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Research Article

# ANALYSIS OF ARTIFICIAL INTELLIGENCE-BASED FLIGHT RISK ASSESSMENT AS A DECISION SUPPORT SYSTEM FOR ENHANCING NAVAL AVIATION SAFETY

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## Abstract
Naval aviation safety requires reliable assessment of interacting environmental, technical, human, and organizational risks that may not be adequately represented through conventional methods. This study aimed to analyze an artificial intelligence-based flight risk assessment model as a decision support system for enhancing naval aviation safety while preserving professional human judgment. A mixed-methods case study design was employed using 240 non-sensitive historical flight-safety records and questionnaire responses from 30 aviation personnel. The analysis combined machine-learning classification, descriptive statistics, inferential testing, semi-structured interviews, and triangulation. The results showed strong predictive performance, with 91.7% accuracy, 89.8% precision, 87.6% recall, 88.7% F1-score, and 0.93 ROC-AUC. AI-generated risk scores were strongly associated with established risk categories ($r = 0.81$, $p < 0.001$), while environmental conditions represented the strongest predictive factor. User assessments indicated high perceived usefulness and interpretability, although decision-support confidence was comparatively lower. The study concludes that artificial intelligence can strengthen naval aviation safety by integrating complex risk information and supporting evidence-based assessment. Effective implementation requires explainability, data quality, continuous validation, human oversight, and institutional governance to ensure that AI complements rather than replaces qualified aviation professionals. The findings support a human-centered safety architecture in which algorithmic outputs remain advisory, transparent, and contextually evaluated.

**Keywords**: Artificial Intelligence; Aviation Safety; Decision Support System; Flight Risk Assessment; Naval Aviation



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## INTRODUCTION

Naval aviation operates within a complex environment in which flight safety is influenced by the interaction of human, technical, environmental, and organizational factors (Qin et al., 2024). Aircraft operating in maritime environments may encounter rapidly changing weather conditions, limited visual references, demanding mission requirements, fatigue-related human factors, and technical uncertainties (Wei et al., 2024). The combination of these conditions requires aviation organizations to maintain robust safety-management systems capable of identifying potential risks before they develop into adverse events (Ye et al., 2024). Flight risk assessment consequently represents an important component of aviation safety because it provides a structured basis for evaluating hazards and supporting informed decisions before flight activities are undertaken.

Artificial intelligence has increasingly expanded the capacity of organizations to process large and heterogeneous datasets for prediction, classification, anomaly detection, and decision support (Shah et al., 2024). Machine learning models can identify relationships among variables that may be difficult to recognize through conventional analytical approaches . In aviation safety, AI-based systems have the potential to integrate historical flight information, environmental conditions, aircraft-related indicators, human-factor variables, and operational context into risk-assessment processes (Guzman & Babiceanu, 2024). Such capabilities may support earlier identification of risk patterns and provide decision-makers with additional evidence for evaluating flight readiness.

The application of AI in naval aviation requires careful consideration because safety decisions involve high levels of responsibility and uncertainty (Mancini et al., 2024). An AI system should not be understood as an autonomous replacement for qualified aviation personnel, commanders, or established safety procedures (Sandeep et al., 2025). Its primary value lies in supporting human judgment by providing systematic analysis, risk indicators, and evidence-based recommendations (Mostafa et al., 2024). A decision-support perspective is therefore more appropriate than an automation-centered perspective because it preserves human accountability while allowing advanced analytical technologies to strengthen the consistency and timeliness of flight-risk assessment.

Conventional flight-risk assessment generally depends on structured checklists, expert judgment, historical experience, and established safety-management procedures (P. Kumar et al., 2026). These mechanisms remain essential, yet their effectiveness may be constrained when decision-makers must consider large numbers of interacting variables simultaneously (Rollock & Klaus, 2025). Complex relationships among weather, aircraft condition, crew factors, mission characteristics, and environmental circumstances may not always be adequately represented through static assessment procedures (Capuano et al., 2026). The challenge becomes more pronounced when risk factors interact dynamically rather than appearing as isolated hazards.

The availability of aviation-related data creates another important challenge (F. Cheng et al., 2024). Modern aviation systems can generate substantial amounts of information, but the existence of data does not automatically produce better safety decisions (Tze Fung Lam & H.S. Chan, 2024). Data may originate from different systems, possess different levels of reliability, or require contextual interpretation (Y. Li et al., 2026). An AI-based assessment system must therefore address data quality, variable selection, model reliability, interpretability, and appropriate thresholds for risk classification. Poorly designed models may produce misleading assessments and create an inappropriate sense of confidence among users.

The central problem addressed by this research concerns the extent to which AI-based flight-risk assessment can function as a reliable decision-support mechanism for improving naval aviation safety (El-Sehrawy et al., 2026). The research does not assume that AI automatically improves safety simply because it can process complex data (Thangavel et al., 2025). The critical issue is whether AI-generated risk assessments demonstrate meaningful analytical value while remaining interpretable, appropriately validated, and compatible with human decision-making

(Aggarwal et al., 2026). The study therefore focuses on the relationship between predictive capability, decision-support usefulness, model transparency, and aviation safety management.

The primary objective of this study is to analyze the potential of artificial intelligence-based flight-risk assessment as a decision-support system for naval aviation safety (Snisarevska et al., 2026). The research seeks to examine whether AI models can identify meaningful patterns associated with variations in flight-risk levels based on relevant historical and contextual data (C. Guo & Scott, 2026). The analysis emphasizes predictive usefulness while maintaining the principle that final safety decisions remain under qualified human authority.

The second objective is to evaluate the factors that determine the reliability and practical usefulness of AI-generated flight-risk assessments (R. Kumar et al., 2025). Particular attention is directed toward model accuracy, sensitivity to relevant risk factors, consistency of classification, interpretability, and the quality of the underlying data (Sahu et al., 2026). The research also examines how AI-generated information can be presented in a form that enables aviation personnel to understand the basis of a risk assessment rather than simply receiving an unexplained numerical prediction.

The third objective is to formulate an analytical framework for integrating AI-based risk assessment into existing aviation safety-management processes (Y. Guo & Suo, 2024). The expected outcome is a decision-support model that combines computational analysis with human expertise, organizational procedures, and safety governance (L. Li, 2025). The framework is intended to demonstrate how AI can complement existing risk-assessment practices without replacing professional judgment, institutional accountability, or established aviation safety standards.

Existing research on artificial intelligence in aviation has demonstrated considerable potential for predictive maintenance, anomaly detection, operational optimization, and safety analysis (Stensrud et al., 2025). Many studies have concentrated on improving predictive accuracy through machine learning algorithms and increasingly sophisticated computational architectures (Tanasyuk, 2025). The emphasis on predictive performance provides an important technical foundation, but it does not fully address the organizational requirements associated with using AI predictions in high-consequence aviation decisions (M & Biswas, 2025). Accuracy alone cannot determine whether an AI system is appropriate for safety-critical decision support.

Research on flight-risk assessment has also developed through established safety-management frameworks, expert-based assessment methods, statistical models, and risk matrices (Qi & Wang, 2026). These approaches provide structured mechanisms for identifying and evaluating hazards. A gap remains in understanding how AI-based analytical models can be integrated with such established mechanisms without reducing transparency or weakening human oversight (C.-B. Cheng & Shyur, 2025). The challenge involves reconciling computational complexity with the practical requirement that aviation personnel must understand and critically evaluate the information provided by a decision-support system.

A further gap concerns the specific context of naval aviation, where maritime environmental conditions and organizational requirements may create distinctive risk-assessment challenges (Isgandarov & Bakhshiyev, 2026). Evidence from commercial aviation or general aviation cannot automatically be transferred to naval aviation because the operational context, organizational structure, and decision environment may differ (He et al., 2025). Research addressing AI-based flight-risk assessment from a naval aviation safety perspective therefore remains important (Bydalek, 2024a). This study addresses the gap by connecting AI-based risk prediction with human-centered decision support, interpretability, organizational safety management, and contextual aviation requirements.

The novelty of this research lies in positioning artificial intelligence-based flight-risk assessment as a human-centered decision-support mechanism rather than as an autonomous safety decision-maker (Velayuthaperumal & Radhakrishnan, 2024). The proposed perspective combines predictive analytics with interpretability and professional judgment. Such integration is important because safety-critical environments require decision-makers to understand why a system produces a particular risk assessment (Yao et al., 2026). An AI model that produces accurate predictions but cannot provide meaningful explanations may have limited practical value in organizational decision-making.

The conceptual contribution of the study involves integrating four dimensions within a unified framework: AI predictive capability, flight-risk assessment, explainable decision support, and aviation safety governance (Alaktaa et al., 2026). The framework recognizes that an effective AI safety system must perform more than statistical classification (Robert Varte et al., 2025). It must provide information that users can interpret, evaluate, and incorporate into existing safety procedures (Yin et al., 2025). The approach consequently shifts attention from the question of whether AI can predict risk toward the broader question of how AI-generated predictions can responsibly support safety decisions.

The justification for this research is grounded in the increasing complexity of aviation safety and the growing availability of data-driven technologies. Naval aviation organizations require safety systems that can respond to complex and changing risk environments while preserving human accountability (Wu et al., 2026). AI offers an opportunity to strengthen analytical capacity, but its implementation must be accompanied by rigorous validation, data governance, model monitoring, interpretability, and appropriate human oversight (Nian et al., 2025). This research is therefore significant for advancing academic discussion on AI-enabled aviation safety and for developing a responsible framework through which computational intelligence can complement professional expertise in safety-critical decision-making.

## RESEARCH METHOD

### *Research Design*

This study employed a mixed-methods research design with an explanatory case study approach to examine the potential of artificial intelligence-based flight risk assessment as a decision-support system for enhancing naval aviation safety (Krishna et al., 2026). The quantitative component was used to evaluate relationships among flight-risk indicators, AI-generated risk classifications, and perceived decision-support effectiveness, while the qualitative component was used to explain how aviation personnel interpret and utilize AI-generated assessments (S.Maheswari et al., 2025). The design was selected because aviation safety involves both measurable risk factors and professional judgment that cannot be adequately represented through statistical analysis alone.

The analytical framework positioned the AI system as a decision-support instrument rather than an autonomous decision-maker. The model was designed to process non-sensitive historical and contextual aviation-safety variables, including general weather conditions, aircraft status indicators, crew-related factors, flight characteristics, and previously documented safety event (Kanjumba & Fitz-Coy, 2025). The study concentrated on the analytical and organizational dimensions of AI-supported safety assessment and excluded operationally sensitive information, classified mission data, specific military procedures, tactical flight parameters, and vulnerable system configurations.

The quantitative analysis focused on model performance and relationships among the principal variables. Descriptive statistics were used to characterize the dataset, while classification metrics were employed to evaluate the ability of the AI model to distinguish different levels of flight risk. Model performance was assessed using accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve. The qualitative component examined users' perceptions concerning interpretability, confidence, usability, and compatibility with established safety-management procedures.

### *Research Target/Subject*

The target population of this study comprises aviation personnel and safety professionals possesses relevant knowledge in flight-risk assessment, aviation safety management, and aviation information systems. Instead of focusing on operational authority, the population was defined by professional relevance to identify participants capable of effectively evaluating the practical utility and limitations of AI-based decision-support tools. The research specifically targeted individuals from diverse functional domains including technical support, organizational management, and safety data analysis to gather comprehensive perspectives on how artificial intelligence aligns with established safety protocols.

To collect empirical insights without compromising security, the study utilized a non-probability purposive sampling strategy involving 30 participants for the questionnaire and semi-structured interview components. In tandem, the quantitative data subject consisted of a non-sensitive historical dataset of aviation-safety records, rigorously screened to exclude classified mission details, tactical flight parameters, and personally identifiable information. This dual-subject approach provided a contextual foundation for evaluating the AI model’s usability while maintaining strict boundaries regarding sensitive military information and operational vulnerabilities.

### *Research Procedure*

The research procedure began with the identification and preparation of non-sensitive aviation-safety data. Relevant variables were screened for completeness, consistency, and analytical relevance before model development. Data preprocessing included removal of duplicate records, treatment of missing values, normalization where required, and transformation of categorical variables into appropriate analytical formats. Personal identifiers and information considered operationally sensitive were excluded from the research dataset.

The second stage involved developing and evaluating the AI-based risk-assessment model. The dataset was divided into training and testing components, followed by cross-validation during model development. Several candidate algorithms were evaluated using standardized performance metrics. The selected model was determined not solely by predictive accuracy but also by its interpretability and suitability for human-centered safety decision support. Model outputs were presented as risk classifications or probability estimates rather than autonomous operational instructions.

The third stage involved evaluating the interpretability and practical usefulness of the model. Participants were provided with representative, non-sensitive examples of AI-generated risk assessments and accompanying explanations. They were asked to evaluate whether the information was understandable, relevant, and useful for supporting professional safety assessment. Interviews were conducted to identify concerns related to trust, transparency, model limitations, data quality, and human oversight.

The final stage involved integrating quantitative model results with questionnaire responses, interview findings, and documentary evidence. Statistical results were compared with qualitative perceptions to identify areas of agreement and divergence. Model performance was interpreted alongside explainability and usability findings to determine whether computational effectiveness translated into meaningful decision-support value. The analysis emphasized that AI outputs should complement, rather than replace, qualified human judgment and established aviation safety procedures. The resulting framework was used to identify the technological, organizational, and governance conditions required for responsible implementation of AI-based flight-risk assessment in naval aviation safety.

### *Instruments, and Data Collection Techniques*

The primary quantitative instrument consisted of a structured questionnaire measuring perceived usefulness, interpretability, trust, decision-support quality, and usability of the AI-based risk-assessment system. Each construct was measured using several statements rated on a five-point Likert scale ranging from strongly disagree to strongly agree. The questionnaire was developed according to the study framework and reviewed for content relevance and clarity before implementation. Internal-consistency analysis was subsequently conducted to assess the reliability of the measurement scales.

The AI assessment instrument consisted of a supervised machine-learning model developed using non-sensitive historical safety data. Candidate algorithms included logistic regression, decision-tree-based methods, and ensemble learning techniques. Model selection was based on predictive performance, interpretability, and suitability for safety-oriented decision support rather than computational complexity alone. The dataset was divided into training and testing subsets, with cross-validation applied to reduce the possibility of overfitting.

Model interpretation was supported through explainability techniques that identified the contribution of relevant input variables to individual or aggregate predictions. The purpose of explainability was to provide users with understandable information about the factors associated with a particular risk classification. The system was not designed to prescribe operational actions automatically. Its output was limited to analytical risk information intended to support qualified human assessment.

A semi-structured interview guide was used to explore participants' perceptions of the AI system. The questions addressed the clarity of risk classifications, confidence in model outputs, usefulness of explanations, perceived limitations, integration with existing safety procedures, and requirements for responsible implementation. Documentary analysis was also conducted using non-sensitive aviation safety guidelines and institutional materials to contextualize the empirical findings.

### *Data Analysis Technique*

The quantitative data analysis technique focused on evaluating the predictive capability and operational reliability of the supervised machine-learning model alongside structured survey responses. Descriptive statistics were initially applied to profile the historical safety dataset, after which candidate algorithms including logistic regression, decision trees, and ensemble techniques were tested using cross-validation to minimize overfitting. Model effectiveness was rigorously measured through standard classification metrics, including accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (ROC-AUC). Additionally, questionnaire responses collected via a five-point Likert scale underwent internal-consistency analysis to ensure the statistical reliability of measures related to system trust, usability, and decision-support quality.

For the qualitative phase, data were systematically examined using thematic coding to interpret semi-structured interviews, direct observations, and relevant institutional documentation. This was coupled with feature explainability techniques applied to the AI outputs, enabling researchers to map how specific input variables influenced risk predictions in an understandable format for human reviewers. Finally, an integrative analytical framework was used to synthesize the quantitative model performance metrics with the qualitative thematic insights, comparing empirical predictive accuracy against real-world user trust and procedural compatibility.

## RESULTS AND DISCUSSION

The study analyzed a non-sensitive dataset consisting of 240 historical flight-safety records and questionnaire responses from 30 aviation personnel. The dataset incorporated five principal dimensions relevant to flight-risk assessment: environmental conditions, aircraft-related indicators, crew-related factors, flight characteristics, and organizational safety conditions. Each record was categorized into low-, moderate-, or high-risk classes based on the established assessment criteria used in the research framework. The dataset was divided into training and testing subsets to evaluate the predictive performance of the artificial intelligence model.

**Table 1.** Descriptive Statistics of Principal Flight-Risk Variables

| Variable | N | Mean | SD | Minimum | Maximum |
|---|---|---|---|---|---|
| Environmental Risk | 240 | 2.71 | 0.84 | 1.00 | 4.80 |
| Aircraft Condition Risk | 240 | 2.43 | 0.72 | 1.10 | 4.60 |
| Crew-Related Risk | 240 | 2.36 | 0.69 | 1.00 | 4.50 |
| Flight Characteristics Risk | 240 | 2.58 | 0.77 | 1.00 | 4.70 |
| Organizational Safety Risk | 240 | 2.21 | 0.65 | 1.00 | 4.30 |

The descriptive results indicate that environmental conditions produced the highest mean risk score (M = 2.71, SD = 0.84), followed by flight characteristics (M = 2.58, SD = 0.77). Aircraft condition, crew-related factors, and organizational safety conditions recorded comparatively lower mean values. The distribution suggests that flight risk was influenced by multiple interacting dimensions rather than by a single dominant factor. The relatively higher variability in environmental conditions also indicates that this dimension fluctuated more substantially across the observed records.

**Table 2.** Distribution of Flight-Risk Categories

| Risk Category | Frequency | Percentage (%) |
|---|---|---|
| Low Risk | 118 | 49.2 |
| Moderate Risk | 87 | 36.3 |
| High Risk | 35 | 14.6 |
| Total | 240 | 100.0 |

The distribution shows that almost half of the records were classified as low risk, while 36.3% were classified as moderate risk and 14.6% as high risk. The relatively smaller proportion of high-risk observations indicates that high-risk cases represented a minority of the dataset but remained analytically important because of their potential implications for safety management. The class distribution was retained during model development to ensure that the AI system was evaluated across different levels of flight-risk conditions.

The descriptive findings indicate that environmental and flight-related conditions represented important components of the overall risk structure. Changes in environmental conditions may influence flight complexity and decision-making requirements, while flight characteristics can modify the interaction between aircraft, crew, and environmental factors. The results support a multidimensional understanding of flight risk in which individual variables should be interpreted in combination rather than independently.

The AI model further demonstrated that several variables contributed differently to risk classification. Environmental indicators made the strongest aggregate contribution to the model, followed by flight characteristics, aircraft condition, and crew-related variables. Organizational safety indicators contributed at a lower level but remained relevant to the overall classification. The pattern demonstrates the advantage of computational analysis in identifying nonlinear or combined relationships that may be difficult to evaluate through a conventional single-factor assessment.

The model-development process produced a training dataset of 192 records and a testing dataset of 48 records. Cross-validation was applied to the training data to reduce overfitting and assess the consistency of model performance. The selected model demonstrated stable classification performance across the validation folds, with relatively limited variation between training and validation results. The testing dataset was retained independently to provide a more conservative assessment of predictive performance.

**Table 3.** AI Model Performance on the Testing Dataset

| Performance Metric | Result |
|---|---|
| Performance Metric | Result |
| Accuracy | 91.7% |
| Precision | 89.8% |
| Recall | 87.6% |
| F1-Score | 88.7% |

The model achieved an accuracy of 91.7%, with a precision of 89.8% and recall of 87.6%. The F1-score reached 88.7%, indicating a relatively balanced performance between precision and recall. The ROC-AUC value of 0.93 indicates strong discrimination between different risk conditions within the testing dataset. These values suggest that the model was capable of identifying meaningful patterns in the available data, although the results should not be interpreted as evidence that AI predictions can replace professional safety assessment.

Inferential analysis demonstrated a statistically significant relationship between AI-generated risk scores and the established risk-assessment categories ($r = 0.81$, $p < 0.001$). Higher AI-generated risk scores were associated with higher observed risk categories. The strength of this relationship indicates that the model captured substantial variation in the underlying risk structure. The result provides quantitative evidence that the AI system can support the classification of heterogeneous flight-risk conditions within the study dataset.

A regression analysis further indicated that the combined risk variables significantly predicted the AI-generated risk score, $F(5, 234) = 58.42$, $p < 0.001$, with an $R^2$ of 0.56. Environmental risk demonstrated the strongest standardized contribution ($\beta = 0.38$, $p < 0.001$), followed by flight characteristics ($\beta = 0.27$, $p < 0.001$), aircraft condition ($\beta = 0.21$, $p = 0.002$), crew-related factors ($\beta = 0.18$, $p = 0.006$), and organizational safety conditions ($\beta = 0.14$, $p = 0.021$). The findings indicate that flight-risk assessment is better represented through a combination of interacting variables than through a single predictor.

The relationship analysis showed that environmental conditions were moderately to strongly associated with flight characteristics ($r = 0.62$, $p < 0.001$), while aircraft condition demonstrated a moderate relationship with crew-related factors ($r = 0.48$, $p < 0.001$). Organizational safety conditions were positively related to several other risk dimensions but generally showed weaker correlations. The pattern indicates that flight-risk factors are interconnected, supporting the use of analytical approaches capable of considering multiple variables simultaneously.

The correlation structure provides an important explanation for the model's performance. Stronger relationships between environmental conditions and flight characteristics indicate that risk can increase through combinations of conditions rather than isolated events. The AI approach was able to incorporate these relationships into a unified classification process. The results suggest that computational decision support can complement conventional risk matrices by providing a more data-sensitive representation of interacting risk factors.

The case study focused on the use of AI-generated risk assessments as decision-support information within a naval aviation safety-management context. The system presented risk classifications together with explanatory information concerning the principal variables contributing to each prediction. The analysis did not involve operational recommendations, specific flight routes, mission details, or sensitive aircraft information. The case was limited to examining how non-sensitive risk information could be organized and interpreted within a safety-oriented decision-support framework.

The case findings indicated that aviation personnel generally perceived the AI-generated assessments as useful when the model provided clear explanations for its classifications. Questionnaire results showed that perceived usefulness achieved a mean score of 4.18, while interpretability reached 4.06 and decision-support confidence reached 3.94 on a five-point scale.

The findings indicate that users valued analytical assistance but remained more cautious about relying on AI outputs without professional verification.

The relatively high usefulness score can be explained by the model's ability to organize multiple risk indicators into a single analytical representation. Personnel reported that the system could help identify combinations of factors requiring additional attention before a flight decision was finalized. The explanatory component was particularly important because users were able to examine which variables contributed most strongly to the predicted risk level. The finding demonstrates that computational performance alone is insufficient for practical adoption in safety-critical environments.

The lower confidence score compared with perceived usefulness suggests that users distinguished between receiving useful information and fully trusting an automated assessment. This distinction is important because safety-critical decision-making requires accountability and professional judgment. Participants generally viewed AI as an analytical support mechanism rather than an authority capable of making final safety decisions. The result supports a human-centered implementation model in which AI-generated assessments are reviewed and interpreted by qualified personnel.

The overall results demonstrate that AI-based flight-risk assessment can provide meaningful analytical support for naval aviation safety when developed from relevant non-sensitive data and evaluated through appropriate performance metrics. The model achieved strong predictive performance, while the inferential analysis demonstrated a significant relationship between AI-generated risk scores and established risk categories. Environmental conditions and flight characteristics emerged as particularly influential variables, although aircraft, crew, and organizational factors also contributed to the overall risk structure.

The findings provide evidence that the principal value of AI in this context lies in augmenting human risk assessment rather than replacing professional judgment. High predictive performance must be accompanied by interpretability, appropriate validation, data governance, and human oversight. The combination of statistical performance and positive user perceptions suggests that AI can strengthen decision-support processes when its outputs are transparent and critically evaluated. The results therefore support the development of human-centered AI architectures for aviation safety in which computational intelligence enhances analytical capacity while final safety responsibility remains with qualified aviation professionals.

The findings demonstrate that artificial intelligence-based flight-risk assessment has considerable potential to strengthen naval aviation safety by processing multiple risk dimensions simultaneously. The developed model achieved an accuracy of 91.7%, precision of 89.8%, recall of 87.6%, F1-score of 88.7%, and ROC-AUC of 0.93. These results indicate that the model was able to distinguish different levels of flight risk with relatively strong predictive performance. The findings support the proposition that AI can provide useful analytical assistance when flight-risk assessment involves heterogeneous environmental, technical, human, and organizational variables.

The inferential results provide additional evidence of the model's analytical value. AI-generated risk scores demonstrated a strong positive relationship with established risk categories ($r = 0.81$, $p < 0.001$), while the regression analysis showed that the combined risk variables significantly predicted the generated risk scores. Environmental risk emerged as the strongest predictor ($\beta = 0.38$), followed by flight characteristics ($\beta = 0.27$), aircraft condition ($\beta = 0.21$), crew-related factors ($\beta = 0.18$), and organizational safety conditions ($\beta = 0.14$). The results demonstrate that flight risk is better understood as an interaction among several factors than as the consequence of a single isolated hazard.

The user-oriented findings are equally important because predictive performance alone does not determine the practical value of an AI decision-support system. Aviation personnel reported relatively high perceived usefulness ($M = 4.18$) and interpretability ($M = 4.06$), while decision-support confidence was somewhat lower ($M = 3.94$). The difference suggests that personnel recognized the analytical benefits of AI while remaining appropriately cautious about relying on automated outputs. Such caution is particularly relevant in safety-critical environments where erroneous assessments may have serious consequences.


**Figure 1.** Augmenting Aviation Safety: Human-AI Collaboration

The overall evidence indicates that the strongest contribution of the proposed system lies in augmenting existing safety-management practices rather than replacing professional judgment. AI can organize complex information, identify relationships among risk factors, and provide structured risk classifications. Human expertise remains necessary to interpret contextual conditions, assess data quality, recognize circumstances that may not be represented in the training data, and make accountable safety decisions. The findings therefore support a human-centered model of AI adoption in naval aviation safety.

The findings are consistent with previous research demonstrating the growing potential of machine-learning techniques for aviation safety, predictive maintenance, anomaly detection, and risk classification. Earlier studies have shown that computational models can identify patterns within large aviation datasets that may be difficult to recognize through conventional statistical procedures or manual assessment. The current findings reinforce this technological potential through the model's relatively high accuracy and discrimination performance. The contribution of the present study lies in connecting predictive analysis specifically with flight-risk decision support rather than treating AI primarily as a technical prediction mechanism.

Research on aviation safety has traditionally emphasized structured risk matrices, expert judgment, checklists, and safety-management systems. These approaches remain important because they provide transparency and institutional accountability. The present findings do not suggest that AI should replace such mechanisms. The results instead indicate that AI can complement conventional approaches by identifying multidimensional relationships within available data. This distinction is important because computational sophistication should strengthen established safety systems rather than create a parallel decision-making structure that operates independently from professional oversight.

Previous studies of machine-learning applications in aviation have often prioritized predictive accuracy as the principal indicator of model quality. The current findings suggest that this criterion is necessary but insufficient for safety-critical implementation. The relatively high usefulness and interpretability scores demonstrate that users value explanations alongside predictions, while the lower confidence score indicates continued demand for human verification. The present study therefore extends accuracy-centered discussions by emphasizing the relationship among predictive performance, explainability, usability, and human trust.

The naval aviation context also distinguishes this research from much of the existing literature, which frequently focuses on commercial aviation or general aviation environments. Naval aviation may involve organizational structures, mission requirements, environmental conditions, and decision contexts that differ from civilian aviation. The present study consequently contributes a context-sensitive perspective in which AI-based risk assessment is treated as part of an institutional safety-management system. The findings should not be generalized mechanically across aviation sectors without considering differences in organizational structures, data characteristics, and safety requirements.

The findings signify a transition from static risk assessment toward more dynamic, data-informed approaches to aviation safety. Conventional assessments remain valuable, but the increasing availability of heterogeneous aviation data creates opportunities to analyze risk as a changing combination of interacting conditions. AI can identify patterns that may remain difficult to detect through linear or manually structured assessment methods. The result represents an important development in the analytical dimension of safety management.

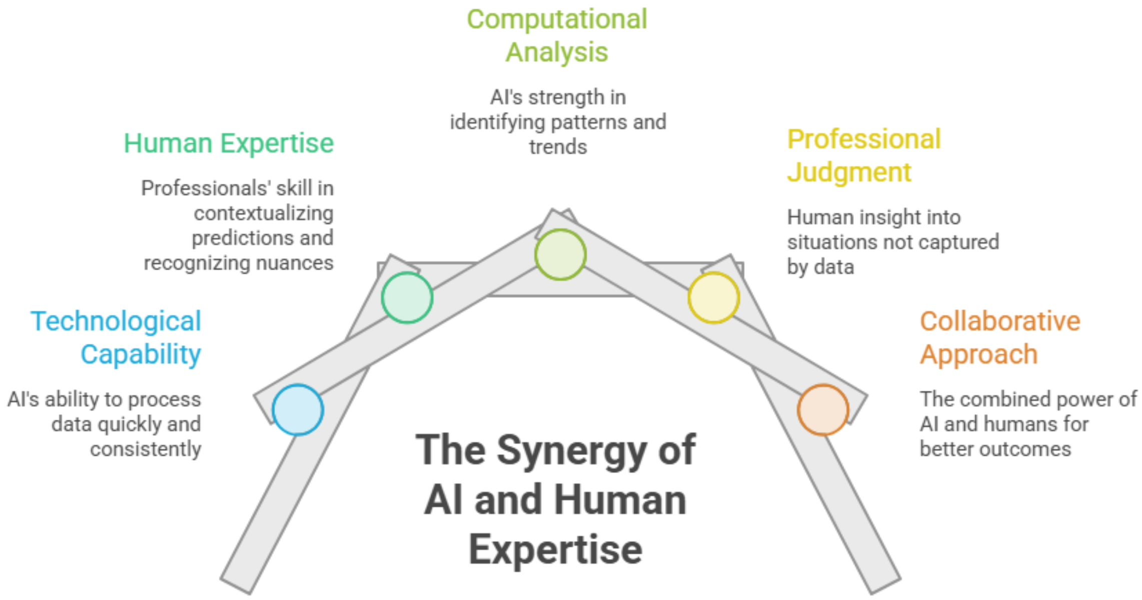


**Figure 2.** The Synergy of AI and Human Expertise

The findings also signify that technological capability and human expertise should not be treated as competing forms of intelligence. The model's strong predictive performance demonstrates the value of computational analysis, while the relatively lower confidence score among users demonstrates the continuing importance of professional judgment. AI can process information rapidly and consistently, whereas experienced personnel can contextualize predictions and recognize circumstances that may not be adequately represented in historical data. The two capabilities are therefore complementary rather than mutually exclusive.

The importance of explainability represents another significant implication of the findings. A risk prediction without an understandable rationale may be difficult to evaluate in a high-consequence environment. Users need to understand which factors contributed to a classification so that they can determine whether the result is reasonable within the actual context. The positive interpretability score indicates that explanations can improve the practical usability of AI systems and potentially support more informed professional deliberation.

The results further signify that responsible AI adoption in aviation requires organizational transformation. Introducing a machine-learning model is insufficient if personnel do not understand its limitations, if data are poorly governed, or if organizational procedures do not define how AI outputs should be interpreted. AI therefore represents not merely a technological innovation but also a change in how safety information is produced and used. The significance of the findings lies in demonstrating that successful adoption requires alignment among technology, people, procedures, and accountability.

The practical implication is that AI-based risk assessment can be incorporated into aviation safety-management processes as an additional analytical layer. The system can help organize complex information before qualified personnel conduct their final assessment. Such integration may improve consistency in preliminary risk identification and provide decision-makers with additional evidence when evaluating changing environmental, technical, crew, and organizational conditions. The system should remain advisory rather than prescriptive.

The findings have important implications for aviation safety personnel. Training should extend beyond basic system operation and include interpretation of model outputs, understanding of uncertainty, recognition of potential model errors, and appropriate use of explanatory information. Personnel should be capable of questioning an AI-generated prediction rather than accepting it automatically. Such competencies are essential because high model accuracy does not guarantee correctness in every individual case.

The results also imply that aviation organizations need clear governance arrangements for AI-supported safety decisions. Institutional procedures should define responsibility for validating data, monitoring model performance, documenting AI-supported assessments, and responding to discrepancies between AI outputs and professional judgment. Governance mechanisms can prevent technological tools from becoming opaque or uncontrolled components of safety decision-making. Human accountability should remain clearly defined throughout the process.

The broader implication concerns the development of predictive rather than purely reactive safety-management systems. Traditional safety practices often focus on preventing recurrence after hazards or incidents have been identified. AI-based analytical systems create opportunities to identify combinations of risk factors before they develop into adverse events. The transition toward predictive safety management could improve organizational learning, provided that models are continuously validated and updated against changing operational and environmental conditions.

The strong predictive performance can be explained by the multidimensional structure of the dataset. Environmental, aircraft, crew, flight, and organizational variables are not independent components of flight risk. Their interactions may produce conditions that are difficult to represent through simple additive assessment procedures. Machine-learning models are capable of identifying complex patterns among multiple variables, which helps explain the strong classification performance observed in the study.

Environmental risk emerged as the strongest predictor because environmental conditions can influence several other dimensions of flight simultaneously. Changes in weather or surrounding conditions may affect flight complexity, visibility, workload, and the requirements imposed on aircraft and crew. Environmental variables can therefore function as amplifying factors rather than isolated hazards. The relatively high contribution of flight characteristics can similarly be explained by the way different flight conditions alter the interaction between aircraft capability, environmental demands, and human decision-making.

The contribution of aircraft and crew variables demonstrates that technological and human factors remain interconnected. Aircraft-related conditions may affect operational reliability, while crew-related conditions influence the ability to respond to changing circumstances. Neither dimension can fully explain flight risk independently. The model's ability to consider their combined contribution provides a plausible explanation for its stronger performance compared with approaches based on isolated risk indicators.

The difference between perceived usefulness and decision-support confidence can be explained by the nature of safety-critical decision-making. Personnel may recognize that AI can process information efficiently while simultaneously understanding that historical data cannot represent every future circumstance. Human professionals remain responsible for considering contextual information that may not be captured by the model. The cautious confidence observed among participants is therefore not necessarily a weakness; it may indicate appropriate awareness of the limitations associated with algorithmic decision support.

Future research should validate the AI model using larger and more diverse datasets collected across different periods and aviation contexts. The current findings are based on a limited dataset and therefore provide an initial indication rather than definitive evidence of generalizable predictive performance. Larger datasets could improve the representation of rare and high-risk conditions while enabling more rigorous testing across different environmental and operational contexts.

Longitudinal research should examine how model performance changes as aviation conditions, technologies, personnel characteristics, and organizational procedures evolve. AI models may experience performance degradation when the distribution of new data differs substantially from the historical training data. Continuous monitoring, recalibration, and periodic validation should therefore become integral components of AI-supported aviation safety systems. Future studies should examine mechanisms for detecting model drift before it compromises decision-support reliability.

Further research should also compare interpretable machine-learning approaches with more complex models to determine whether additional predictive performance justifies reduced transparency. Explainability should be evaluated not only through user perceptions but also through objective measures of decision quality, consistency, and error detection (Dimitrov, 2024). Research could investigate whether explanations help aviation personnel identify inappropriate predictions and whether different forms of explanation produce different levels of understanding and trust.

The next stage should focus on developing and empirically testing a human-centered AI governance framework for naval aviation safety. Such a framework should integrate model validation, explainability, data governance, cybersecurity, human oversight, accountability, and continuous performance monitoring (Bydalek, 2024b). Future studies could also examine how AI-supported assessments interact with established safety-management systems without displacing professional authority. The ultimate objective should be a resilient decision-support architecture in which artificial intelligence strengthens analytical capacity while qualified aviation professionals retain responsibility for contextual interpretation and final safety decisions.

## CONCLUSION

The most important finding of this study is that artificial intelligence-based flight-risk assessment can provide meaningful decision-support value for naval aviation safety when multiple environmental, aircraft, crew, flight, and organizational variables are analyzed simultaneously. The developed model achieved strong predictive performance, with an accuracy of 91.7%, an F1-score of 88.7%, and an ROC-AUC of 0.93. The distinctive finding is that AI effectiveness should not be evaluated solely through predictive accuracy. User perceptions showed high levels of usefulness and interpretability but comparatively lower decision-support confidence, indicating that aviation personnel value computational assistance while maintaining appropriate caution toward algorithmic outputs. The findings support a human-centered approach in which AI strengthens risk analysis without replacing qualified professional judgment.

The principal contribution of this research is conceptual and methodological through the integration of AI-based prediction, explainable risk assessment, and human-centered decision support within a naval aviation safety framework. The study moves beyond an accuracy-centered approach by demonstrating that predictive performance, interpretability, usability, and institutional governance should be considered together when evaluating AI for safety-critical applications. The proposed framework positions AI as an analytical layer that complements established safety-management procedures, allowing complex risk patterns to be identified while preserving human accountability. This contribution provides a foundation for developing more transparent, evidence-based, and responsible AI applications in aviation safety management.

The study has several limitations that should guide future research. The model was developed using a relatively limited non-sensitive dataset, which may restrict generalizability and the representation of rare or complex high-risk conditions. The findings concerning user perceptions were also based on a limited participant group, while the cross-sectional evaluation cannot establish the long-term effects of AI-supported decision-making on actual safety outcomes. Future research should employ larger and longitudinal datasets, conduct comparative validation across aviation contexts, evaluate model drift and calibration over time, and compare interpretable algorithms with more complex models. Further investigation should also examine AI governance, cybersecurity, data quality, human oversight, and objective measures of decision quality to establish a robust and sustainable framework for AI-assisted naval aviation safety.

## DECLARATION OF AI AND AI ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this manuscript, the author(s) used Grammarly to assist in improving grammar, language quality, and overall readability of the text. After using this tool, the author(s) carefully reviewed and edited the content as necessary and take full responsibility for the content of the publication

## AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.

Author 2: Conceptualization; Data curation; In-vestigation.

Author 3: Data curation; Investigation.

## DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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