RESEARCH AND TECHNOLOGY CHALLENGES FOR HUMAN DATA ANALYSTS IN FUTURE SAFETY MANAGEMENT SYSTEMS

Chad L. Stephens Lawrence J. Prinzel III, Ph.D. Kyle K. Ellis, Ph.D.
Michael J. Vincent Samantha I. Infeld Ph.D.
NASA Langley Research Center
Hampton, VA

Nikunj C. Oza, Ph.D. Misty D. Davies, Ph.D. Robert W. Mah, Ph.D.
NASA Ames Research Center
Moffett Field, CA

Paul A. Krois, Ph.D.
Crown Consulting, Inc.
Aurora, CO

James Ackerson
Flight Research Aerospace
Louisville, KY

Enabling new and novel concepts of operations for Advanced Air Mobility poses an important need to evolve current safety management systems (SMS) and is posited to be realized through advances in Machine Learning (ML) Data Sciences and Artificial Intelligence. The "In-time Aviation Safety Management System" (IASMS) concept of operations supports the need to evolve today's SMS to become more tailorable, scalable, and interoperable in response to forecasted changes expected for the future airspace system. Key to IASMS is integration of proactive and predictive ML algorithms trained to provide "in time" detection and mitigation of hazards and emergent risks through new methods and novel data types. IASMS research and technology development includes human factors design considerations for these systems to include human-system teaming, innovations in human interfaces and management of complex digital data information, human-system interaction/model-based system engineering, and verification and validation for data assurance and trust.

Expanding future sustainable operations for today's commercial air carriers, combined with envisioned transformations of the National Airspace System (NAS) integrating Urban Air Mobility (UAM) and other innovations that lead to Advanced Air Mobility (AAM), pose significant opportunities for advancing today's Safety Management Systems (SMS) (Prinzel et al., 2021; Ellis et al., 2022). Today's data aggregation, risk assessment, and decision making typically involve data assessed in silos with limited cross-silo comparisons. These and other constraints limit scalability and rapid identification of known and emergent risks. This time scale subsequently results in more time taken before mitigations can be determined and implemented. The augmentation of today's SMS forms part of the foundation of the In-time Aviation Safety Management System (IASMS).

Advanced data analytics technologies, as part of the SMS toolbox, can significantly enhance the human's capability to evaluate the growing volume of available safety data . The National Academies of Science (2018) argued that envisioned changes to the NAS, within the next decade or two, will vastly outpace the ability of the current system to identify precursors, anomalies, and indicators of early hazard emergence and risk; the organization argued that safety analysis will need to become more "in time" and integrated than exists today. To address the recommendation and to help achieve the Federal Aviation Administration (FAA) (circa 2035) and National Aeronautics and Space Administration (NASA) (circa 2045) visions for a transformed NAS, significant investments will be needed in Machine Learning (ML) Data Sciences and Artificial Intelligence (AI) methods that can provide needed in-time safety data analysis capabilities. However, the change also affects the role and responsibilities of the human analyst that currently is responsible for a large majority of monitoring, assessing, and decision-making (for mitigation or actions, if any, that need to be taken based on assessment of the risk or hazard). The future of integrated safety management and assurance will rely more and more heavily on big data analytics that will challenge, if not be impossible, for the human analyst to fully understand the underlying methods/process for the ML-based data outcomes. It is envisioned that, for the foreseeable future, the human will retain responsibility for what decisions are made on actionable data, but also of necessity may have to accept more reliance and trust in the system. The present paper discusses IASMS research and technology development needs for ML and data visualization with specific focus on human factors "use, misuse, disuse, and abuse" design considerations and concerns potentially involved with advanced data analytic systems (Parasuraman & Riley, 1997). Existing guidance may serve to mitigate some of these known historical human-system interaction issues. However, progress in innovations on how to achieve human-autonomy teaming in design and practice and new modeling and system engineering/integration will be critical to IASMS success (Ellis et al., 2022; Holbrook et al, 2020; NASA, 2022).

The FAA Concept of Operations (ConOps) for an information-centric NAS (ICN) takes an expansive, layered Integrated Safety Management approach to safety controls, data, and risks resulting from the integration of distributed and diverse systems (2022). As part of an ICN (circa 2035), timely analysis will correct issues at system boundaries and adapt the system to changes in risks or the operational environment. Safety management with new entrants will scale enabled by interoperability across air vehicle operations with their diverse performance and mission requirements.

Further, NASA foresees a "Sky for All" NAS (circa 2045) having a cornerstone for in-time Integrated Safety Management Systems and Safety Assurance (through verification and validation and new certification approaches) that will integrate monitoring and assessing known and emerging hazards, mitigating risk, and assuring the safe performance of the future aviation system (FAA, 2023; NASA, 2022). This includes establishing standards and metrics for the safety data architecture and management, integrating hazards monitoring for situation awareness and developing simulation tests for validating systems and performance-based airspace functional requirements and guidance for new operations, leveraging predictive modeling and cooperative in-time crowd-sourced information using ML-based automated systems identification of risks and mitigations. The maturation of in-time integrated safety management provides Safety for All with seamless, integrated and highly autonomous safety mitigation.

NASA has been maturing the IASMS concept to augment current SMS relative to forecasted changes of the NAS as recommended by the National Academies (2018). These changes include fusing existing, new, and underutilized data sources and adopting increasingly sophisticated data analytics and ML. With this architecture, IASMS will more quickly monitor and assess large data sets to identify known and emergent risks in-time for implementing risk mitigations. This vision for IASMS, viewed through the lens of the FAA ICN ConOps, highlights the tailored safety for different sized operators flying diverse aircraft and missions and the in-time safety assurance of automated systems with their safety-critical technologies.

SMS for Commercial Air Carriers

Enabling future visions of the NAS poses an important need to augment the current SMS to take advantage of integrating advances in ML and Data Science and meet the needs of in-time safety management. The concept of SMS was established by the International Civil Aviation Organization (ICAO) establishing policies and procedures requisite for managing safety (2018).

The FAA provides guidance and methods for developing and implementing an SMS through Advisory Circular (AC) 120-92B, titled "Safety Management Systems for Aviation Service Providers." (2015). The AC shows how a commercial air carrier can show means of compliance for meeting federal SMS regulations although there could be other means to meet requirements. Keys to a successful implementation of SMS include how data and information are analyzed and interpreted, how informed decisions are made, and how it leads to new operational and business methods. Another key is scalability of SMS relative to the size and complexity of the air carrier. FAA-sanctioned SMS programs include Flight Operations Quality Assurance (FOQA), Aviation Safety Action Program (ASAP), Aviation Safety Reporting System (ASRS), Line Operations Safety Audit (LOSA), and Continuing Analysis and Surveillance System (CASS). FAA AC 120-103A addresses fatigue risk management systems.

Aviation Safety Data Analysis and Sharing Systems

Commercial air carriers and other stakeholders share confidential and anonymous SMS data through the Aviation Safety Information Analysis and Sharing (ASIAS) system to improve NAS-wide safety. ASIAS aggregates data from carriers with data analysts manually fusing data sets together to undertake targeted and prioritized studies of safety issues. With today's SMS, an air carrier typically collects and analyzes data within the data silos built for different SMS methods. Analysts review their data and compare trends with analysts working with data from other methods. Data boards, management boards, safety executives, and others lay eyes on trends, make comparisons, ask questions, discuss operational conditions and risk controls, and decide on possible risk mitigations.

FAA planned evolution of ASIAS from today's system, called ASIAS 1.0, to future visions called ASIAS 2.0 and 3.0, is foreseen to replace today's data silos with integrated fusion of disparate data sources including using new and underutilized data sources (Office of Inspector General, 2021). Manual data analysis will be replaced with faster analysis using higher volumes and more varied data. ASIAS 3.0 will transform collaboration with more agile, innovative interactions with new communities and use increasingly sophisticated predictive analytics and advanced tools to identify emerging risks. ASIAS efficacy will increase through decision fusion leading to predictive safety and prescriptive risk mitigation.

Data Challenges

Commercial air carriers face numerous challenges with data coming from the range of SMS methods. Challenges include using new and underused sources of data, fusing data using novel techniques, and developing and verifying predictive analytic models. These challenges are compounded by the large volume of data associated with radar tracks of flight trajectories and weather data. The velocity of data involves the fast flow of these data types to be logged and stored each month. The veracity of the data relates to its variable fidelity, including missing data, duplicate tracks, tracks ending in midair, and reused or duplicate flight identifiers. Lastly, the variety of data spans numerical types (e.g., radar or Global Positioning System), air traffic control or aircraft voice recordings, textual voluntary safety reports, radar and airport meta data, and actual and forecast weather data.

Data Analytics

Data analytics involve different ML algorithms and statistical methods applied to the previously identified common performance data sources (e.g., FOQA data). Analysis may focus on known adverse events and identifying their precursors and associated trends, or be exploratory to identify hidden anomalies or emergent trends using predictive analytics. While there is a need for increasingly autonomous fusion of aviation safety data and advanced data analytics, these processes would be managed by human decision-makers to ensure acceptability and practicality of any findings. In other words, findings may be statistically significant but of limited operational value, or have high operational value even though there may be limited operational data to achieve statistical significance.

Unsupervised learning can identify existing topics and emerging trends. The methodology involves automatically parsing a report's narrative and partitioning narratives based on operational relevance and not according to some a priori taxonomy. Findings showed that maintenance reports; flight attendance reports; and cabin smoke, fire, fumes, or odor incidents were most consistently separable possibly due to the different vocabulary used compared to other reports.

Voluntary safety reports can also be analyzed using natural language processing (NLP). One air carrier successfully applied NLP to aircraft maintenance to improve safety and efficiency involving coding voice transcriptions of mechanics' findings and actions (Carvalho, 2022). An NLP study of safety reports on losses of separationcoded free-text narratives based on the Toolkit for ATM Occurrence Investigation taxonomy and found that unsupervised topic modeling successfully detected unknown recurrent behaviors or conditions (Buselli et al., 2022). Results reframed human behavior from being a sequence of errors leading to an undesired outcome and instead showed safety events to be emergent from complex interactions of the system.

Anomaly detection involves methods allowing FOQA or FOQA-like data to "speak for themselves" in revealing trends leading to degraded system safety and performance. The conundrum is that a complex engineering system involves multiple interdependently functioning components so the variety of ways in which problems can arise can be complex. Consequences from degraded or failed performance can result in damaged equipment, human injury, or other unacceptable outcomes. Oza et al. (2021), for example, used data containing nominal and anomalous states to identify statistical anomalies and the precursors that could be disrupted to mitigate the anomalies. Findings showed that anomaly detection with domain expert validation of the operational significance of identified anomalies can effectively detect and explain operationally significant anomalies during operations. These methods automatically identify precursors and allow domain experts to effectively explain their undesirable effects. This study demonstrated effective teaming of human domain experts trusting ML algorithms to identify sequences of events that lead to anomalous operations.

LOSA observations are coded using an extensive taxonomy comprised of threats, errors, and undesired aircraft states. Coded data are analyzed for prevalence as the percentage of flights involving particular threats, errors, and undesired aircraft states, and mismanagement as the percentage of taxonomy codes leading to a flight crew error. Important trends can be identified such as based on higher prevalence, mismanagement, or demographic factors (e.g., city pairs, fleet). For example, the LOSA archive shows for the threat of "aircraft malfunctions unexpected by the crew" that 13% were mismanaged and further analysis showed many flight crews flying one of several fleets failed to properly reference the Quick Reference Handbook.

Data Analyst Must Integrate Aviation Knowledge with Data Analytics Methods

Two vital pragmatic considerations necessary for data analysts to adopt ML methods are developing aviation domain knowledge to understand the origins and limitations of the data to be analyzed and establishing a working knowledge of data analytics methods. Previous SWS research efforts have involved collaboration with ML data scientists, but with limited or no experience with specific types of aviation safety data (e.g., human performance data, Napoli et al., 2022; flight operational data, Garcia et al., 2022). During these research efforts, the time required to enable sufficient working knowledge of the data to permit appropriate application of ML methods was approximately 6-12 months. A cross-functional and cross-discipline collaboration between data scientists and aviation domain experts is needed to mature these methods for future SMS/IASMS.

Overcoming Human Analyst Limitations with Big Data

The forecasted increase in volume and complexity of big data sets will necessitate integration of ML to overcome human limitations in analyzing and understanding these risks. Given the scale of changes with flight safety data between current and future data analysis needs, data analysts will increasingly address risks which cannot be adequately solved without ML. ML solutions are effective when data analysis rules for identifying safety issues involve too many factors and these rules overlap or need fine tuning. Furthermore, ML approaches are well suited to scale to ever increasing volumes of data which analysts cannot effectively analyze with traditional methods.

Human-System Interaction Issues

The complexity of human-system interaction (HSI) is reflected by critical design features needed to enable the human analyst to detect, identify, and understand data anomalies. Collaboration with operational experts can lead to informed decisions about operational significance of these anomalies. The design of algorithms and the processes for their use provide a context for potential issues with HSI involving "use, misuse, disuse, and abuse." Issues shaping the use of automation include trust, over-reliance on automation to detect problems, reduced attentiveness to deal with false alarms, and degradation of skills. For example, a data analyst might miss something in reviewing and coding an ASAP report when focused on something else. When automation and processes are used rigidly, such brittleness makes it difficult to handle gaps in the models used by automation and unanticipated emergent behaviors resulting from mismatching between multiple automated systems.

Data analysts will use visualization techniques to review and better understand safety risks and elevated risk states. Techniques for data visualization can involve statistical tables and figures represented by histograms and frequency distributions representing simple to complex statistics. Integrated results can be shown as a dashboard laying out key statistics such as events displayed by locations (e.g., airports), organization divisions (e.g., flight operations, ground handling, Mx), and types of data (e.g., FOQA, ASAP). Relationships could be shown between data types over time or binning data into a risk matrix (e.g., counts of events classified as red, yellow, or green based on frequency and consequence).

The human remains the decision maker using data analytics to inform effective safety assurance actions. Data visualization for the data analyst may be different for safety executives. These data may also provide understanding and insight into the air carrier’s efficiency and environmental considerations. The IASMS will provide faster identification of precursors, anomalies, and trends and emergent risks that represent hidden, masked, or previously unknown risks. Architectures can be integrated and interoperable between operators for in-time safety management through design of automated Services, Functions, and Capabilities (SFCs). The size and complexity of these architectures and SFCs will be scaled based on complexity of operations and vehicles. SFCs represent what data will be aggregated and how data will be fused and analyzed using ML. SFCs may provide initial risk analysis although the human analyst will retain final decision making for risk analysis. SFCs may provide alerting when a risk threshold is reached and automated mitigation, as appropriate.

Discussion

The research and technology challenges we presented (i.e., aviation safety data analysis/data sharing systems, data analysts’ roles and responsibilites, HSI issues, etc.) must be addressed to permit a key enabler of IASMS: safety intelligence (SI). ICAO considers SI to be an outcome of the process of analyzing safety data and safety information to support decision-making. SI is a prerequisite for in-time safety management being able to rapidly evaluate existing data patterns and discover new patterns that can lead to the next safety event before such an event might occur. The benefit from looking at safety management through the lens of SI is improved speed and characterization of system-wide risk using ML. SI integrates the knowledge gained from reactive, proactive, and predictive safety systems . The IASMS concept progresses today’s SMS to be responsive to expanded use of new and underutilized data sources, advancements in use of ML and possibly other areas of AI for safety management, and future evolution of the NAS with AAM. Challenges surface with use of novel sources of data and innovations in predictive modeling. IASMS provides a framework for improving SI facilitated through integration of proactive and predictive algorithms trained to detect known hazards and identify emergent risks more quickly and effectively. Importantly, understanding and addressing the research and technology challenges for the human data analyst in future safety management systems is a paramount need to ensure a future “Sky for All” system that is assured to be “Safe for All” (NASA, 2022).

Acknowledgements

The authors extend their appreciation to Mrs. Laura Bass (Analytical Mechanics Associates, Inc.) for her valuable contributions in the development of this paper.

References

Buselli, I., Oneto, L., Damnbra, C., Gallego, C., Martinez, M., Smoker, A., Ike, N., Pejovic, T., and Martino, P. (2022). “Natural language processing for aviation safety: extracting knowledge from publicly available loss of separation reports,” Open Research Europe.

Carvalho, T. (2022). “Natural Language Processing (NLP) in Airline Maintenance Operations,” Aviation Week Aerospace IT.

Ellis, K., Prinzel, L., Krois, P., Davies, M., Oza, N., Stephens, C., Mah, R., Infeld, S., & Koelling, J. (2022). A Future In-time Aviation Safety Management System (IASMS) Perspective for Commercial Air Carriers. AIAA 2022 Conference. Chicago, IL: AIAA.

Federal Aviation Administration (2022). Charting Aviation’s Future: Operations in an Info-Centric National Airspace System. Washington, DC: FAA.

Federal Aviation Administration. (2015). “Safety Management Systems for Aviation Service Providers,” AC No. 120-92B.

Garcia, E.J., Stephens, C.L., & Napoli N.J. (2022). Detecting Risk and Anomalies in Airplane Dynamics through Entropic Analysis of Time Series Data. AIAA Aviation Forum 2022.

Holbrook, J., Prinzel, L., Chancey, E., Shively, R., Feary, M., Dao, Q., Ballin, M., & Teubert, C. (2020). Human-Autonomy Teaming Research Challenges and Recommendations. AIAA Aviation Forum 2022-3250. doi.org/10.2514/6.2020-3250.

International Civil Aviation Organization (2018). “Safety Management Manual,” ICAO Doc 9859, 4th Edition.

Napoli, N., Stephens, C., Kennedy, K. Barnes, L., Garcia, E., Harrivel, A. (2022). NAPS Fusion: A framework to overcome experimental data limitations to predict human performance and cognitive task outcomes. Information Fusion, 91, 15-30.

National Aeronautics and Space Administration (2022). Sky for All Portal. https://nari.arc.nasa.gov/skyforall/

National Academies of Sciences, Engineering, and Medicine. (2018). In-time Aviation Safety Management: Challenges and Research for an Evolving Aviation System. doi.org/10.17226/24962.

Office of Inspector General, Department of Transportation. (2021). “FAA Has Made Progress in Implementing ASIAS, but Work Remains to Better Predict, Prioritize, and Communicate Safety Risks,” FAA Report No. AV2021022.

Oza, N., Bradner, K., Iverson, D., Sahasrabhojanee, A., and Wolfe, S. (2021). “Anomaly Detection, Active Learning, Precursor Identification, and Human Knowledge for Autonomous System Safety,” AIAA Sci Tech Forum.

Paradis, C., Kazman, R., Davies, M., and Hooey, B. (2021). “Augmenting topic finding in the NASA Aviation Safety Reporting System using topic modeling,” AIAA Sci Tech Forum.

Parasuraman, R., & Riley, V. (1997). “Humans and automation: Use, misuse, disuse, abuse,” Human Factors, 39, 230-253.

Prinzel, L., Ellis, K., Krois, P., Koelling, J., Davies, M., and Mah, R. (2021). “Examining the changing roles and responsibilities of humans in envisioned future in-time aviation safety management systems,” International Symposium of Aviation Psychology.