



UTILIZING ARTIFICIAL INTELLIGENCE FOR PREDICTIVE MAINTENANCE IN AIRCRAFT: ENHANCING EFFICIENCY, SAFETY, AND OPERATIONAL RELIABILITY

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Abstract

Artificial intelligence (AI) based predictive maintenance in the aviation is revolutionizing the aircraft maintenance and operation. AI systems can even predict potential faults before they occur by reading data from an array of aircraft sensors, and therefore initiate timely and effective repair initiatives. By applying a proactive rather than reactive strategy, the maintenance expenses decrease, safety increases and unscheduled downtime decreases. Predictive maintenance uses artificial intelligence (AI) by using technologies like machine learning, data analytics, and internet of things (IoT) to keep monitoring and checking the rest state of a aircraft parts continuously. This review lays out in tremendous detail the advantages of AI-based predictive maintenance, its impact on the aviation industry and how it works. Thus, anyone could understand the sense of and great possibilities of the AI predictive maintenance. Predictive maintenance provides a great chance for airlines to save expenses, boost operational effectiveness and safety. The difficulties to put these ideas into practice are far outweighed by their possible advantages. As technology advances, predictive maintenance will become an important facet in modern aviation, allowing airlines to run more efficiently as well as give customers more service. By utilizing cutting edge sensors and data analytics, as well as machine learning, airlines can flip from reactive to proactive maintenance and ensure that at all times their fleet is in top shape. Beyond that, this method makes air travel safer and more reliable which means saving money as well.

Keywords:

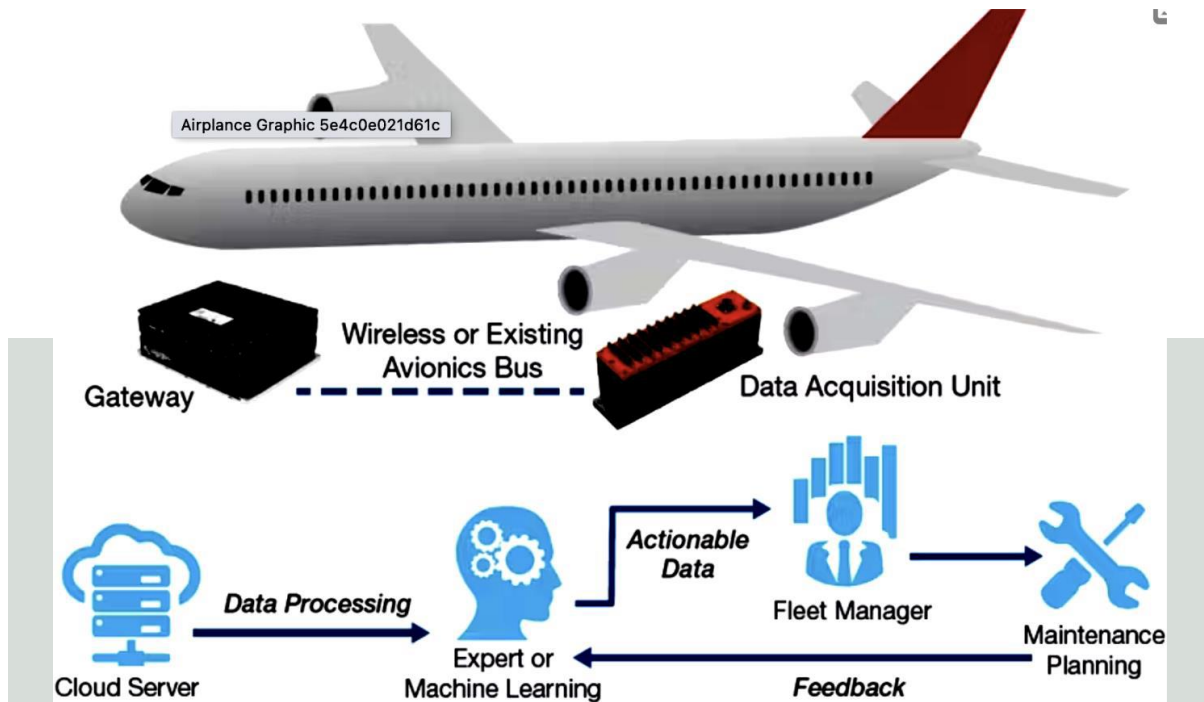
Aircraft Predictive Maintenance, AI, AWS, IoT, Sage Maker Trainings, Prediction Models

1. INTRODUCTION

Since today's consumer is both exceedingly frugal and airlines are facing fierce competition, airlines are under continual pressure to continuously find new ways to cut costs. Airlines can save costs significantly in maintenance area. Recent gains in efficiency have only reduced this surprise maintenance to about 20% of maintenance cost, and an additional 5% fuel consumption. Along with increasing cost, these unforeseen problems similarly tend to aggravate travelers and cause delays. Data analytics and predictive maintenance is a viable way to address such issues. By leveraging new technology to monitor the condition of parts of aircrafts, followed by predicting any faults early themselves, airlines can plan the maintenance more effectively. Such a proactive strategy may both reduce total maintenance cost, increase safety and decrease unscheduled downtime (Aslan, M. E., & Tolga, A. C. (2022). There are challenges in deploying predictive maintenance, however. New technology requires investments from airlines and training for their staff to use the same. They also have to combine information from other sources like sensors and maintenance logs to get a complete picture of the condition of the aircraft. This is due to the fact that deployment of these new technology needs approval from aviation authorities, and thus regulatory and compliance issues are to be considered. The advantages of predictive maintenance outweigh these challenges (INFUS 2022). If used properly, these technologies can allow airlines to save a lot of money, increase the operational efficiency and provide better experience to the customers. With technological advancement, predictive maintenance will be crucial in the future aviation industry.

LITERATURE REVIEW

Predictive maintenance is a clever strategy to keep your aircraft in good running order. Instead of relying on a set maintenance plan, we utilize technology that is able to keep an eye on the aircraft performance in real time. Suppose an aircraft is mounted with a number of small sensors. These sensors amass information concerning anything from component wear as far as engine execution. This data is reviewed by computers for trends and patterns. Anytime something starts to look abnormal, it raises a red flag for us. It also helps us to know the ideal time to replace or repair things before it becomes an emergency (Bachtiar, T. A. (2019). It's safer, it's more effective and it saves the airlines a ton of money. Also, travelers may sleep with one less eye open since their flight is less likely to be cancelled or delayed for unexpected technical problems. Predictive maintenance basically keeps aircrafts in the air while passengers are always happy (Benbya, H., Davenport, T. H., & Pachidi, S. (2020). Predictive maintenance based on operating and operating collected data from each aircraft fused with one another to predict condition of the aircraft's systems. Many aircraft sensors track important variables like air pressure, temperature, speed, and fuel flow. These sensors give some information about whether the system has the highest performance (Buss, A., Pop, C. L., Reid, G., & Kirsch, A. (2020). However, if the data indicates that the avionics system is experiencing problems, then the appropriate repair may be planned at the appropriate time. Ideally, predictive maintenance data should indicate to airlines how much time it will take to a noticeable worsening (again, or in the worst case failure) of an avionics equipment.



The image illustrates the process of predictive maintenance for aircraft using a combination of data acquisition, processing, and actionable insights to improve maintenance planning. Here's a detailed breakdown of the components and their roles:

Components of the Predictive Maintenance System:

Aircraft and Sensors: Of aircraft there are many sensors, onboard aircraft, that is keeping an eye on critical variables such as fuel flow, air pressure, temperature and speed. The real time data collected from these sensors is necessary to determine the condition of all such systems aboard.

The Data Acquisition Unit (DAU) is where the sensors' gathered information is received. This device has to gather and prepare all sensor data for transmission.

The data is sent to the gateway through the wireless or the current avionics bus. It provides this in terms of data flow between the ground system and the aircraft.

The gateway takes the role of a middle man to make it easier for data to leave the airplane and go into the cloud server. By securing data, it assures safe and effective movement of the same.

The data is downloaded to the cloud server, saved and is made ready for processing whenever it reaches the cloud server. Cloud servers also make processing and storage of large amounts of data simpler due to their scalable processing and storage capacities.

Data Processing: Sophisticated algorithms process the data that is saved in the cloud. This processing may involve cleaning, normalizing or doing some initial analysis on the data in order to find abnormalities or trends that will lead to possible issues.

If we are talking about Machine or Expert Learning, it is the Experts or machine learning models that examine the processed data. Machine learning algorithms are taught using historical data to find trends and make failure predictions. They can

predict when maintenance is needed, what condition aircraft systems are in.

Actionable information: Which is the result of transforming data produced by experts or learning algorithms. In this, the information is presented in a clear and practical manner.

For instance, actionable data is delivered to Fleet Managers; those in charge of the fleet in whole, its upkeep, and operation. This information helps fleet managers determine the best way to deploy resources and service schedules.

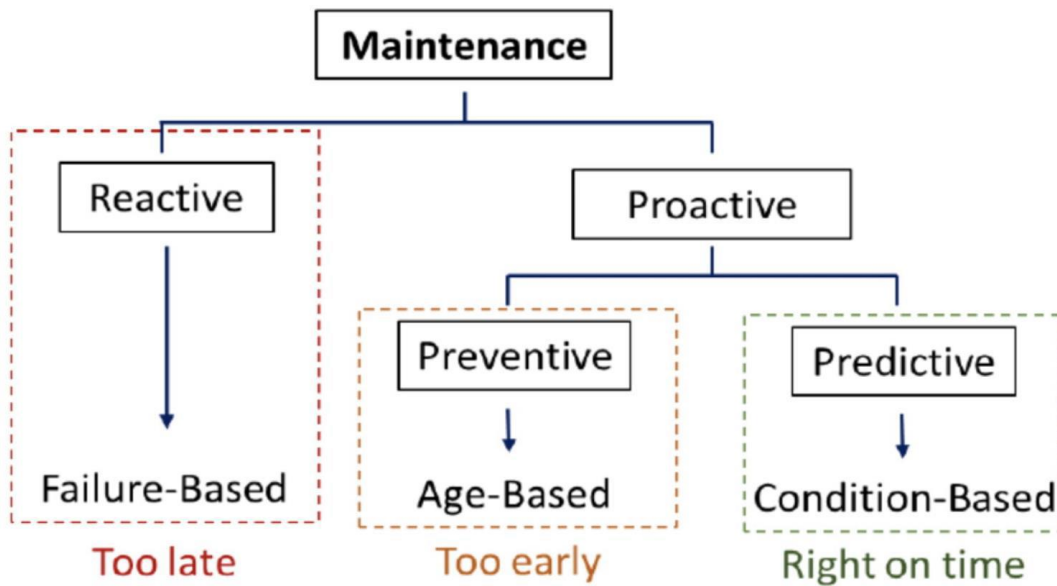
Fleet Maintenance Scheduling: Fleet managers create the schedule for maintenance tasks based on actionable data. Predictive maintenance instead than

scheduling maintenance at predetermined intervals which could be too early or too late, allows for repair only when needed.

This feedback loop allows the outcomes from maintenance operations to be fed back into the system. This ongoing input improves machine learning model and consequently future forecast accuracy.

Aircraft Maintenance: Reactive vs. Proactive Approaches

Aircraft maintenance strategies can be broadly categorized into two main types: reactive and proactive. Each of these approaches has distinct characteristics and implications for operational efficiency and safety.



Reactive Maintenance: Reactive maintenance is also known as failure-based maintenance, in this type of maintenance, repair or replacement is done only after a component fails or breaks. This strategy act too late, it only works whenever there is an issue that needs to be addressed. Since emergency repairs and possible safety hazards may arise at the moment

of this type of maintenance, it will lead to unanticipated downtime and additional expenses (Cheng, T., Wen, P., & Li, Y. (2016, December). Only reactive maintenance can be applied, failure based: if a system or a component failure occurs, it is repaired or replaced. Expensive downtime and emergency repairs may disrupt flight schedules and

passenger satisfaction. Maintenance is carried out only after the problem has occurred leading to safety risk and increased costs of maintenance. Proactive maintenance aims to stop a problem before it starts. Its two subcategories are preventative maintenance and predictive maintenance (European Union Aviation Safety Agency. EASA, (2020). This is planned examinations and substitutions given to a component by age or use. This method might sometimes yield 'pre- mature' maintenance, by changing components before they actually wear out, and hence unnecessarily costs. Components are routinely replaced or fixed irrespective of their true state (age-based). This timetable was based on manufacturer suggestions and historical data. Sometimes Preventive maintenance can cause unnecessary replacements of components and higher costs due to component replacement conditioned on life or use rather than true condition (Gold, H., Faqiri, H., Yeung, J., & Hu, C. (2023, October 8). Real time data and some analytics is used to predict how and when a component will break. This method enables maintenance to be done 'just in time' and thus maximizes component life and reduces downtime.

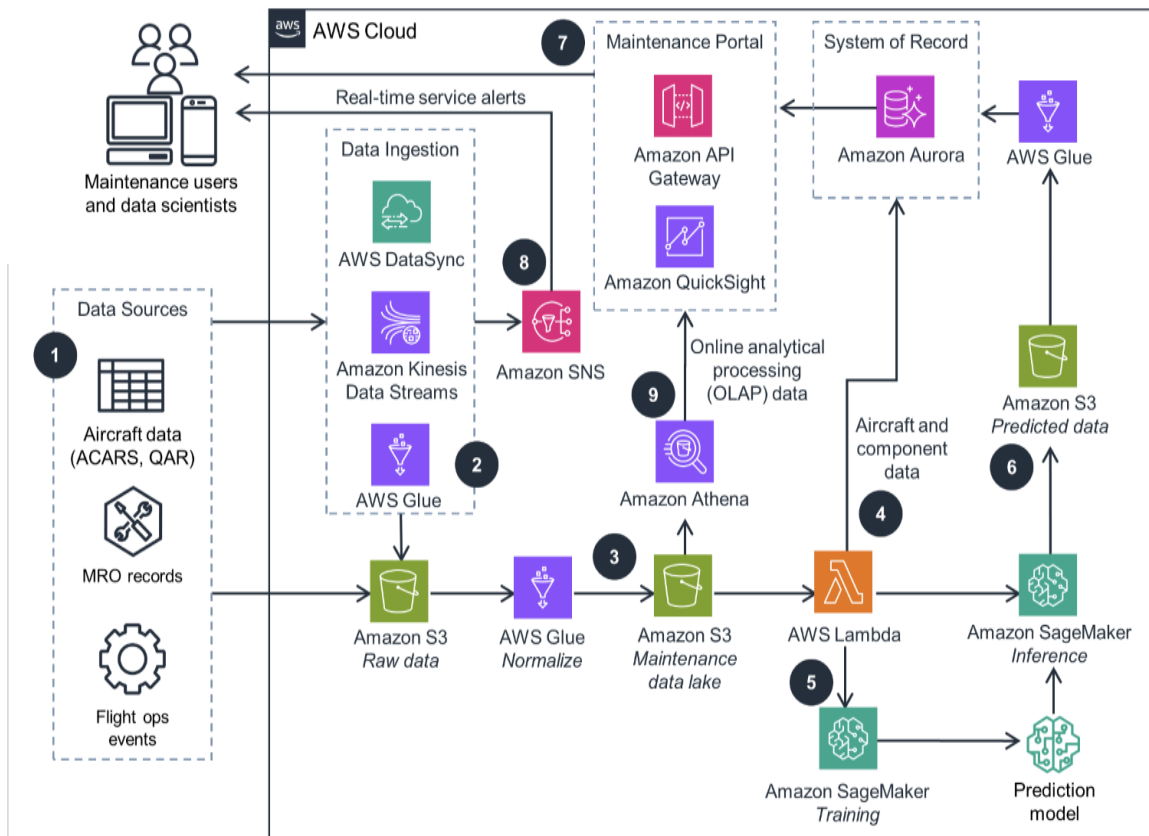
Blind Sensor: A sensor component has no knowledge of the real state of the thing being tracked. Maintenance is carried out only when there is enough evidence on the component to suggest that

it is about to reach the end of the useful life (SumithaK. (2023). Predictive maintenance ensures that parts remain or are replaced at the correct point in time in order to avoid unnecessary expenses and prevent unanticipated breakdowns.

Methodology

Predictive Aircraft Maintenance Using AWS AI Services

This figure shows the whole infrastructure to use AWS AI and machine learning services for predictive maintenance within the aviation industry, and uses a number of AWS products to intake, store, process and analyze various data sources from several sources such as aircraft sensors, maintenance records and flight operation events (Kashyap, R. (2019). The system is built to be able to anticipate probable maintenance requirements and send real time notifications in order to enable preventive measures. This configuration produces a centralized, scalable, and effective solution for saving the health and safety of aircraft by employing Amazon cloud services such as Amazon S3, Sage Maker, and Quick Sight. The aims are to reduce unscheduled downtime, streamline maintenance plan and improve operational efficiency in general (Kulida, E. L., & Lebedev, V. G. (2020).



Data Sources

Diagram Reference: The leftmost section labeled "1" in the diagram.

Details: This point represents the origin of the data used for aircraft maintenance analysis. It includes:

Data from an aircraft (ACARS, QAR): In an airplane’s onboard systems, systems status, flying circumstances and engine performance are monitored. This data is used to understand the aircraft’s past performance and present condition.

The MRO records contain all procedures performed for the maintenance of the aircraft, i.e. inspections, replacements and repairs. It gives a chronicle of the aircraft state and a repair made to the aircraft.

Events related to aircraft operations: Data collected during the course of aircraft operating can include aspects like unexpected alarms in systems or slippage away from the planned itineraries, which may hint at the need to be fixed.

2. DATA INGESTION

The following goes back to the “data ingestion” section, numbered as “2” in the diagram.

Details: The collected data is brought into the AWS Ecosystem.

AWS DataSync: moves historical data into the AWS cloud from other systems or on-premises storage.

Amazon Kinesis Data Streams: Captures and streams data in real time from the aircraft and

associated systems in order to immediately process and analyze this information.

AWS Glue ensures that the data comes in consistently and the quality is good before storing it.

3. Storing Raw and Normalized Data

The diagram reference at "3", is the part that stores the data, "Amazon S3 Raw data", into the "AWS Glue Normalize".

Details:

Amazon S3 (Raw data): It will contain the raw unfiltered data from the intake stage. It contains all the original data obtained from the aircraft and other data sources.

AWS Glue (Normalize) processes the raw data and produces the data in a standardized and usable format. The normalized data is also kept in dedicated "Maintenance data lake" on Amazon S3 for further analysis.

4. SYSTEM OF RECORD

The reference to the Diagram is from the "System of Record" section which has been highlighted and categorized under "Amazon Aurora". The reference is marked as "4".

Details:

The important information relating to the systems and parts of airplanes is stored in the database of Amazon Aurora. It is the go to source of truth for all relevant data like the complete set of specs for the item, its total maintenance history, status in Lifecycle, etc.

5. TRAINING PREDICTION MODELS

Diagram Reference: The process involving "Amazon SageMaker Training," marked as "5".

Details:

Amazon SageMaker: It is used to create and hone machine learning models that forecast when upkeep is necessary. In order to find patterns and signals that point to possible failures or problems, the training process makes use of past data kept in the Maintenance data lake.

6. GENERATING PREDICTED DATA

Diagram Reference: The "Amazon S3 Predicted data" and "Amazon SageMaker Inference" parts, marked as "6".

Details:

The models are able to infer (predict) future maintenance requirements after training. These forecasts' outcomes, including expected component failures or necessary maintenance, are saved as projected data on Amazon S3. Maintenance teams use this information to plan and prioritize preventative maintenance tasks.

7. MAINTENANCE PORTAL

The above diagram location: Maintenance Portal Site is "Amazon API Gateway" and "Amazon QuickSight", which "7".

Details:

Amazon API Gateway: A safe interface that allows to use APIs for accessing data and features. This way the data and models can communicate with other applications, such as the maintenance site.

With visual analytics, Amazon Quick Sight: provides maintenance teams with dashboards and reports. Visualizing the data makes it easier to spot

patterns, problems and find insights in historical and predictive data.

8. REAL-TIME SERVICE ALERTS

The box '8', which is the "Amazon SNS" box, in the diagram reference.

Details:

Amazon SNS (Simple Notification Service): SNS provides real-time notifications once conditions are met or whenever prediction algorithms detect potential issues. These notifications can instantly warn maintenance personnel and other interested parties, so prompt maintenance and intervention is possible in order not to let problems get out of hand.

9. ONLINE ANALYTICAL PROCESSING (OLAP)

Diagram Reference: The "Amazon Athena" section, labeled as "9".

Details:

It makes the data stored in it very accessible for us to analyze it in detail with SQL queries through a service called Amazon Athena. It helps analysts to run Queries like sophisticated Queries on the Amazon S3 data. This could mean in the context of aviation maintenance, trend analysis, root cause investigation or schedule optimization enabled by data insights.

FINDINGS

Implementing Predictive Maintenance

In order to apply predictive maintenance, airlines need to perform couple of crucial actions. They need to install sophisticated sensors on their aircraft in order to monitor several factors as well as gather data in real time (Kumar, M. (2022)). This real time data is needed to keep the health of the aircraft.

Second, airlines need to combine many sources of data, ranging from sensors, maintenance logs to information about how the aircraft is operating. This combined data also provides more specific information regarding the aircraft's operation and or any issues that may have occurred. All gathered data has to be looked into by the airlines using the machine learning algorithms and data analytics. However, they can foresee probable failures and operate particular correctives at the proper time. Another important step is ensuring that maintenance staff and similar other workers have the proper training (Lee, J. D., & See, K. A. (2018)). These people need to understand new technology and data insights so that they are able to understand and use predictive maintenance methods to ensure these methods are employed in time. In the last place, once airlines utilize predictive maintenance technology, they need to work alongside aviation authorities to make sure that it adheres with all the legal criteria and regulations. There are many advantages of predictive maintenance. It may also save money, for example, allowing airlines to predict failures before they occur so maintenance can be done on a planned downtime instead of on bought emergency repair. A raised overall aviation safety, monitoring aircraft in real time and detecting problems in advance, is the key result of predictive maintenance. This also has the added benefit of operational efficiency: predictive maintenance could help airlines make better maintenance scheduling, extending the periods in which an aircraft is in the air and thereby reducing the number of touchdowns for repairs. In addition, airlines that maintain their airplanes well also use less fuel and have less of an environmental impact (Liang, Y., Wang, X., & Hou, J. (2021)). Lastly, the overall travel experience of passengers is improved by fewer cancellations and delays caused by unforeseen maintenance issues.

2. CONCLUSION

Predictive maintenance provides a great chance for airlines to save expenses, boost operational effectiveness and safety. The difficulties to put these ideas into practice are far outweighed by their possible advantages. As technology advances, predictive maintenance will become an important facet in modern aviation, allowing airlines to run more efficiently as well as give customers more service. By utilizing cutting edge sensors and data analytics, as well as machine learning, airlines can flip from reactive to proactive maintenance and ensure that at all times their fleet is in top shape. Beyond that, this method makes air travel safer and more reliable — which means saving money as well.

3. REFERENCES

- Aslan, M. E., & Tolga, A. C. (2022). Evaluation of Artificial Intelligence Applications in Aviation Maintenance, Repair and Overhaul Industry via MCDM Methods. In C. Kahraman, A. C. Tolga, S. Cevik Onar, S. Cebi, B. Oztaysi, & I. U. Sari (Eds.), *Intelligent and Fuzzy Systems. INFUS 2022. Lecture Notes in Networks and Systems (Vol. 504)*. Springer.
- Bachtiar, T. A. (2019). *Hamas: Kenapa dibenci Israel? Hikma*. Bandyopadhyay, T., Sen, S., & Dutta, S. (2018). Artificial Intelligence in Air Traffic Management Systems: A Review. 2018 International Conference on Computing, Power and Communication Technologies (GUCON).
- Benbya, H., Davenport, T. H., & Pachidi, S. (2020). *Artificial Intelligence in Organizations: Current State and Future Opportunities* (December 3, 2020). [Available at SSRN:<https://ssrn.com/abstract=3741983>]
- Buss, A., Pop, C. L., Reid, G., & Kirsch, A. (2020). *User Experience in Unmanned Aircraft Systems: A Survey and Research Agenda*. IEEE Access: Practical Innovations, Open Solutions, 8, 144421–144434.
- Cheng, T., Wen, P., & Li, Y. (2016, December). Research status of artificial neural network and its application assumption in aviation. In 2016 12th International Conference on Computational Intelligence and Security (CIS) (pp. 407-410). IEEE.
- European Union Aviation Safety Agency. EASA, (2020). *Artificial Intelligence Roadmap: A human-centric approach to AI in Aviation*. Retrieved October 12, 2023 from:
- Gold, H., Faqiri, H., Yeung, J., & Hu, C. (2023, October 8). *Israel formally declares war against Hamas as it battles to push militants off its soil*. CNN. Retrieved from
- SumithaK. (2023). “Exploring the Role of Artificial Intelligence in Improving Passenger Satisfaction in the Airline Industry: An Analysis of Customer Feedback and AI-Driven Solutions.”
- Kashyap, R. (2019). *Artificial Intelligence Systems in Aviation*. In T. Shmelova, Y. Sikirda, N. Rizun, & D. Kucherov (Eds.), *Cases on Modern Computer Systems in Aviation* (pp. 1–26). IGI Global.,
- Kulida, E. L., & Lebedev, V. G. (2020). *About the Use of Artificial Intelligence Methods in Aviation*. 2020 13th International Conference “Management of large-scale system development” (MLSD), Moscow, Russia, 2020, pp. 1-5,
- Kumar, M. (2022). *Optimized application of artificial intelligence (AI) in aviation market*. International Journal of Recent Research Aspects, 9(4).
- Lee, J. D., & See, K. A. (2018). *Trust in Automation: Designing for Appropriate Reliance*. Human Factors, 50(1), 97–110.

Liang, Y., Wang, X., & Hou, J. (2021). Understanding User Needs for Artificial Intelligence in Aviation: A User-Centered Design Perspective. *IEEE Access : Practical Innovations, Open Solutions*, 9, 1838–1847.

Liu, Y., Li, Y., Wang, G., & Dong, Z. (2020). A Comprehensive Review of Predictive Maintenance: Issues and Challenges. *Applied Sciences (Basel, Switzerland)*, 10(8), 2847.

Merlo, T. R. (2024). AI and data analytics applications in organizational management. *IGI-Global*.

Patterson, R. E., Broy, N., & Leiden, K. L. (2022). User Empowerment in the Age of Artificial Intelligence: Designing for User Training and Interaction in Complex Systems. *Human Factors*, 54(1), 5–24.

Ranganathan, G. (2023). Airline CEO's AI system for driving personalization. *Journal of Revenue and Pricing Management*, 22, 166–170.

Saballa, J. (2023, October 13). Israel military using new AI system in combat operations: report. *The Defense Post*. Retrieved from

Samatas, G. G., Moumgiakmas, S. S., & Papakostas, G. A. (2021, May). Predictive maintenance-bridging artificial intelligence and iot. In *2021 IEEE World AI IoT Congress (AIIoT)*; pp. 413-419. IEEE.

Smith, A. M., Hancock, P. A., & Clegg, B. A. (2019). Task Load Management: Implications for Human-System Interaction. *Applied Ergonomics*, 74, 234–242.

Stanton, I., Munir, K., Ikram, A., & El-Bakry, M. (2023). Predictive maintenance analytics and implementation for aircraft: Challenges and opportunities. *Systems Engineering*, 26(2), 216–237.