP)	Development of predictive models to enhance aviation safety by identifying and categorizing human factors contributing to incidents through the analysis of textual information in incident reports.	The predictive models with Micro F1 scores of 0.900, 0.779, and 0.875 for different levels of the taxonomic framework. The effectiveness of the semi-supervised LS algorithm, especially in levels with fewer labels, suggests the potential reliability of the supervised SVM for larger and more balanced datasets. The TF-IDF model proves to be a computationally expensive but interesting alternative to Doc2Vec (D2V) in certain framework levels. Bayesian optimization is emphasized for finding near-optimal hyper-parameter combinations, with fANOVA marginal contribution analysis providing valuable insights.

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Table 2. Continued

(Publication year)	Application (AI/ML/DL)	Domain	Results
Pattern recognition (n = 2)			
Rajendran et al. (2021)	ML (DT, RF, NB, GBM, KNN)	the utilization of ML to predict situational awareness in pilots using electrocardiogram (ECG) signals. The research focuses on enhancing aviation safety by developing a predictive model based on physiological data collected in a flight simulator. ECG signals are utilized to infer the cognitive state of pilots and predict their levels of situational awareness.	The study reveals that the Decision Tree (DT) classifier, particularly emphasizing maximum and minimum ECG values, outperforms other classifiers. It achieves 98% accuracy and 97% Area Under the Curve (AUC) across ten repetitions. This indicates that the DT model, when applied to electrocardiogram (ECG) signals, is effective in predicting pilot awareness states, specifically distinguishing between distracted and non-distracted states with high accuracy.
Baomar and Bentley (2016)	ML (ANNs)	Development of an Intelligent Autopilot System (IAS) that utilizes ML and ANNs to learn piloting skills from human pilots through imitation. The study demonstrates the IAS's effectiveness in calm and stormy weather conditions. In calm weather, the IAS accurately imitates human pilot actions, while in stormy conditions, it generalizes and imitates rapid stabilization actions, outperforming the simulated Aircraft Flight Controller (AFC).	Experimental results indicate that the IAS performs take-off, climb, and slow ascent tasks with high accuracy, even when provided with limited examples. This is demonstrated by the Mean Absolute Error and Mean Absolute Deviation metrics. The IAS is capable of imitating low-level sub-cognitive abilities, such as rapid and continuous stabilization attempts during turbulent weather, as well as high-level strategic skills, including the sequence of sub-tasks necessary to pilot an aircraft from the stationary position on the runway to a steady cruise.

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Table 2. Continued

(Publication year)	Application (AI/ML/DL)	Domain	Results
IV. Prevention of human errors Training enhancement (n = 3)			
Bach et al. (2021)	AI (FSMs)	Development and implementation of the finite state machines (FSMs) framework, in creating dynamic and realistic scenarios for effective pilot training.	The research involves simulations, focusing on the prefight procedure for a Boeing 737 captain, with 65 commands and 20,000 simulated trainees. The study doesn't explicitly provide the numerical or quantitative results obtained from the simulations. Overall, the study suggests that the system has the potential to enhance pilot training by recommending relevant information through dynamic hyperlinks, improving the efficiency of the learning process in flight simulators.
Källström et al. (2022)	ML	Implementing ML algorithms into pilot training simulations, provides a more realistic and personalized experience for pilots, ultimately improving their decision-making abilities.	The study included a survey of human pilots, revealing that situation awareness maps were valuable for coordinating with synthetic pilots. While mixed teams and pure agent teams achieved an 80% success rate, human pilots expressed concerns about synthetic agents' behaviour in conflicts and suggested modifications to the agents' action and observation spaces. The results of the study indicate similar performance between the two types of teams, with mixed teams performing slightly better in certain scenarios.
Mao, Ren, and Zhao (2022)	ML	Development of ZEMAX software and ZPL-macro programming to define optical specifications and corresponding surface expressions for the flight vision display system, enhancing pilot training during take-off and landing by designing a free-form surface for the flight vision display system.	The results of the study demonstrate the effectiveness of the ML approach in predicting free-form surface coefficients. The network's performance is evaluated using mean absolute error (MAE), explained variance regression score function (EV), and R2 regression score function. Results indicate small MAE, with EV and R2 values close to one, demonstrating superior performance in regression prediction. However, the actual numerical results for the evaluation metrics (MAE, EV, R2) are not explicitly mentioned.

(Continued)

Table 2. Continued

(Publication year)	Application (AI/ML/DL)	Domain	Results
Automation and decision support systems (n = 7)			
Lyu, Nandiganahalli, and Hwang (2018)	ML (GFHMM)	Propose and implement a Generalized Fuzzy Hidden Markov Model (GFHMM) for flight deck mode confusion detection within an intent-based framework to model the behaviour of both the automation system and pilot interactions.	The algorithm proposed for detecting mode confusion was tested and demonstrated using the real-life example of the Asiana 214 accident in 2013. The results indicate that if the divergence of intent could have been detected 35 seconds before the impact, the pilot would have had enough time to respond and potentially prevent the accident.
Álvarez, González, and Gracia (2020)	AI	The Cockpit Automation Procedures System (CAPS) was designed to automate procedures in a simulated civil Airbus A330 aircraft, offering crew assistance and augmentation during system failures and associated procedures.	The study discussed the methods employed for the prototype development, including the creation of a CAPS database and its integration with the aircraft simulator. The validation process involves crew-in-the-loop evaluations in various flying scenarios with system failures. However, the results or outcomes of the CAPS prototype were not mentioned.
Würfel, Djartov, Papenfuß, and Wies (2023)	AI	Development of an Intelligent Pilot Advisory System (IPAS), which is an AI-based decision support system for enhancing decision-making on the flight deck by providing intelligent advisories to pilots based on real-time data and analysis.	The proposed concept model of IPAS with eight detailed use cases, categorizing them into Information Support and Decision Support. The system model includes modules for data collection, AI-based situation assessment (AICOM), and presenting results to pilots (AICIS). However, the IPAS was not validated and no results were presented in this study.
Ramos et al. (2023)	AI	Development and conceptual design of an Integrated Flight Advisory System (IFAS) based on AI models. The focus is on providing real-time guidance and advice to flight crews during flight operations, with the aim of enhancing decision-making processes, improving situational awareness, reducing workload, and increasing overall safety in aviation.	The conceptual design of IFAS was described, for enchaning pilots' situation awareness (SA) and reducing workload for safer flights. The IFAS model was not validated and no results were presented in this study.

(Continued)

Table 2. Continued

(Publication year)	Application (AI/ML/DL)	Domain	Results
Watkins, Gallardo, and Chau (2018)	ML	A Pilot Support System employing ML to enhance pilot decision-making was introduced. The system analyzes various flight data and employs a Pattern Recognition Function to identify patterns similar to those before previous accidents, triggering alarms in cases of potential pilot impairment or inattention.	The system's methodology, algorithms, and applications, were presented on mitigating pilot errors through real-time analysis of flight data but lacks validation of its results in the study.
Zhang, Sun, and Zhang (2021)	AI	Applied a system dynamics approach to investigate the evolutionary game and collaboration mechanism of human-computer interaction in future intelligent aircraft cockpits. The study establishes an evolutionary game model involving a flight crew and an intelligent decision-making system, providing insights into modelling complex interactions in intelligent cockpit environments.	The study provided preliminary proof of the proposed method with a dynamic simulation of human-computer interaction in an intelligent aircraft cockpit, triggered by an error mode. Findings indicate fluctuations in task load and human error probability, with a tendency for the system to favour collaborative states. Sensitivity analyses show that higher human error probability amplification factors and task load change rates influence decision-making strategies.
Pitchammal and Sadda (2013)	AI	Discusses the application of AI techniques in the critical mission computer (MC) of fighter aircraft to address the increasing complexity of modern cockpit environments. The paper outlines the development of an Intelligent Mission Computer (IMC) and its potential to reduce the pilot's workload, improve decision-making, and assist in various mission-related tasks.	The IMC highlights the role of cognitive automation in improving aircraft performance and mission capabilities. Testing methods such as rules and cross-reference verification, line of reasoning assessment, and empirical testing were employed, however, the validation of the results in the study was insufficient.

DISCUSSION

The systematic review provides a comprehensive overview of recent advancements in assessing, managing, detecting, reducing, predicting, and preventing human factors risks in aviation through the use of AI, ML, and DL in human-centric flight operations for continuous airworthiness.

The studies in the assessment and management of the human factors risk category underscored the importance of AI in diverse aspects of human factors risks, from mental workload detection to crew resource management. The findings suggest that AI can significantly contribute to enhancing pilot performance, safety measures, and cockpit design by addressing technical, social, and cognitive aspects. Jiang et al. (2021) achieved a 94% detection accuracy for pilots' mental workload using multi-dimensional data fusion and an LSTM model. Paces and Insaurralde (2021) introduced an AI-based system for manual pilot performance assessment, emphasizing its potential in pilot training. Piera et al. (2022) also introduced a socio-technical simulation model to enhance pilot performance in single-pilot cockpits.

Articles for the detection of human errors highlighted the role of AI and ML in real-time monitoring and biometric analysis for the detection of human errors, including the analysis of physiological signals such as EEG, ECG, and other bio-signals, is a recurring theme in the literature. They demonstrate the potential of AI in tracking physiological parameters to identify signs of fatigue, stress, or other conditions that may contribute to errors. Binias, Myszor, and Cyran (2018) used EEG signals to detect pilots' reactions to unexpected events, providing insights into cognitive responses. Lee et al. (2023) introduced MentalNet, a hybrid deep neural network for continuous monitoring and analysis of pilots' mental states using EEG signals.

Concerning the reduction and prediction of human errors, research studies explored the potential of AI in analysing large datasets, predicting potential errors, and mitigating risks. They ranged from predicting unstable approaches to enhancing runway safety, showcasing diverse applications of AI in improving aviation safety. Jain, Misra, and Truong (2022) leveraged DL techniques to predict unstable approaches for general aviation aircraft. Odisho, Truong, and Joslin (2022) conducted a comprehensive study on runway safety improvement, developing predictive models for runway excursions.

Articles under the category of the prevention of human errors emphasized the proactive measures of preventing human errors, including AI-based training programs and decision support systems. They highlighted the potential of AI and DL in improving training effectiveness, decision-making on flight decks, and overall situational awareness. Bach et al. (2021) introduced a novel hierarchical structure of finite state machines for interactive pilot training. Lyu, Nandiganahalli, and Hwang (2018) addressed mode confusion detection in the flight deck using a Generalized Fuzzy Hidden Markov Model. It is worth noting that the majority of studies in this category focused on conceptual applications, with fewer studies involving empirical testing.

This systematic review identifies research gaps and suggests future trends in AI applications for aviation safety. Studies in this systematic review were conducted in simulated or controlled environments, which implies the need for potential research that integrates AI applications with human factors considerations and impacts decision-making for crew operations in real operational settings to ensure their practical utility under the complexities of actual flight conditions. It involves collaboration with airlines and aviation authorities to implement and assess AI systems in actual flight scenarios. The adaptability and robustness of AI models in handling unforeseen or novel scenarios are limited in existing studies from this review.

Understanding how AI systems respond to unexpected situations is essential for ensuring safety across a wide range of circumstances. Given the dynamic nature of flight operations like turbulence, bad weather conditions and wind shear effects while landing which are very common for crew to face in every flight. Future research is likely to focus on enhancing the adaptability of AI systems to unforeseen scenarios. It involves developing AI models capable of handling novel situations, providing real-time insights and ensuring the robustness of these systems in diverse operational conditions.

Generalization across different civil aircraft types from different aircraft manufacturers such as Boeing and Airbus, researchers may need to explore the generalizability of AI models across different types of aircraft and operational contexts, for example, can the AI application be adapted to Boeing B787 and Airbus A350 in each aspect to access, assist or monitor pilot behaviour during their flight operation. Understanding how the applications can be adapted and optimized for various aircraft types will be crucial for their widespread implementation.

The literature emphasizes the importance of understanding the dynamics of human-AI collaboration and establishing trust between pilots and AI systems. The studies included in the review likely use diverse AI technologies, algorithms, and models. Heterogeneity in these approaches makes it challenging to draw direct comparisons or make overarching conclusions about the effectiveness of AI in aviation safety. Moreover, the ethical implications of AI in aviation, including issues related to flight operation data privacy, algorithmic bias, and airliner flight database transparency, require further exploration. Future research should delve into the ethical dimensions and contribute to the development of robust regulatory frameworks for AI in aviation, investigate optimal interfaces and communication strategies to ensure effective collaboration, the adoption of safety-critical AI and mitigate AI trustworthiness issues (Will Hunt, 2020).

Moreover, this review highlights the potential for future research in developing and testing improved human factors risk assessment (HRA) models assisted by computational intelligence in piloted aircraft operations, with the ultimate aim of enhancing flight safety.

CONCLUSION

The systematic review suggests that future research should focus on validating the effectiveness of computational intelligence models in real operational settings, assessing their adaptability to unforeseen scenarios, exploring generalizability across different aircraft types, and understanding the dynamics of human-AI collaboration to advance continuous airworthiness and human factors research in piloted aircraft operations.

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