2023 Annual Conference & Exposition
Baltimore Convention Center, MD | June 25 - 28, 2023

The Harbor of Engineering
Education for 130 Years

ASEE

Paper ID #37967

Learners' Peer-to-Peer Interactions of Aerospace and Aviation Education with Unmanned Aerial Systems Designs Using Data Methods Integration

Vicleese Sloan, University of Maryland Eastern Shore, Department of Engineering and Aviation Science, Aviation Management Senior Student

My background experience in education with The University of Maryland Eastern Shore has been on two recent applications of model-based learning with developing solutions in mitigating coronavirus in aviation. I've also worked on the 5G Smart City Model for Project Based Learning, also in the Student Model Project Based Learning. AREN/NASA Fellows Internship with the University of Maryland Eastern Shore to include working with Aviation Science Students, Engineering Students, Trio/CCBC Outward Bound Program, for STEM Research and Development all as a DOT Eisenhower Fellowship participant for the Fall 2021. Prior to college my background and experience are Working as a Field Service Representative (FSR) after the military in Information Technology and Services, Defense & Space, and Computer Software. While doing so in working with NATO subcontract as a Wireless Network Technician in their Italian Region contract, then prior to that with NAVSEA as an Electronics External Communications Technician for Research and Development on a Wallops Island contract, prior to that with Testing and Evaluation as an Electronics Communications with NAVAIR/Special Operations as a DOD civilian in the Middle East. Prior to that my experience is from the military working in 101st Airborne Division and Field Artillery as Signal Communications, Signal Communications as an S6 Chief of Combat Networking RF Communications from the Army. Prior to that 1st AD Division Operations, Logistics, Arms Ammunitions Explosives with Physical Security Access and Customer Relations overseas with the Army. Prior to that in Navy Aviation USS Wasp LHD1 and AIMD/IM3/Norfolk as an Aviation Electrician's Mate, Navigational Systems, Helo Automatic Stabilization Equipment Automatic Flight Control Systems I/Level, Configuration Management, and Micro-Miniature Electronics Repair.

Mr. Fasil Tesfaye Amado, University of Maryland Eastern Shore

Fasil Amado undergraduate student at the University of Maryland Eastern Shore majoring in Aviation Science. Interested in aviation research and innovation serving to make changes in the industry.

Cameron Smith
Bryan Stivell Campbell, University of Maryland Eastern Shore
Dr. Willie L. Brown Jr., University of Maryland Eastern Shore

Dr. Willie L. Brown, Jr. is the Vice Provost for Faculty Affairs and an Associate Professor of Engineering and Aviation Sciences at the University of Maryland Eastern Shore (UMES) (Princess Anne, Maryland). Dr. Brown received dual bachelors' degrees regarding a B.S. in Aviation Science and a B.S. in Computer Science from Elizabeth City State University. Dr. Brown received a M.S. in Software Engineering (Aeronautics) from Embry- Riddle Aeronautical University (ERAU) and through the partnership program established by ERAU of aeronautics' disciplinaries, he received a Ph.D. in Business Administration specializing in Homeland Security Leadership and Policy (Aviation Safety and Security) from Northcentral University. Dr. Brown also has received a M.S. in Data Analytics from the University of Maryland Global Campus. Dr. Brown is currently obtaining a M.S in Strategic Communication at the University of Maryland Global Campus.

Lanju Mei, University of Maryland Eastern Shore

Lanju Mei received her Ph.D. degree in the Department of Mechanical and Aerospace Engineering, Old Dominion University. She is currently an Assistant Professor in University of Maryland Eastern Shore. Her current research interests include electrokinetic

Learners' Peer-to-Peer Interactions of Aerospace and Aviation Education with Unmanned Aerial Systems Designs using Data Methods Integration

Vicleese Sloan, University of Maryland Eastern Shore
Fasil Tesdaye Amado, University of Maryland Eastern Shore
Cameron Smith, University of Maryland Eastern Shore
Bryan Stivell Campbell, University of Maryland Eastern Shore
Harry Godwin, University of Maryland Eastern Shore
Sean Irwin, University of Maryland Eastern Shore
Willie L. Brown, Jr., University of Maryland Eastern Shore
Ibibia K. Dabipi, University of Maryland Eastern Shore
Dinesh Kumar Sharma, University of Maryland Eastern Shore
Etahe Johnson, University of Maryland Eastern Shore
Lanju Mei, University of Maryland Eastern Shore
Weiwei Zhu-Stone, University of Maryland Eastern Shore
Lei Zhang, University of Maryland Eastern Shore

Abstract

The work in progress on aerospace and aviation education calls for peer-to-peer interactions and the improvement of project design using data methods using technology integration. The field of aerospace and aviation education is currently undergoing progress and requires peer-to-peer interactions and the utilization of data methods with technology integration to improve project design. This study involves undergraduate students in engineering and aviation sciences who are exploring the design of unmanned aerial systems (UAS) for advancement. The investigation aims to examine the limitations of peer-to-peer interaction using project-based learning methods and offers insight into student capabilities, resources, interest, and connection to course learning outcomes. Through this investigation, the students gained an understanding of the design approach and the integration of UAS, which led to the discovery of the critical need for safety management systems (SMS) and human factors. This, in turn, added to the design process by emphasizing the importance of utilizing SMS and human factors to create awareness of integration challenges and advance technology. The peer-to-peer environments created an understanding that user-friendly design concepts are essential to engineering and aviation education, which is a multidisciplinary effort. To integrate UAS technology into aerospace design, the ability to achieve and maintain a level of security, safety, technology readiness, acceptability, regulatory demands of the mission practice, and management of systems must be considered. In adopting the SMS approach, which was explored through peer-to-peer interactions of project-based learning, the performance measures of system requirements were assessed and established in accordance with standard operations, procedures, and risk mitigation. Additionally, this approach established a feedback loop to improve the design process and

allowed technological advancement to be communicated in a systematic structure.This integration of UAS technology and SMS is explored and written from a student perspective, as it was the result of peer-to-peer interactions and project outcomes of UAS integration in engineering and aviation design requirements for education performances.

Keywords: *Aerospace, Aviation, Unmanned Aerial Systems, Design, Safety Management Systems, Project-Based Learning, Peer-to-Peer Learning, Data Methods*

Introduction

This study explores the use of heterogeneous data methods to combine results and examine the overall performance rates of unmanned aerial systems (UAS) design process using safety management systems (SMS) methods. By assessing operational forecasts, the study suggests that benchmarking various datasets can lead to an integrated framework to investigate peer-to-peer interactions and specific strategies for project-based learning (PBL). PBL methods can be used to combine outcomes and advance aerospace and aviation education for UAS designs, with the goal of creating a strategic decision-making process that supports modeling comparison. SMS techniques can be used to improve analytic practices in PBL. By using data analytics methods to advance aerospace and aviation education, a comparative aspect can be introduced to decision-making regarding human factors in engineering designs. This analysis is a key deliverable in the design phase of PBL strategies and provides a framework for reasoning.

Predictive modeling and data analytics methods are facilitating the emergence of innovations in services from a dynamic perspective. These tools enable the presentation of proposed model results and comparison, allowing for the examination of outputs and interpretation of traditional approaches with new entities and scenarios. Through the exploration of these innovative approaches, further investigation and improvement can be achieved in the practice. The data set utilized in this study has incorporated previous methods with feedback and output results to better examine the various conditions and scenarios of UAS strategies and their overall effectiveness. By leveraging these tools, advancements can be made in the integration of UAS designs into aerospace and aviation education.

Learners’ Peer-to-Peer Interactions in PBL of Aerospace and Aviation Designs for UAS Integration

The user guide for the project solution includes key performance indicators (KPIs) that serve as operational guidelines for assessing the effectiveness of the project outcomes. The KPIs are designed to align each indicator with the project solution and use data analysis methods to evaluate the peer-to-peer interaction in project-based learning (PBL) of aerospace and aviation designs, specifically focusing on UAS integration. The validation of peer-to-peer interaction as a performance measure has led to the development of a framework to enhance flight operation. The four KPIs for measuring the overall effectiveness of the project solution are based on the user guide for rotorcraft systems and include::

- Indicator 1: Investigation of key performance measures and the flight analysis data related to the ability to create an interactive model according to the user’s decision- making approach;
- Indicator 2: Interpretability of the system design requirements and the UAS integration to performance the necessary input to execute in various conditions and limitations;
- Indicator 3: Formulation of data analysis concepts and the system capabilities regarding the

flight dynamics for analysis according to the data collection findings and risk assessment for safety management;

- Indicator 4: Implementation of a safety management system to advance predictability of characteristics as severe limitations to an application will be allowed to indicate the handling of maneuvers and the response performances associated to environmental conditions and parameters.

This project aims to address the aviation safety culture and the increased risk concerns in general aviation by proposing an integrative framework for data analysis. By examining both internal and external operations of UAS systems, this project seeks to establish a formal approach for modeling purposes in engineering education and design. A safety culture environment will be implemented to evaluate human performance and assess significant differences in operation responses through verification and validation. The investigation of peer-to-peer interactions in PBL has the potential to improve data collection strategies based on an integrative framework of aerospace concepts and UAS integration conditions. Overall, this project could have a significant impact on advancing safety in aviation and aerospace engineering.

Background: Data Methods of Imbalanced Target Variables in the UAS Design Process

The design data includes various features aimed at understanding, modifying, modeling, and assessing the presented dataset. To modify the features, replacement and impute functions were implemented and applied to the dataset. The replacement inputs were used to partition the dataset into training, validation, and test sets, with allocations of 60%, 30%, and 10%, respectively. The impute function was used to transform variables, including modified features, using maximum normal and dummy methods, and the transformed variables were used as inputs for the neural network and regression models. To address imbalanced target variables, a cutoff function was connected to each model, including decision tree, logistic regression, and neural network. The cutoff criterion was changed for each of these models, and the results are shown in Table 1. Overall, these data analytics methods were employed to effectively analyze and assess the UAS integration dataset.

Model Results Node: Cutoff	**Probability Obtained**	**Optimal Cutoff Value Applied**	**Transform Variables with Methods**
Decision Tree	Training Data	0.30	No
Neural Network (Model Selection: Misclassification)	Training Data	0.50	Yes
Regression (Model Selection: Stepwise-Validation Misclassification)	Training Data	0.40	Yes

Table 1. Cutoff diagnostic of prior probability results of training data for optimal cutoff value to address imbalanced target variables.

During the development of predictive models, the combination of each data methods node is interpreted using two of the average, maximum, and voting methods. These methods are applied to the decision tree, logistic regression, and neural network models to compare their results [1] [4]. The comparison of the results is based on the train interval target and class target, which are determined by using the following methods [4] [5]. For the interval target, the predicted values are described through the conditions of the data nodes, including averages and maximums [6] [7]. On the other hand, the class target is associated with the predicted values and uses the methods of average, maximum, and voting. The voting posterior probabilities results to the average for each approach. Table two (2) provides a detailed description of the combination of the data nodes used for interpretation and investigation.

Class Target- Posterior Probabilities	**Model Connections and Applied to the Data Node for Results**
Maximum	Decision Tree, Neural Network, and Regression
Average	Decision Tree, Neural Network, and Regression
Maximum	Decision Tree, Neural Network, and Regression
Voting	Decision Tree, Neural Network, and Regression

Table 2. Data node with model result integration design and selection.

Methodology

The methodology used for UAS performance datasets is comparable to understanding individual feature selection methods and complexity measures [2]. This approach from peer-to-peer interactions in PBL environments is combined with design ranking practices. The resulting methods yield a conceptualized UAS design approach to improve analysis and observations for flight operation. The potential performance benefits of re-examining UAS integration in PBL underline the scalability, efficiency, and demands using a scientific modeling approach [2]. The proposed methodology is designed to achieve optimal results of PBL by using a defined user demonstration.

This investigation also provides insight into event classification as a methodology for peer-to-peer environments in aerospace and aviation designs. Using a heterogeneous data approach to address misclassification rates provides an increase in performance due to diversity and accuracy among results and outputs [3]. The methodology offers an interpreted ranking system of misclassification rates as the best approach using engineering design strategies. Identifying that neural network models capture better insight during learning for system deployment was key in creating a heterogeneous approach. This approach was developed to investigate accuracy, structure, and target prediction methods to address complexity by simplifying different features [4] [2].

Results

The study performed event classification and conducted a model comparison to identify the optimal data node method, based on maximum, average, and voting. The comparison included several models, such as decision tree, ensemble-avg, regression, and neural network. The results, presented in a classification chart, showed that the neural network outperformed the other models for SMS methods. However, further analysis revealed that the ensemble-avg method produced superior results for the target "yes" in the classification chart. The findings are summarized in the table below (see figures below).

Model	**Data**	**Misclassification Rate**	**Ranking**
Decision Tree	Train	0.08558	3
Ensemble-avg (voting)	Train	0.085505	2
Ensemble-avg (avg)	Train	0.088471	4
Regression	Train	0.094022	6
Ensemble-avg (max)	Train	0.089577	5
Neural Network	Train	0.082223	1

Table 3. Event Classification models

The study conducted a comparison between the ensemble model results and the current findings, using the ensemble node approach. This comparison aimed to investigate the performance of various techniques, such as bagging, boosting, gradient boosting, HP forest (random forest), and decision tree, as presented in table four (4).

Model	**Data**	**Misclassification Rate**	**Ranking**
Decision Tree (regular)	Train/Validation	0.093658 (Train) 0.102583 (Validation)	3
HP Forest (random forest)	Train (out-of- bag)	0.10418	4
Gradient Boosting	Train	0.09113	2
Bagging	Train	0.121433	5
Boosting	Train	0.19708	6
Ensemble (Bagging and Boosting)	Train	0.08184	1

Table 4. Overall, model comparison results determine the best ensemble model approach.

The study explored the relationship between UAS design and integration by analyzing the models' performance based on their descriptions. The first model comparison involved a decision tree, neural network, regression, and ensemble-avg (max) techniques. The second model comparison included the same models as the first comparison, but with ensemble-avg (avg) added to the mix. Finally, the last model comparison featured a decision tree, neural network, regression, and ensemble-avg (voting) techniques (see figures below).

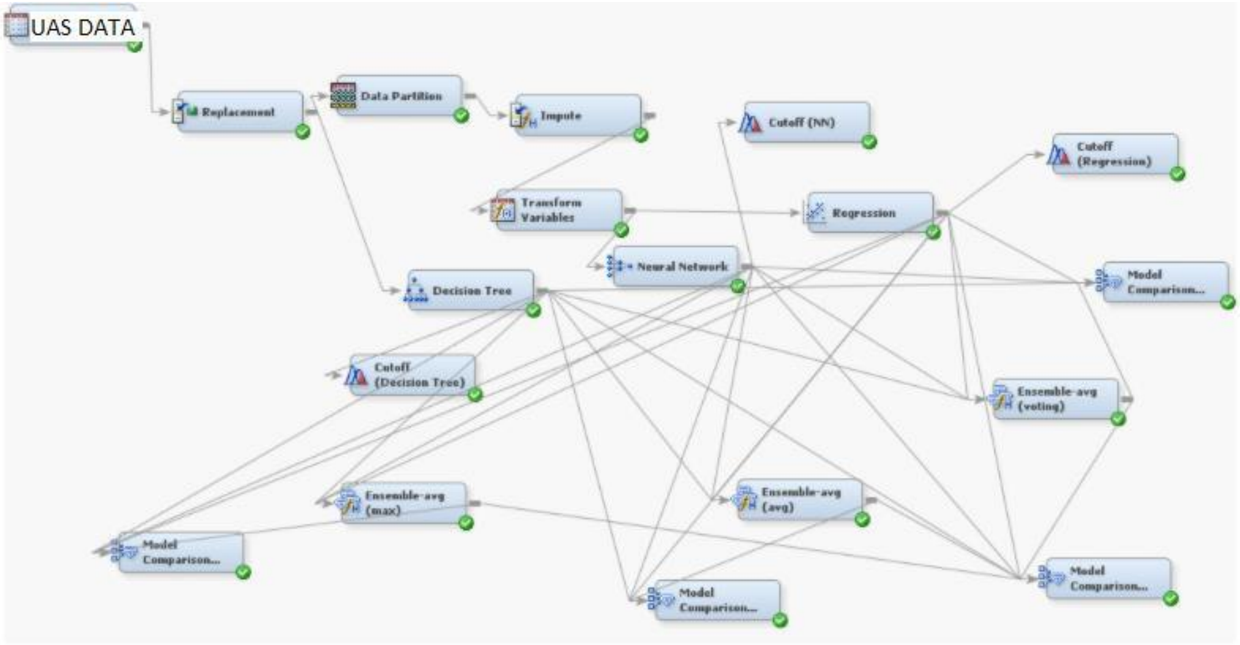

Figure 1. UAS data of the PBL designs to determine integration operational performances using ensemble models in SAS Enterprise Miner

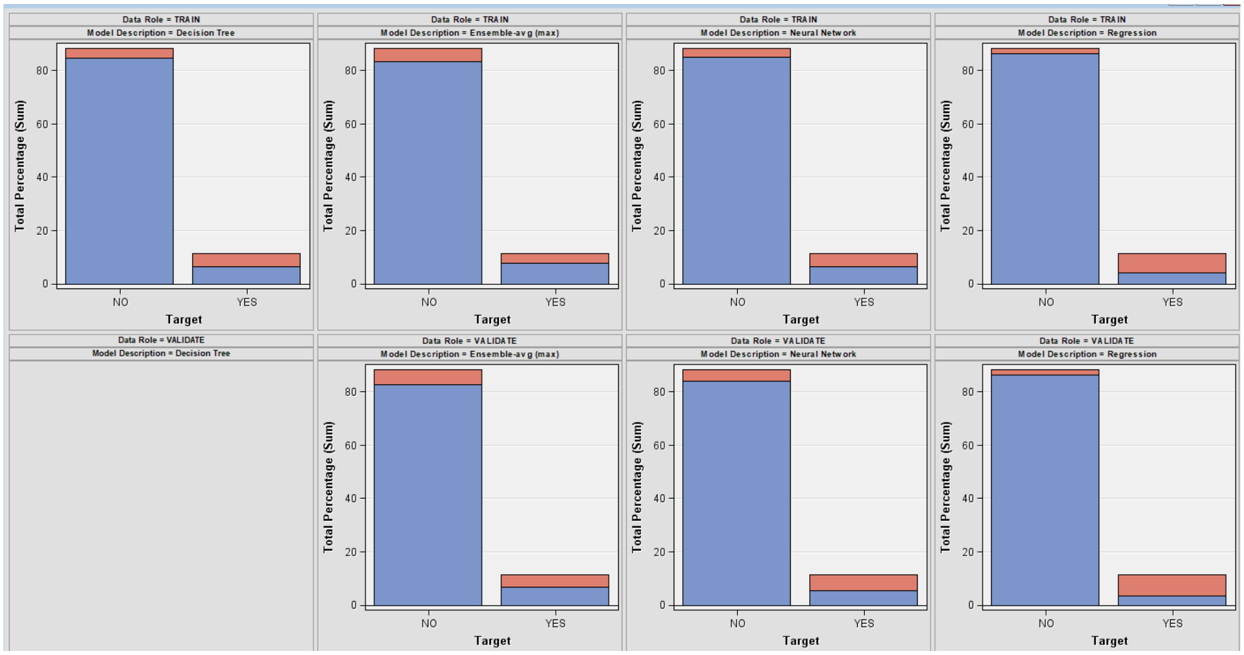

Figure 2. Model comparison assessment classification chart includes the findings of a decision tree, neural network, regression, and ensemble-avg (max).

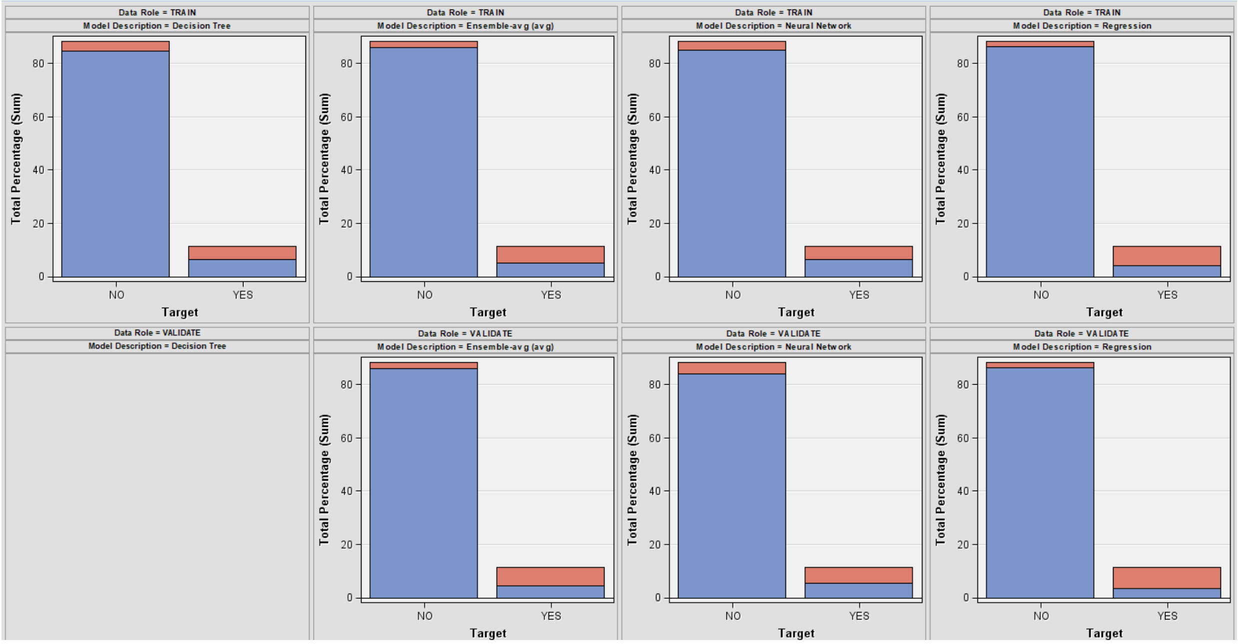

Figure 3. Model comparison assessment classification chat includes the findings of a decision tree, neural network, regression, and ensemble-avg (avg).

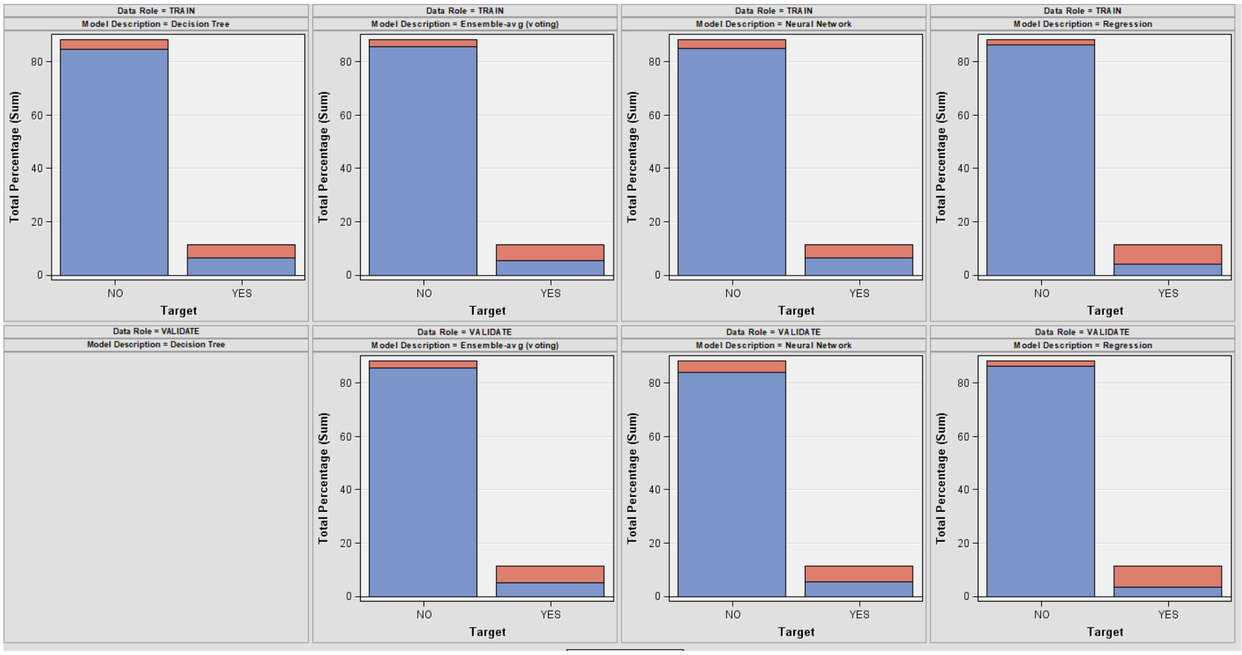

Figure 4. Model comparison assessment classification chat includes the findings of a decision tree, neural network, regression, and ensemble-avg (voting).

Data Set and Findings of the Learners' Peer-to-Peer Interaction

The study collected survey data on learners' peer-to-peer interactions, which was approved by the Institutional Research Board (IRB). The data aimed to investigate PBL and aerospace performance research in the classroom, specifically regarding UAS integration of peer-to-peer interactions. The learners adopted the proposed investigative approach as a theoretical framework for the research. The survey consisted of six categories related to PBL and SMS for UAS integration in aerospace and aviation designs. Each learner's data was analyzed to understand the impact of PBL and SMS on UAS designs in practice (see figures below).

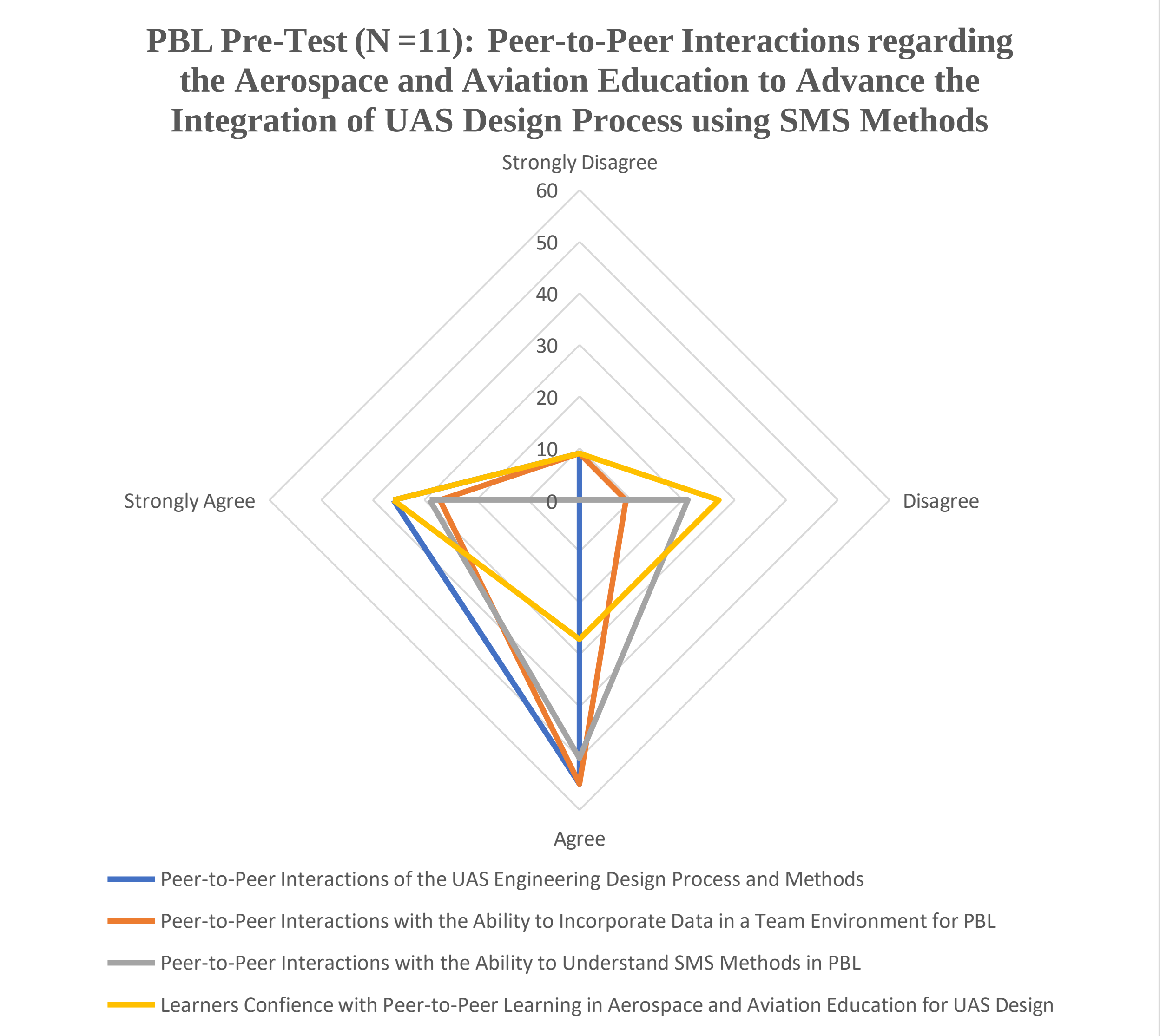

Figure 5. PBL Pre-Test (N =11): Peer-to-Peer Interactions regarding the Aerospace and Aviation Education to Advance the Integration of UAS Design Process using SMS Methods

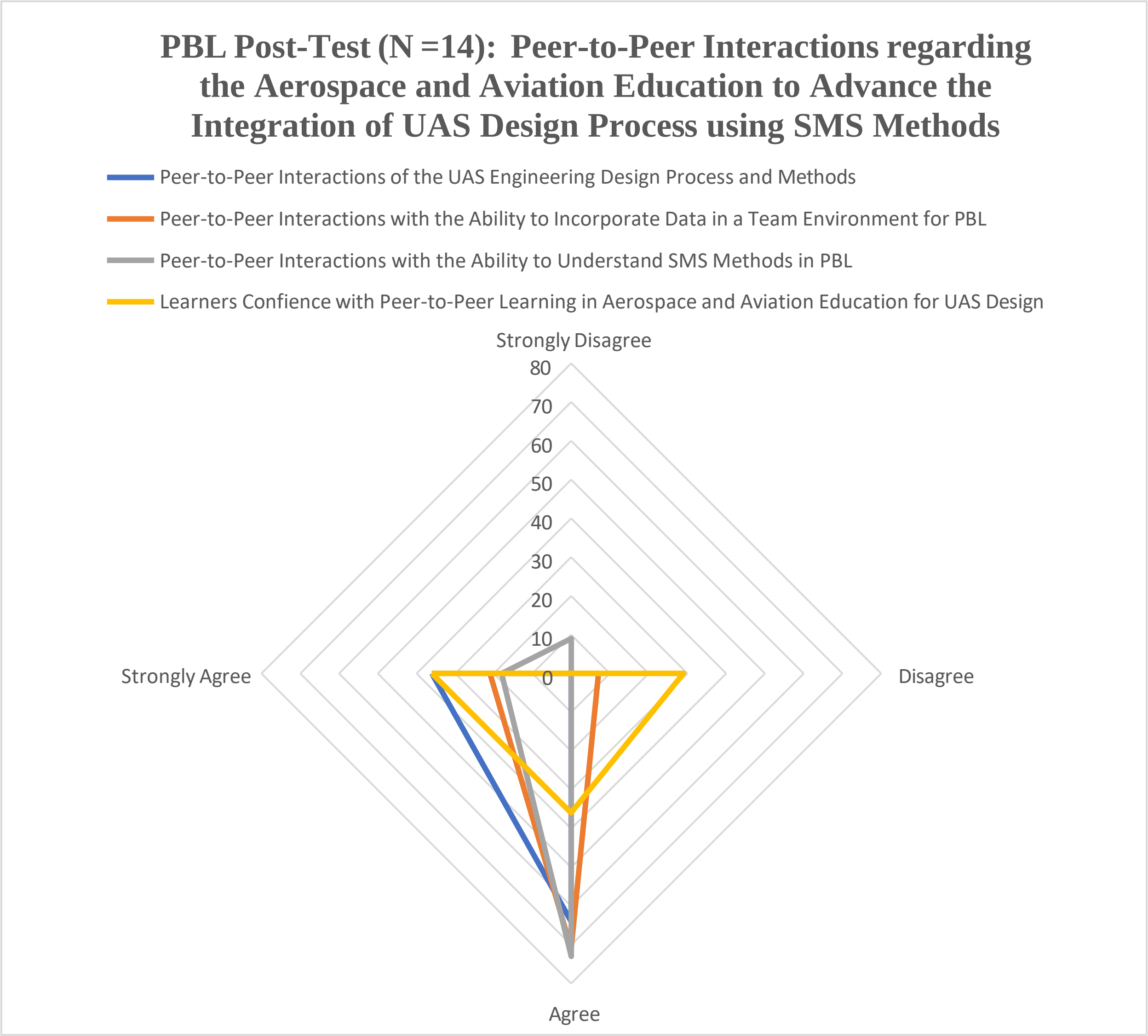

Figure 6. PBL Post-Test (N =14): Peer-to-Peer Interactions regarding the Aerospace and Aviation Education to Advance the Integration of UAS Design Process using SMS Methods

The study found an average agreement among the results of the learners' peer-to-peer interactions survey segments across the categories. The study suggested that applying a methodology to analyze the flying qualities could lead to a level of suitability based on the specifications and criteria of flight test data parameters [5] [6]. To close the loop of the study, a dynamic response design is required to collect input and output spectral analysis data, which is then defined by performance [5] [7]. The study also proposed an implementation design and deployment plan for UAS flight characteristics.

Implementation Design and Deployment of the UAS Flight Characteristics

This gap analysis review highlights the need to develop applications using mathematical modeling to support advanced configuration for the characterization, identification, and analysis of rotorcraft flight maneuvers, including simulated and flight data [6] [7]. To address this need, an integrative framework is proposed to model and investigate flight dynamics, focusing on critical issues related to the handling qualities of rotorcraft systems (see figures seven through nine below) [6] [8]. This approach aims to address the gaps in current research and develop a comprehensive methodology for rotorcraft flight analysis.

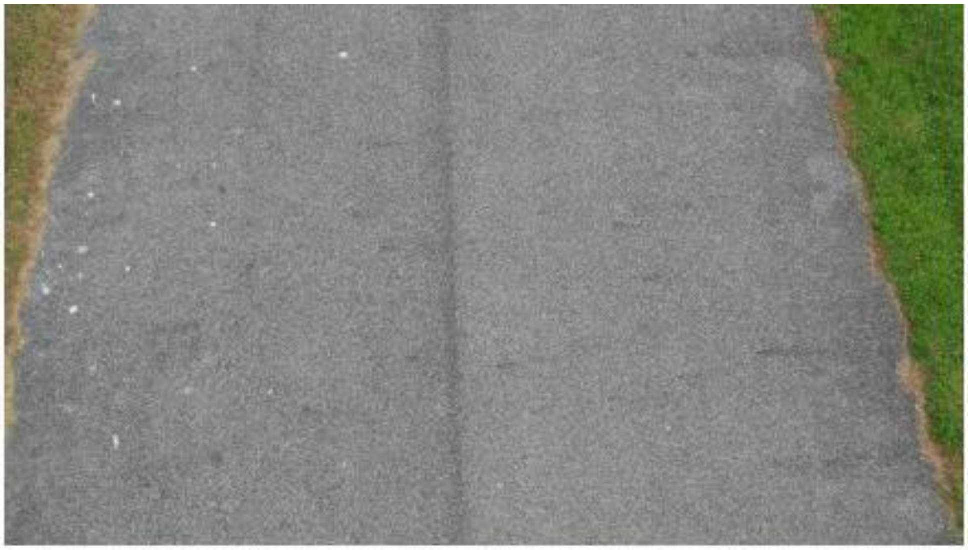

Figure 7. UAS Design Integration and Safety Assessment for 20ft Flight Environments near Airports using Project-Based Learning

Figure 8. UAS Design Integration and Safety Assessment for 50ft Flight Environments near Airports using Project-Based Learning.

Figure 9. UAS Design Integration and Safety Assessment for 100ft Flight Environments near Airports using Project-Based Learning.

The project focused on developing an integrative framework to enhance UAS designs and capabilities in response to hazards, environments, and user performance [8] [9]. The project yielded three key findings, including the implementation of standardized user interactions for data discoveries and recommendations, the integration of complex systems and decision strategies to assess risk under operational conditions, and the exploration of rotorcraft performance through standardized data collection methods to investigate flight parameters. The three (3) finding offered this project the ability to:

a) Implement the capabilities and functional designs to standardize the user interactions regarding data discoveries and recommendations;
b) UAS integration of complex systems and the decision strategies for mission driven requirements and the safety concerns to assess the levels of risk under the operational conditions;
c) Exploration of rotorcraft performance and the emergence of data collection methods to

define a standard investigate the parameters of flight conditions.

Peer-to-peer interaction surveys conducted in classroom environments were used to evaluate the effectiveness of UAS operation and design strategies [7] [9].

Conclusion and Future Implications

Therefore, designing a UAS flight envelope that considers the specific modeling environment and conditions is crucial for optimizing parameters and constraints in aerospace education. An integrative approach that can demonstrate maneuvers from multi-complexity conditions and evaluation based on pilot-in-the-loop feedback is essential for developing such a solution [7]. Additionally, incorporating predictive modeling concepts to influence control laws can lead to a dynamic flight envelope with boundaries that relate to the current conditions, facilitating effective assessment purposes.

In conclusion, the analysis of the relationship between data selection methods and ensemble models enabled the formulation of a measurement based on the degree of difference between training, validation, and test. The study provides practical guidelines for improving data methods and performance, offering insight into the theoretical and experimental examination of the misclassification rate with conditions that satisfy classes for training and validation [8][9]. Furthermore, the study highlights the importance of accurate and interpretable variable selection for conducting a data-independent evaluation and assessment of methods with feature sets. This approach ensures that the misclassification rate of actual data analysis can be scale-adjusted based on pre-specified values and dimensions, resulting in a high degree of accuracy [3][9].

Balancing peer-to-peer interaction and aerospace design is a challenge that can be addressed by recognizing the functions for advancement. As the use of SMS methods in UAS integration increases, it is essential to maintain and improve the goals of project-based learning. Expanding the implementation model can promote a strategy to build a peer-to-peer environment [9].

References

[1] M. C. Dorneich, W. Rogers, S. D. Whitlow, and R. DeMers, “Human performance risks and benefits of adaptive systems on the flight deck,” International Journal of Aviation Psychology, vol. 26, pp. 15-35, 2016

[2] B. Seijo-Pardo, I. Porto-Díaz, V. Bolón-Canedo, and A. Alonso-Betanzos, “Ensemble feature selection: Homogeneous and heterogeneous approaches,” Knowledge-Based Systems, vol. 118, pp. 124–139, 2017

[3] X. Li, J. Zhang, and J. Han, “Trajectory planning of load transportation with multi-quadrotors based on reinforcement learning algorithm,” Aerospace Science and Technology, vol. 116, 2021

[4] L. Zhang, B. Whiteley, D. K. Sharma, I. Dabipi, W. L. Brown, W. Zhu, and X. Tan, “On the exploration of game-based learning in STEM education with the development and application of virtual reality course modules,” ASEE Annual Conference and Exposition, 2017

[5] J. O. Filho and D. Andrade, “Management process of a frequency response flight test for

rotorcraft flying qualities evaluation,” Journal of Aerospace Technology and Management, vol. *8*(3), pp. 289–306, 2016

[6] R. Chen, Y. Yuan, and D. Thomson, “A review of mathematical modelling techniques for advanced rotorcraft configurations. Progress in Aerospace Sciences,” vol. 120, 2021

[7] C. L. Bottasso, and P. Montinari, P. (2015). Rotorcraft flight envelope protection by model predictive control. *Journal of the American Helicopter Society*, *60*(2), 1–13.

[8] C. Collins, N. Andrienko, T. Schreck, J. Yang, J. Choo, U. Engelke, A. Jena, and T. Dwyer, T, “Guidance in the human–machine analytics process,” Visual Informatics, vol. 2(3), pp. 166–180, 2018

[9] X. Lei, and K. Guo, “The model identification for small unmanned aerial rotorcraft based on adaptive ant colony algorithm,” Journal of Bionic Engineering, vol. 9(4), pp. 508–514, 2012