Predictive Data Analytics in Aviation Maintenance: A Cultural Perspective

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ABSTRACT

The use of predictive data analytics in an aviation maintenance environment has been validated as a proven method for improving operational efficiency, safety, and inventory management. The implementation of predictive maintenance processes, however, remains challenging. While the use of predictive techniques has shown clear benefits, a willingness to adopt such practices must exist at all levels to be successful. This paper is the first in a two-part series aimed at evaluating the current perceptions of aircraft maintainers regarding the use of predictive models in scheduling maintenance and repair operations. The results will allow leaders within this industry to effectively communicate the benefits of data-driven analysis, thus improving confidence in predictive solutions. This study also highlights the challenges related to the incorporation of such approaches, including cultural barriers, and provides recommendations for effective implementation in aviation maintenance organizations.

Keywords: Aviation Maintenance · Predictive Maintenance · Data Analytics · Hofstede's Theory

INTRODUCTION

The landscape of the aviation maintenance industry is rapidly changing. Recent technological advances have led aviation maintenance organizations to begin to embrace the concept of including data analytics, as well as the use of artificial intelligence (AI), to improve efficiency, effectiveness, and resource allocation. According to Apostolidis, Pelt, and Stamoulis (2020), the ability to quickly assess data, coupled with ensuring data fidelity are key components in ensuring that aviation maintenance organizations are able to maintain a competitive advantage in the aviation maintenance, repair, and overhaul (MRO) industry. This necessitates the need for big data collection and interpretation in developing and maintaining a predictive aviation maintenance strategy as identified by Badea, Zamfirroiu, and Boncea (2018). Benefits to collecting and utilizing big data include increasing levels of operational efficiency, lowering cost, and reducing the required amount of inventory needed to support maintenance operations (Badea, Zamfirroiu, and Boncea, 2018). While accessibility and data quality are important, it is perhaps just as important to develop a generation of aviation maintenance technicians who can, and are willing to, embrace the infusion of technology and be able to accurately interpret the collected data. Simply put, the benefits that can be realized through the collection and utilization of data in aviation maintenance operations cannot be fully achieved without the acceptance and support of the aviation maintenance technician workforce.

DATA ANALYTICS

HSI The efficacy of these analytical techniques is well established, and it is increasingly clear that the future of aviation maintenance will rely even more heavily on them in the future. This importance, described by Ning et al (2021, p. 923), highlights that "…in commercial aviation sectors, operational, and maintenance data produced on modern aircraft is increasing exponentially, and predictive analysis of these data is an exciting and promising field in aviation maintenance, which has a potential to revolutionize aerospace maintenance industry." Additionally, Ning et al (2021) in discuss how many systems on modern aircraft collect huge volumes of data, commonly through Aircraft Condition Monitoring Systems (ACMS) that collect the operating data of subsystems and components. These data are often transmitted to the ground through the Aircraft Communications Addressing and Reporting System (ACARS) and then either processed in real time or recorded to storage equipment such as Quick Access Recorder (QAR). This vast amount of data collected by ACMS, ACARS, and the QAR must then be effectively analyzed and interpreted if the promises of improved safety, reduced costs, and improved maintenance and operational efficiencies are to be observed. For this purpose, companies like Airbus, Boeing, and GE have developed advanced systems to exploit big data to achieve these gains. These systems include: Airbus's Real-Time Health Monitoring, Boeing's Airplane Health Management, and GE's Predix. These systems are primarily used to compile the data for intelligent analysis at present, and all intend to increasingly employ advanced computing techniques including artificial intelligence and machine learning to further amplify their utility by adding predictive capabilities (Ning et al, 2021).

ARTIFICIAL INTELLIGENCE

HSI Artificial intelligence and machine learning are the primary methods thought to have the most promise to leverage this vast store of data and convert the big data into actionable predictive information. While the employment of these techniques in aviation maintenance is still nascent, this gap is rapidly being filled by aviation maintenance leaders and researchers (Ning et al, 2021).

As one example that is representative of these efforts, consider AI applied to corrosion control. As reported in a study conducted by Brandoli et al (2021), the approaches are very math and logic oriented and employ complex data analysis, statistical methods, and computer algorithm approaches that are not familiar, or traditionally taught, to aviation maintainers. Excitingly, their work permits computer analysis of photographs of aircraft skins to determine areas where corrosion is most likely to be found in the structure underneath. Their research involved employing 210 photographs of Boeing 727 and Airbus 300 aircraft skins and adapting existing deep neural network machine learning algorithms to identify areas where corrosion under the skin was likely with 90.2 to 92.2% accuracy, depending on the computational model employed (Brandoli et al, 2021). From Brandoli et al (2021, p. 13), “the manual visual inspection of aircraft structural integrity has a significant chance of inadequately identifying corrosion, and there is extensive time and human labor involved.” Even in their infancy as applied to aircraft structural maintenance, these techniques highlight how adoption of these tools could completely overhaul the current methods employed by aviation maintainers.

To the extent that maintenance managers and technicians trust the results of these computer-based tools, this will not only help focus limited resources on these areas, but it does so with the promise of reducing indiscriminate non-destructive inspection (NDI) requirements while enhancing safety in early and more precise identification of these anomalies.

While the literature clearly demonstrates the growing interest in, and application of, data analytics and artificial intelligence in the field of aviation maintenance, along with clear evidence of their effectiveness, there is a gap in understanding how these approaches are being accepted by maintainers actually scheduling and doing the work. Filling this gap is important to optimize the effectiveness of big data techniques through synergies between the automated systems that increasingly recommend maintenance and the technicians charged to perform that maintenance.

HOFSTEDE'S THEORY OF CULTURAL DIMENSIONS

As noted by Huang et al (2019), culture can influence how one perceives technology use. Furthermore, Huang et al. utilized Hofstede’s Theory of Cultural Dimensions in their research to assess how culture influenced the acceptance, and use, of technology in Chinese and Spanish universities (Huang et al, 2019). With a major training and education presence in Europe, Asia, South America and the United States, Embry-Riddle Aeronautical University (ERAU) is uniquely positioned to investigate how cultural difference may impact the willingness of technicians to trust and adopt new technologies and approaches in the practice of aviation maintenance. To this end, an initial investigation was conducted among ERAU maintenance students from the United States and Singapore. The survey was limited to 25 respondents and served the purpose of gathering feedback on the initial survey questions, as well as in identifying post hoc analysis methodologies.

Hofstede’s Theory of Cultural Dimensions has been used by researchers (Krishen et al, 2021; Mohammed and Gurvirender, 2017; and Rojo et al, 2020) to determine the role of cultural dimensions in multiple industries. However, a gap in research currently exists regarding the impact of cultural dimensions on technology acceptance and utilization by those functioning within the aviation maintenance industry.

Hofstede’s Theory of Cultural Dimensions consist of Power Distance Index (societal acceptance of inequality among its’ members), Individualism versus Collectivism (focused on the extent to which individuals should take care of themselves versus family, group, or team members), Masculinity versus Femininity (the amount of competitiveness versus nurturing within the society), Uncertainty Avoidance (acceptance of change and newly emerging ideas), Long Term versus Short Term Orientation (the extent to which members choose norms over a future-driven approach), and Indulgence versus Restraint (enjoyment versus restraint) (Huang et al, 2019).

Utilizing the Country Comparison Tool provided by Hofstede the following comparisons can be made, as shown in Table 1, between the United States and Singapore. Based on each country’s score the largest cultural dimension gaps exist in the Power Distance, Individualism, Masculinity, Uncertainty Avoidance, and Long Term Orientation dimensions.

Table 1. Country Comparison of United States and Singapore. *Note.* Adapted from "Hofstede's Cultural Comparison Tool" [5].

Cultural Dimensions	United States Score	Singapore Score
Power Distance	40	74
Individualism	91	29
Masculinity	62	48
Uncertainty Avoidance	46	8
Long Term Orientation	26	76
Indulgence	68	46

RESEARCH PURPOSE, QUESTION, AND HYPOTHESIS

The focus of this first study was in developing an initial survey mechanism and analysis methodology for examining the influence of cultural differences on one's willingness to accept emerging predictive maintenance practices. Subsequent research will specifically consider maintenance professionals living in the United States, Germany, Brazil and Singapore. An expanded Hofstede country comparison, focused on Uncertainty Avoidance and Long Term Orientation, will also be conducted to include Germany and Brazil. The future study will seek to answer the following questions and accept or reject the following hypotheses:

R1: To what extent does national culture impact aviation maintenance technician acceptance of "predictive technology" for scheduling aircraft maintenance.

H1: Aviation maintenance technicians from the United States will have a statistically significant difference in perception regarding the use of "predictive technology" in scheduling aircraft maintenance than those from Europe, Asia and South America.

R2: To what extent does national culture impact aviation maintenance technician acceptance of "predictive technology" for assisting in (e.g. troubleshooting) aircraft repairs.

H2: Aviation maintenance technicians from the United States will have a statistically significant difference in perception regarding the use of "predictive technology" for assisting in (e.g. troubleshooting) aircraft repairs than those from Europe, Asia and South America.

METHOD

For this initial investigation, an 8 question survey was completed by 28 Embry-Riddle Aeronautical University (ERAU) maintenance students located either in the United States or Singapore. The survey questions gathered 5-point scale Likert responses on familiarity with the terms “data analytics,” “artificial intelligence,” and “predictive maintenance,” as well as an individual’s confidence level in leveraging predictive technologies for scheduling, troubleshooting and assisting in aircraft maintenance. Remaining questions more specifically targeted education and training support available. Demographic data regarding race, gender, and aviation maintenance experience were also obtained.

RESULTS

As the sample size of this initial investigation was limited to 28 respondents, the ability to analyze data through the use of inferential statistical models was compromised. However, the results did yield indicators which highlighted potential cultural differences in the respondent’s willingness to allow “predictive technologies” to assist in the repair of an aircraft versus in determining when said repair should occur. This is potentially significant as a primary benefit, if not the primary benefit, of predictive technologies is realized when “just in time maintenance” (JIT) is conducted vice routine, preventive repair based upon traditional approaches such as established maintenance intervals bases solely on mean time between failures (MTBF) scheduling. The advantages in terms of productivity and predictability through the use of JIT scheduling have been realized by the logistics industry (Kannan and Tan, 2004; Towill, 1996). Additionally, Towill (1996) reports that, by utilizing a JIT approach, a 50% reduction in forecasting errors could be realized further supporting the position that a JIT approach, supported by data analytics, could lead to more efficient and effective aviation maintenance operations. Smart sensors gathering unique data sets on individual aircraft flight history, combined with artificial intelligence (AI) interpretation of those data, requires a greater degree of trust when scheduling a repair as compared to using the information to assist a maintainer during routine inspections and to troubleshoot potential malfunctions. This drives the question regarding to what degree, if any, cultural differences influence the maintainer’s degree of trust in fully recognizing the benefits that can be achieved by adopting a data-driven approach to JIT aviation maintenance.

Of the 28 respondents, 26 were male, 2 were female; while 21 had active-duty military aviation maintenance experience and 7 had no active-duty military aviation maintenance experience. Seventeen (17) reported fewer than 5 years of maintenance experience, five (5) reported between 5 and 10 years of experience, three (3) reported between 10 to 15 years of experience, and three (3) reported greater the 15 years of maintenance experience. Twelve (12) identified themselves as Caucasian, 3 identified themselves as Asian, 2 identified themselves as Black, 1 identified themselves as Latino and 10 responded identifying themselves as “other”. Based on the number of military respondents in the current study it is not surprising that familiarity with the term “predicative maintenance” was greater than that of “artificial intelligence” and much more than “data analytics.” This could be based in part on the military’s aviation maintenance approach where terms such as predictive, condition-based monitoring, and proactive are found in United States Air Force aviation maintenance management publications and discussed as a maintenance-management practice (Teeter, 2021). Confidence in technicians using predictive technologies to troubleshoot issues was significantly higher than in scheduling repairs.

DISCUSSION

The adoption of predictive maintenance practices is underway within the industry and may offer significant operational and business savings (Basora, Olive, and Dubot, 2019). As Sanghavi reports in [123 “with 10 times return on investment for aviation companies and a potential 70 to 75 percent reduction in airplane breakdowns, there is a clear case for automated predictive maintenance in the aviation industry.” Despite compelling evidence from cost-based predictive maintenance models that indicate potential significant savings as compared to traditional approaches, the industry is yet to realize the actual benefits of the technology (Manco et al, 2021; Hirshman et al, 2020). In part this is do to hesitance among frontline workers to embrace change (Hirshman et al, 2020).

Operationally, traditional preventative maintenance schedules may be better optimized at the fleet, aircraft, system and component levels. This allows for shorter maintenance downtimes and more flights in between repairs. All of which help the profit bottom line. As highlighted by Sanghavi (2016, p. 33), “42% of delayed flights are caused primarily by airline processes, such as maintenance. When you take into account that a grounded plane can cost an airline $10,000 per hour, an efficient predictive maintenance process to reduce downtime for an aircraft can same millions of dollars each year.” Additionally, system level sensors can pinpoint decreases in component operating efficiency, allowing technicians to quickly locate systems requiring a minor “tune up.” Such procedures allow aircraft maintainers to reduce the level of entropy in components and systems, allowing aircraft to operate at peak efficiency for longer periods of time and yield savings in fuel and replacement/repair costs. Improvements in sustainable operations with lower carbon emissions may also be realized.

However, in order for these benefits to be realized, predictive maintenance technologies and methodologies must be accepted by individuals at all levels of the decision-making process within the organization. Undeniably there exists risk and uncertainty with these new practices, as it accompanied by any new change to an existing system (Kotter and Von Ameln, 2019). That is the tradeoff at hand and is complicated by the multi-faceted nature of the problem. Aircraft are not simple machines. They are a complex integration of systems (e.g. structural, aerodynamic, and electrical) made of advanced materials, computer software algorithms, avionics, and more. There exists component and system redundancies, factors of safety, varying flight profiles, weather exposures, etc. Statistical uncertainty in failure rates, combined with risks associated with failure, makes conservative policies logical, but ultimately fail to take advantage of emerging technologies and improved maintenance practices.

In this study, we consider the willingness of maintenance technicians to adopt emerging predictive maintenance practices. Moreover, the investigation questions whether geographic region and culture influence adoption rates. Using Hofstede's cultural dimensions of uncertainty avoidance and long-term orientation, aircraft maintainers from the United States and Singapore were provided an initial survey in order to better understand regional biases, as well as to inform future research methodologies. Based upon the survey results received, there exist indications that the rate of adoption may have a varying cultural dependence when considering the specific application of the maintenance practice. In particular, differences in troubleshooting, assisting, and scheduling were identified. As examples:

Troubleshooting. With an aircraft hangered for regularly scheduled maintenance, how comfortable would a technician be to leverage "advice" from data analytic algorithms or artificial intelligence sources to help pinpoint and/or prioritize a repair?

Assist. With an aircraft hangered for regularly scheduled maintenance, how comfortable would a technician be to leverage "advice" from data analytic algorithms and artificial intelligence sources to guide and/or direct the repair?

Scheduling. How comfortable would a technician be to leverage "advice" from data analytic algorithms and artificial intelligence sources to delay a routinely scheduled repair?

CONCLUSIONS AND RECOMMENDATIONS

Based upon an initial survey of 28 maintenance technicians from the United States and Singapore, there are indicators of a possible cultural disparity in one's willingness to take advantage of emerging predictive maintenance practices. The cultural distinction, however, seems predicated on the specific level of maintenance practice being considered. While the survey sample size was not sufficient to draw statistical inferences, this initial investigation served its intended purpose of informing the development of a future survey instrument and more so in helping to define the range of methodologies for evaluating subsequent results in relation to the Hofstede's Cultural Comparison model.

As a result of the current research a follow on survey is being prepared and will consider aircraft maintainers from four regions: the United States, Asia, Europe and South America. The subsequent study will first identify cultural differences in terms of one's acceptance of change and newly emerging ideas as well as the extent to which members choose norms over a future-driven approach. Secondly, the post hoc analysis will examine any statistically significant differences in predictive maintenance cultural adoption for troubleshooting, repair assistance and scheduling.

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