The Adaptable and Resilient Safety System: The Human Factor in Future In-Time Aviation Safety Management Systems

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In-time integrated safety management will be paramount for safely enabling the envisioned transformations of the future National Airspace System (NAS). The path for realizing the vision includes addressing the increasing need for advanced data analytics and fusion of aviation safety data, managed by human decision-makers. The paper describes safety management systems and its' challenges, and how the concept of In-time Aviation Safety Management Systems addresses the need to ensure an adaptable and resilient future safety system in the envisioned transformed NAS. Finally, it discusses potential human factors challenges, including new human roles and responsibilities, new information and cognitive requirements, new intelligent technologies that change human-system interaction and coordination, and new design paradigms for human-system integration and teaming.

I. Introduction

As we move toward advanced transformations of the National Airspace System (NAS), it is important to consider future needs of integrated safety management. With the emergence of new aviation markets enabled by the increasing autonomy of systems, the way in which humans interact with these systems will be a critical factor in design and operational in-time safety assurance of future safety systems. The increasing complexity of operations will necessitate new ways of managing flight information and how to monitor, assess, mitigate, and assure against potential critical safety risks. The envisioned changes in future markets involve a diverse range of flying vehicles and new operational

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missions (e.g., Advanced Air Mobility(AAM)). These vehicles include legacy conventional passenger jets; sport, ultralight, business, and general aviation aircraft; and new entrants, such as commercial space launches and electric vertical takeoff and landing (eVTOL) [1, 3]. The rapidly evolving landscape presents new safety challenges, particularly with the frequent, short-duration flights of eVTOL vehicles (e.g., battery health limits flight duration) in congested airspace in close proximity to traditional NAS aircraft, including large transport category aircraft. To realize this vision, it is necessary to address the progressive need for increasingly autonomous advanced analytics and fusion of aviation safety data that will always arguably be managed by human decision-makers; a critical need addressed by the In-time Aviation Safety Management Systems (IASMS) concept of operation [2, 4].

The U.S. air transportation system is ultrasafe. However, significant transformations are envisaged for the future NAS that include dramatic changes to how aircraft and reduced crew/uncrewed vehicles will operate in the transportation system. These changes will require an equally transformative approach to safety management of hazards and risks. The IASMS embodies a concept of "in-time" [2, 4-5] and is characterized by several critical attributes that are essential to ensuring the system can retain itself as the safest mode of travel across local, regional, and long distances. Firstly, it monitors and integrates various sources of operational data, analyzes data using machine learning/deep learning, natural language processing and other advanced data analytics, and mitigates hazards and risks based on proactive and predictive safety intelligence. Secondly, it emphasizes in-time collaborative decision-making and execution, utilizing human factors to help inform design to ensure optimal performance. This includes identifying human contributions to safety and the ability to "learn from all operations" and translating those insights and learnings into building predictive safety intelligence [e.g., 6-8].

The IASMS is not intended to be a replacement or adjunct for Safety Management Systems (SMS) but instead represents and characterizes a needed evolution to current safety management for traditional air operators and scalable, tailorable, and responsive means for other operators, such as new entrants, that may be expected to implement SMS in future NAS, and by extension the global air transportation system. The need to evolve SMS is advocated for by the FAA Information-Centric National Airspace System [9-10] and NASA "Sky for All" [11] visions and supported by ongoing activities such as those lead by the International Civil Aviation Organization (ICAO) Annex 19 Part 5 Safety Management Panels and safety intelligence initiative [12-18]. Today's Title 14 Code of Federal Regulations (CFR) Part 121 commercial air carriers are required to have a SMS and the FAA provides a voluntary SMS program for other operators, such as Part 135 operators (consists of aircraft limited in the number of passenger seats and payload) [19-20]. There are potential requirements to have SMS for emergent concepts of operations, such as AAM and lower/upper Class E. The FAA recently issued a final rule requiring SMS for certain Part 139 certificated airports. There are FAA initiatives, helped promulgated through recommendations from the National Transportation Safety Board (NTSB), to extend SMS (see FAA Notice of Proposed Rule Making) [e.g., 21-22] to Part 135 and 91.147 air charter; and manufacturers and certificate holders under Part 21 as specified under the Aircraft Certification, Safety and Accountability Act [23].

The present paper describes the human factor as an integral part of revolutionary changes described in future visions of the NAS with an emphasis on how safety will need to be proportionally transformative and scale with new operations and technologies being designed to safely enable the future of aviation. It describes the concept of IASMS and how it evolves beyond today's SMS to provide for more predictive safety intelligence (SI) and the requisite system-level "services, functions, and capabilities" (SFCs) that address identified safety hazards and emergent concerns that have been posited to be real or potential critical risks to the future NAS. Posited key challenges confronting SMS and how the IASMS tackles these potential barriers and threats are discussed that include how forecasted and possibly inexorable advances in machine learning/artificial intelligence (ML/AI) and new data analytical capabilities may yield multi-agent adaptive joint-cognitive systems between humans and machines. Although necessary to put into effect an ever more adaptive and resilient aviation safety system of the future, the changes may also introduce new burdens and unknown complexities for humans and human-machine teams. One consequence may be shared responsibilities, between humans and machines, for the monitoring, assessment, mitigation, and assurance against hazards and risks in future integrated SMSs of high consequence and complex NAS operations. Paramount research needs include the challenges of designing SFCs that can achieve system objectives to provide for in-time integrated safety management that realizes technological potential while also ensuring that changes to the human roles and responsibilities are well-supported by IASMS, through early life-cycle human factors efforts including cognitive engineering design and human-machine teaming. A discussion of key human factors design considerations and potential challenges are, therefore, provided followed by conclusions on future prospect for an adaptive and resilient safety system in the NAS.

II. Air Transportation System Safety

A. Aviation Safety Statistics

The air transportation system today is statistically very safe, secure, and protected. More specifically, commercial aviation has witnessed a 45% decline in accident rates and a nearly 80% decline in fatal accidents over the past 20 years for aircraft weighing more than 27,216kg (60,000lb) representing 28,385 70-seat regional jets and above types [24]. The international operations rate (2003-2022) was 58.7 million flight hours flown and 26.3 million departures. As reported by the International Air Transport Association (IATA), the global accident rate (2022) was 1.21 per million sectors with a fatality risk of 0.11 that translates into risk of 1 in 25,214 years that a 100% fatal accident would occur for a person taking a flight every day [25]. The fatality risk declined to 0.11 from 0.23 in 2021 and 0.13 for the five years, 2018-2022. Globally, in 2022, the accident rate declined with 25 incidents including three fatal accidents [24].

For U.S. Part 121 scheduled operations, analysis of U.S. aviation safety reflects the worldwide downward trend in number of accidents and fatalities. Since 2010, the U.S. aviation system continues to reflect a laudable record level of safety evinced by the number of deaths associated with U.S. civil aviation accidents decreasing 33% from 541 (2009) to 376 (2021). In 2021, for example, the NTSB reported that U.S. air carrier accident rate decreased by 55 percent to 1 per 8.9 million flight hours. The 10-year accident rate (2010 – 2021) for U.S. scheduled Part 121 air carriers is 0.0021 per 100,000 departures [26]. Looking at the statistics differently, between 2010 – 2021, the NTSB [27] reported there were seven major and five serious injury (at least one fatality and/or serious injury with substantial aircraft damage) accidents with an annual exposure average of 17.558 million flight hours with accident rate of 0.032 and 0.028 per million flight hours respectively. During that same timeframe, the NTSB classification further breakdowns remaining accidents into those with substantial injuries (180 with rate of 0.843 per million hours) and others with damage (151 with rate of 0.707 per million hours) where no person killed but aircraft substantially damaged.

Commercial aviation is not the only operation conducted in the air transportation system. The general aviation (GA) worldwide accident rate in 2019 was 1.029 fatal accidents per 100,000 flight hours. Globally, there were 1,768 GA accidents (2020) with 497 fatalities [28]. For U.S. operations, in 2021, approximately 91% of aviation fatalities occurred in Part 91 GA accidents. Part 135 commuter and on-demand operations, which include charters, air taxis, air tours, and air medical services flights (when a patient or medical personnel are on board) account for the remaining 9 percent with 18 fatalities in 2021. However, since 2001, the rate of GA fatal accidents trended downward from 6.690 (2002) to 5.258 (2021) per 100,000 flight hours. In 2021, the fatal accident rate was 0.951 compared to the high of 1.381 (2005) and low of 0.935 (2017). The Part 135 fatal accident rate has also generally been significantly reduced to 0.179 (2021) compared to a high of 0.710 (2004) and low of 0.069 (2009) [27].

B. Aviation Safety Perspective

Aviation is a high-reliability operation with high potential for catastrophic failures. When considered that 95% of all U.S. transportation deaths occur on roadways, it is important to keep safety in perspective and recognize that the U.S. and global aviation safety statistics are commendable. Over the past 20 years, U.S. carriers have transported more than the world’s population with few fatal crashes. However, to not ‘rest on your laurels’ is an idiom most appropriate and operative here. It is generally the aviation safety community consensus that there is both much more to do to improve aviation safety, and “to be safe” cannot be measured solely by absence of accidents and major incidents. For example, as of October 2023, the NTSB CAROL query system has 290 aviation safety recommendations that are currently open (accessed 10-18-2023). More alarmingly, the year 2023 saw a significant increase in near misses, such as those between Boeing 737 and Boeing 777 at New York John F. Kennedy International Airport; Boeing 767 and Boeing 737 in Austin, Texas; and Embraer 190 and private jet at Boston Logan International Airport. There have been reports that, in July 2023 alone, there were at least 46 such incidents [29].

Safety Defenses-In-Depth

The modern aviation safety system involves many components and actors that include ICAO, regulators, original equipment manufacturers (OEMs), operators, maintenance and repair organizations, air navigation service providers, airports/aerodromes, and investigation agencies. There exist already numerous SFCs in place that identify threats and support error management [30] providing defense-in-depth protections against active and latent “pathogens” [31-34] in the system. These SFCs include, but not limited to, the following examples:

1) Flight deck systems (e.g., head-up and other displays);
2) Avoidance systems, such as ACAS, TAWS, WSAS, weather radar;

3) Automated checklists;
4) EICAS/ECAM;
5) Warnings/alerts;
6) Various aircraft safety systems, such as brake-to-vacate and runway overrun protection);
7) Air traffic control (e.g., various communication, navigation, and surveillance systems, such as enroute decision support tool, Precision Runway Monitoring, and System-Wide Information Management);
8) Integrated NAS Automated System Modeling and Anomaly Detection;
9) Part 139 airports SFCs (e.g., Airport Surface Detection Equipment; Final Approach Runway Occupancy Signal; Surface Movement Guidance Systems; Runway Status Lights).

Other actors (e.g., airline operation centers) in the system have additional safety protection in place that offer a layered approach to system safety. Despite the number and sophistication of the safety defense-in-depth present in the NAS, however, incidents occur every day in the air transportation system; not often resulting in fatal accidents but analyses tend to find that safety net defenses failed and present for such possibility. Part of the solution is development of new and/or better safety SFCs that can address potential safety concerns possible with introduction of new highly automated/autonomous technologies and new types of operations and operators.

C. Aviation Safety Future

Today, how safety is managed includes front-line operators (e.g., pilots, controllers, dispatchers), but also through voluntary SMS program participation at airlines supported by various safety organizations including Commercial Aviation Safety Team (CAST), ICAO, Flight Safety Foundation (FSF), International Air Transport Association, Civil Air Navigation Services Organization (CANSO), regulatory agency surveillance and compliance audits and data systems (e.g., FAA, EASA), data analysis groups (e.g., Joint Implementation Measurement Data Analysis Team (JIMDAT), Aviation Safety Information Analysis and Sharing Program (ASIAS) including Issue Analysis Team, accident investigation (e.g., NTSB), and standards organizations, e.g., Radio Technical Commission for Aeronautics (RTCA) and Society of Automotive Engineers (SAE). The groups and safety organizations publish risk management policies and guidance (e.g., FAA Order 8040.6A on unmanned/uncrewed aircraft systems safety risk management), and operators in the NAS exhibit safety everyday through subject matter expertise and professional competence (e.g., 35-36].

The air transportation safety systems are effective and, despite rare instances where "defenses-in-depth" have failed [31-34], highly capable to meet the current NAS safety needs with the caveat that it must continuously evolve as changes are introduced to the NAS. When looking ahead to the future, the envisioned transformation of the air transportation system offers much in way of prospicience promise to match forecasted demand and new operations. The Future Aviation Safety Team (e.g., [37]) identified and prioritized aviation safety concerns for the future over the next 20 years (2035) that include need to continuously evolve aviation safety systems.

Technological advancements are catalyzing a transformation in the realm of transportation, offering the promise and tantalizing prospect of improving transportation safety. However, they also usher in and pose new challenges and novel quandaries. The amalgamation and integration of high-volume uncrewed, simplified, and remote vehicle operations, cutting-edge air mobility aircraft, vertiports and vertiplexes, new types of commercial aircraft and new operations (e.g., supersonic), autonomous cargo and regional air mobility, more technologically capable general aviation and types (e.g., sports, ultralight), and commercial space launch systems, all within the NAS, may likely increase the operational complexity and the orchestration and governance of airspace operations and air traffic management (ATM). Moreover, current and future forecasts of fewer skilled operators (e.g., air traffic controllers, pilots) and introduction of new and emerging technologies, exemplified by increasingly autonomous/autonomous systems, potentially introduce unknown threats requiring new skill sets, new workforce, and new ways of operating in the NAS including significant changes to the FAA flight certification process. The diverse set and spectrum defining the complex intersection of these operational and technological facets will necessitate deliberation and the cultivation of better and entirely novel changes to NAS, competencies, commensurate with the burgeoning complexity and breadth of future operations. Safety barriers to a transformed NAS include, but not limited to:

1) Increased scale and diversity of operations.
2) New multi-vehicle control (i.e., m:N) operations and reduced/uncrewed operations.
3) Possible changes to role of humans in safety systems.
4) Requirements for highly automated/increasingly autonomous/autonomous operations.
5) Better verification/validation and assurance methods and issues on how to certify new forms of technologies, such as autonomy.

6) How to implement evolutionary changes safely within the time periods envisioned for the NAS.
7) Breakthroughs in data analytics for non-forensic, predictive methods.
8) Limitations of existing SMS processes that need to change.
9) How to make the system-wide safety system be “in-time” requiring fundamental shifts in how data is collected, acted upon, and shared.
10) Need for new distributed safety mechanisms.
11) How to safeguard against unexpected, unknown emergent behavior and drifts into failure.
12) Significant data and cybersecurity issues (e.g., access, protection and sharing of data, etc.).

The promises offered by what is possible in the transformed future NAS must include the prevision that equally transformative technological advances must be matched with equally transformative ways of ensuring and assuring safety as highlighted by SMS evolution enabled by new concepts of opConOpserations described in recent visions from the FAA and NASA [10-11, 38-41].

D. Future U.S. National Airspace System Visions

FAA Information-Centric NAS 2035 Vision.

The FAA recently published the “Charting Aviation’s Future: Operations in an Info-Centric National Airspace System” document [9-10] that describes a vision of the NAS in year 2035 that foresees increasing demands for new emergent operators, such as AAM/ Urban Air Mobility (UAM) [42-49] and Regional Air Mobility (RAM) [50] enabled by in-time integrated safety management. The FAA vision envisages an information-centric NAS (ICN) based on a concept integrating performance-based technologies to increase the performance and efficiency of airspace operations [9-10]. The diversity and complexity of aircraft, airspace, and operations in this envisioned future is illustrated in Figure 1.

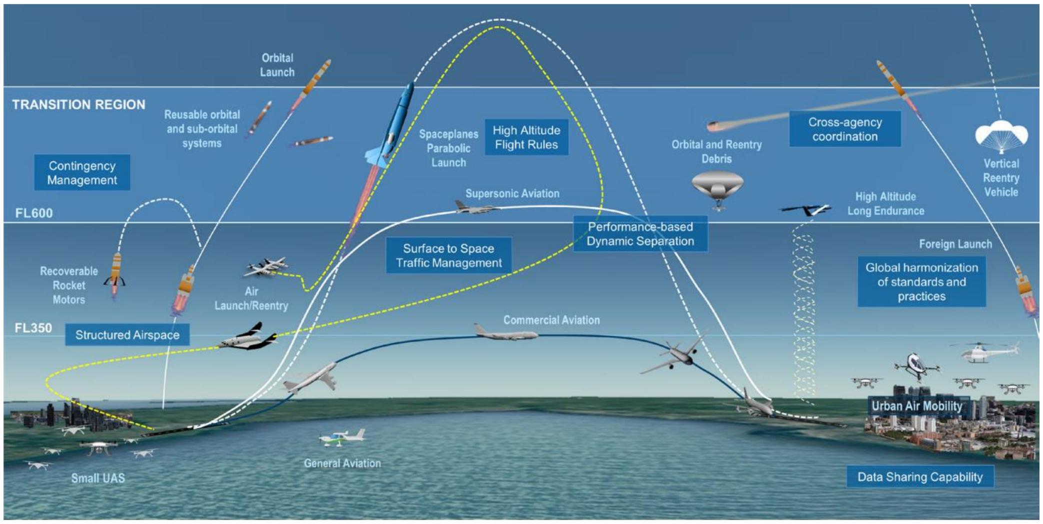

Figure 1. Complexity of future vehicles and national airspace operations [10].

The FAA info-centric NAS vision encompasses three pivotal attributes of transformation - namely operations, infrastructure support, and comprehensive integrated safety management. The facet of integrated safety management involves elevating the management and oversight of the integrated system, introducing tailored safety measures, ensuring interoperability and compatibility, and providing for in-time SA.

1) Tailored safety entails the adaptation of scaling standards, flight rules and operational procedures, and services designed to enable operations, such as UAM, upper-class E airspace, and all other operational concepts of operation.
2) Interoperability is facilitated through a seamless, fully integrated service framework and architecture that encourages collaborative data sharing.

3) In-time safety assurance and alerts are founded on the continuous modeling, monitoring, and verification/validation of safety data.

Utilizing substantial big data resources, in-time safety mechanisms enable the proactive and predictive detection of indicators, precursors, and anomalies and timely notification to stakeholders through established protocols to address in-time hazards and threats that introduce risk to the NAS. The Info-Centric NAS [9-10] requires new enabled operations characterized by collaborative decision-making among and within diverse ATM services and non-FAA service providers supporting novel vehicles, missions, and operations through an integrated, shared SMS; infrastructure changes for more fully integrated information environment for scalable, accessible, and resilient services, functions, and capabilities; and safety assurance that establishes agile systems and services with tailored safety processes and means for compliance [9-10].

NASA Sky for All 2050 Vision

NASA is focused on six major research areas, or Thrusts, for the long-term future of aviation focused on (a) Safe and efficient growth in global operations; (b) Innovation in commercial supersonic aircraft; (c) Ultra-efficient subsonic transports; (d) Safe, quiet, and affordable vertical lift air vehicles; (e) In-time system-wide safety assurance; and (f) Assured autonomy for aviation transformation [11, 51-53]. The Sky for All vision foresees the future NAS characterized by highly automated and distributed systems and services, and cooperative airspace ecosystem that will unleash unprecedented opportunities and transformative benefits for society and traveling public. Five key paradigm shifts are identified that will transform today's aviation system to a Sky for All airspace ecosystem [9]:

1) Sustainable aviation supported by breakthroughs in electrified engines, new fuels, and improved operational efficiencies.
2) Seamless skies through integrated and cooperative airspace.
3) Ubiquitous operational resiliency enabled by distributed, in-time collaborative decision-making and uncertainty management with widely accessible information and tools.
4) Operational interoperability and flexibility for increased access.
5) Tailorable and scalable diverse operations.
6) Adaptive and resilient continuous learning-based system or systems that acquires and synthesizes system-wide knowledge and capability to adapt and evolve to pace of technological innovation.

NASA's vision in the Sky for All concept integrates the monitor, assess, mitigate, and assure functions enabling integrated safety of the future aviation system [9]. The concept of operation achieves this by "identifying hazards, managing risk, facilitating mitigation actions, and building in Design for Safety throughout for whole system performance." In support of NASA's Strategic Implementation Plan for aeronautics [52] Thrust 5 "In-Time System-Wide Safety Assurance," and complementary to FAA's Info-Centric NAS vision [2, 5, 11], key elements for System-Wide Safety involve:

1) Domain-specific in-time safety monitoring and alerting tools.
2) Adaptive in-time safety threat management.
3) Integrated predictive technologies with domain level application.

A critical enabler, which is the focus of the NASA System-Wide Safety project [54], is the needed research and development (R&D) for new and/or better ways to monitor, assess, mitigate, and assure safety and certify new autonomous systems in the future NAS. One high-payoff path is to evolve current SMSs, currently only required for Part 121 commercial air carriers in the U.S. but expected to expand to other operators in the NAS including Part 139 airports, Part 135 air charter, manufacturers and maintenance organizations, and new and emergent operations. Both the FAA and NASA future NAS visions identify this need through in-time integrated safety management, tailored safety processes, interoperable safety systems, and safety assurance. The need to evolve SMS may be achieved through the IASMS concept, which is not intended to replace SMS, but reflects a concept of operations with identified SFCs and technological advancements to help current SMS evolve to be responsive, extensible, scalable, tailorable, integrated, and assured safety system capable of rapidly evaluating existing, and discovering new patterns, in diverse data sets through reactive, proactive, and predictive safety intelligence and provide mitigations ranging from advisories and alerts to autonomous actions [2, 5, 55].

II. Safety Management Systems

A. ICAO Framework

The framework for SMS was established by ICAO [12-17]. According to ICAO, SMS constitutes a systematic approach to managing safety that encompasses the necessary organizational structures, accountability, responsibilities, policies, and procedures. The traditional State Safety Program (SSP) framework of SMS, as outlined in ICAO Annex 19 and informed by ICAO Standards and Recommended Practices (SARPS), is comprised of four components: (a) Safety Policy and Objectives, (b) Risk Management, (c) Safety Assurance, and (d) Safety Promotion. SARPS serve as the foundation for a safe global aviation system, and the SMS components are intended to help manage commercial aviation safety risks in coordination with aviation service providers. The ICAO Safety Management Manual [13] offer guidance on safety management principles and concepts, the SSP, and SMS implementation, with the goal of supporting the continued evolution of safety management and the SSP of each ICAO state, such as the FAA, in accordance with the provisions of Annex 19. 14 CFR Part 5 of the U.S. Code of Federal Aviation Regulations provides for the implementation of SMS by Part 121 Aviation Service Providers (i.e., commercial air carriers). ICAO offers comprehensive directives in the Global Aviation Safety Roadmap (GASR) [56] that offers a structured and universally accepted action plan designed to realize the global aviation safety objectives and established through collaboration among various international safety entities (see also Global Aviation Safety Plan, 57]. It includes the essential elements concerning regulatory safety oversight functions related to SMS, encompassing system and functions, technical guidance, tools, the provision of safety-critical information, surveillance responsibilities, and the resolution of safety-related issues [56-57].

B. FAA Framework

The FAA provides guidance and methods for developing and implementing SMS through Advisory Circular (AC) 120-92B, titled “Safety Management Systems for Aviation Service Providers [19]” and related documents. FAA addresses ICAO SSP requirements in Order 8000.369C, National Policy: Safety Management System [20].

The FAA AC 120-92B [19] provides an SMS framework, shown in Figure 2, that integrates the processes for risk management and safety assurance. Safety risk management (SRM) involves early identification of hazards and ensuring controls are designed to manage known hazards at an acceptable level. Safety assurance monitors performance for how controls are used operationally to confirm that risk is mitigated as intended. Loops between risk management and safety assurance include the operational monitoring of risk controls to validate their efficacy and monitoring of operational data for emergent or different hazards that require new risk controls or a change to them.

For safety assurance, AC 120-92B [19] identifies methods for flight-by-flight monitoring of operational hazards and their associated risk controls that can be used and scaled by size of commercial air carriers. A carrier has the option to devise other method(s) to show means of compliance. The methods and sources of operational performance data identified in AC 120-92B include the following: Line Operations Safety Audit (LOSA), Advanced Qualification Program (AQP), Aviation Safety Reporting System (ASRS)/ Aviation Safety Action Program (ASAP), Flight Operational Quality Assurance (FOQA)/Flight Data Monitoring (FDM), Internal Evaluation Program (IEP), and Continuing Analysis and Surveillance Program (CASS)/Continuous Airworthiness Maintenance Program (CAMP), among others [see 21, 64]. Whereas Flight Data Monitoring systems are required by ICAO SMS Annex 19 and FAA, the other methods listed above are voluntary SMS program safety data and analysis sources include:

1) Accident and incident reports (e.g., FAA, NTSB, Annex 13 investigations)
2) FAA /NTSB database/Bureau of Transportation Statistics/Airlines for America/Europe (A4A/A4E)/ICAO/IATA accident and incident data systems
3) NASA ASRS database
4) FAA Midair Collision System database
5) Air Registry
6) NTSB recommendations (290 currently ‘open’ in CAROL Query database)
7) Runway incursion and other event databases
8) Uncrewed Aircraft System (UAS) accidents and incidents
9) Worldwide/U.S. accident summaries (e.g., Boeing)
10) Safety review committees/teams (e.g., CAST Joint Implementation Measurement Data Analysis Team; Issue Analysis Team)
11) Safety databases (e.g., Aviation Safety Information Analysis and Sharing (ASIAS) system)

Some air charter companies and flight schools (e.g., Embry-Riddle Aeronautical University) provide for safety management through International Standards for Business Aircraft Operations (IS-OBA) [58].

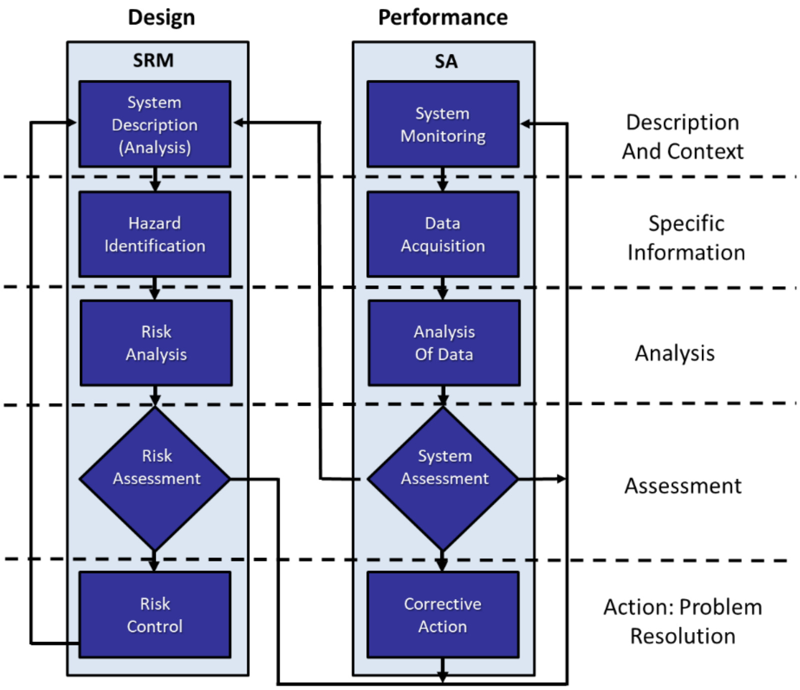

Figure 2. FAA SMS Framework for Part 121 Air Carriers (adapted from AC 120-92B, Figure 2.1)

C. CANSO Model

A broad perspective on SMS was developed by CANSO in its standard of excellence in SMS [59]. CANSO's approach aligns with ICAO and provides guidance that an ANSP can follow to meet or exceed ICAO regulatory requirements; these include provisions to accommodate operator size and operational complexity. The CANSO standard uses a model consisting of a system enabler (safety culture) and a safety culture framework of five components that address 16 elements (see [59] for more detail on CANSO model).

As previously stated, SMS are currently not required for other operators in the NAS. However, the FAA has published several notices of proposed rulemaking to extend SMS [21-22]. SMS may also be required for all emerging new operations [e.g., 60-61]. A historical overview and broad survey of SMS is provided by [62-63] that describe definitions, history, theories and models, purposes, and elements.

III. Need to Evolve Safety Management Systems

The NAS is undergoing continuous transformation, driven by technological advancements, market forces, and emerging opportunities. The NAS is reimagined in the NASA "Sky for All" and FAA 2035 vision concepts. The paramount priority in this evolution of aviation remains safety and overcoming the challenges and constraints in both design and operations are essential for its successful advancement. Today, the overarching SMS has provided significant benefits in reducing aviation accidents and incidents through reactive and proactive safety management. However, the envisioned future concepts of operation present new safety challenges. As such, it is imperative that safety management evolve to provide for a predictive SMS capability that reflects these significant changes that will substantially increase complexity and challenges to assure safety in the future NAS [63]. Part of the impetus for this need to evolve SMS include low public risk tolerance, the human labor-intensive characteristic of today's SMS, and its limited ability to scale requisite to being tailorable and responsive to all operators in the air transportation system of tomorrow.

Overall, the shortfall with today's SMS is its inability to quickly monitor, integrate, and assess large data sets to identify known, as well as emergent risks, in-time so that contingencies can be determined, and mitigations implemented expeditiously - that is, an "in-time" capability. Given these limitations, the National Academies [4] recommended the adoption of IASMS to ensure and assure the safety of the future NAS. The new perspective is seen as critical to addressing the challenges and limitations of the current SMS to ensuring a safe and efficient NAS, and is an integral part of the NASA and FAA future vision concepts.

IV. IASMS Concept of Operations

NASA has been engaged in the development of the IASMS Concept of Operations (ConOps), which draws upon conventional commercial and other aviation operations and scales in complexity to accommodate the advent of newly emerging and evolving operations. The IASMS ConOps was developed in support of NASA's Strategic Implementation Plan Thrust 5, entitled "In-Time System-Wide Safety Assurance," which endeavors to establish a proactive, predictive, adaptive, and resilient in-time safety threat management system [51-52]. The system features fully integrated threat detection and evaluation capabilities that provide reliable mechanisms for dynamic, multi-agent planning, evaluation, and execution of in-time risk mitigation in response to hazardous events. The IASMS changes or system objectives include evolution and extensions to current SMS to achieve [55]:

1) In-time: Through in-time integrated safety management, the IASMS creates a more responsive and expedient SMS. This will entail faster detection, identification, and mitigation of known hazards and emergent risks. This responsiveness would be enabled by an architecture of SFCs designed to continuously monitor, assess, and mitigate safety critical operations and exceedances, described below.
2) Effective: IASMS improves the mitigation effectiveness of SMS. SFC will drive system effectiveness if the monitor, assess, and mitigate functions are tailored to address specific risks or classes of risks. A process to identify and prioritize those risks must be one capability.
3) Scalable: System scales for different operations tailored for the operator size, mission, aircraft, and airspace.
4) Interoperable: IASMS supports interoperability across different operators, service providers, original equipment manufacturers (OEMs), and FAA for sharing data.
5) Assured: It provide in-time safety assurance, and resiliency in non-normal situations.
6) Teaming: IASMS improves the design and operational use of automated safety systems with the human for transparent, trustworthy, and resilient human-machine/-autonomy/-automation teaming (HMT/HAT).
7) Value: It supports the safety business case for gaining FAA certification and public acceptance.

A. Monitor-Assess-Mitigate-Assure

Safety risks can stem from patterns in precursors, anomalies, and trends. These risks may manifest as validated concerns that are known to designers and operators and can be detected and mitigated by the safety assurance SFCs (i.e., “known knowns”). Emergent risks, on the other hand, may be unknown to both designers and operators (e.g., an unexpected and surprising situation) but can be understood, adapted to, and managed by the SFCs through the application of ML or AI (i.e., “unknown knowns”). Additionally, there may be risks that are recognized by designers or operators but are outside the scope of detection and mitigation by the safety assurance SFCs (“known unknowns”). Lastly, there may be unforeseen (“unknown unknowns”) [65] [cf., 66-67] risks that are not recognizable by designers, operators, or the safety assurance SFCs and await discovery. To support in-time integrated safety management, IASMS is empowered by high-level functions, namely Monitor, Assess, Mitigate, and Assure that encompass domain-specific safety monitoring and alerting tools, integrated predictive technologies with domain-level applications, and in-time safety threat management. To identify safety risks arising from patterns in precursors, anomalies, and trends in new data types and increased data volume, SFCs are required to enable predictive safety management, with its new data analytical methods and innovative approaches to system safety thinking.

The IASMS concept is founded upon a comprehensive array of SFCs that work in conjunction to enable its dynamic in-time Monitor-Assess-Mitigate-Assure functions - a unique feature of IASMS [2, 4-5, 55, 68-69]. According to the National Academies, the monitoring function observes and characterizes the system state by collecting, fusing, and assessing data from a variety of sensors [4]. Monitoring is conceptualized as a set of information services and an underlying architecture that allows for acquisition, integration, and quality assurance of heterogeneous safety-relevant data that may come from a diverse set of sources (including vehicles) [2, 4-5, 55, 68-69]. Access to these services must recognize that some data may require protections that de-identify the source and defend against corruption by unauthorized or unauthenticated sources [2, 4-5, 55, 68-69]. The National Academies stated that the assessing function is enabled by sophisticated analytics functions and algorithms that (1) identify and characterize known risk states in the time frame of interest to an IASMS and (2) examine large volumes of stored flight and ground operations data with anomaly detection methods to identify and characterize emergent risks and to update IASMS risk assessment algorithms. Assessment has been defined as, “a set of tools and techniques that provide timely detection, diagnosis, and a predictive capability regarding changes in risk and hazard states. Assessment functions should be capable of spanning hazard types to judge how the overall safety margin is changing based on current context, on recent (in-flight) cascading event sequences, and on longer-term trends that can become evident with access to historical data maintained by monitoring functions" [2, 4-5, 55, 68-69]. The National Academies required an IASMS to have the ability to detect and mitigate elevated risk states on a much shorter time scale than existing SMS. Mitigation has been operationally defined as, "a set of methods, tools, and procedures that provide for multi-agent or automated planning and execution of timely responses to hazardous events or event sequences when/if safety margins are observed or are predicted to deteriorate below acceptable levels." [2, 4-5, 55, 68-69].

B. Services, Functions, Capabilities

A Service serves the purpose of preventing or containing hazards before they can cause harm. The emergence of hazards during the design or operational phases highlights the need for a Service to manage them. Services can be provided by the vehicle, UAM/ Uncrewed aircraft system Traffic Management (UTM)/ATM system, or other agents in the architecture. A Function denotes the action that is required of automation or autonomy, automated/increasingly autonomous systems, and pilots or other human operators. It integrates streams of information and data to determine the necessary steps and timing to prevent or contain risks, as well as utilizing predictive analytics to known and unknown but emergent indicators, precursors, anomalies, and trends from system-wide performance data. A Capability encompasses the utilization of technology, including sensors and models, to detect, validate, generate, and distribute information and data across network architectures, serving as the foundation for the Functions and Services [2, 4-5, 55, 68-69]. Young et al. [5] provide an example of the architecture and information requirements and SFCs necessary to assess and predict flight safety risks during highly autonomous urban flight operations.

C. Safety Intelligence

The growing complexity of aviation safety issues requires the development of novel analytical techniques and tools for identifying intricate patterns and detecting emerging risks. The primary aim is to swiftly uncover patterns within data that might predict negative outcomes before the next safety incident occurs. This innovative approach allows for proactive and predictive safety through data analytics, enhancing actionable safety intelligence and risk visualization that extends past forensic, reactive safety.

Reactive Safety Management

Initially, ICAO safety management primarily revolved around reacting to safety events, aiming to respond to risks after an accident, incident, or safety-related event is identified, but after it has already occurred. Reactive SMS seeks to mitigate the impact of safety-critical situations once the hazard has already taken effect. However, reactive SMS primarily learns from a limited number of accidents and incidents, which restricts its ability to generalize to routine, everyday operations. SMS has evolved since the early adoption of Annex 19, and the aviation safety community recognized the need for a complementary proactive safety management approach [14, 17-18].

Proactive Safety Management

While reactive SMS focus on mitigating safety events after the hazard is detected and the system has been exposed to it, proactive SMS aim to preemptively address potential risks before an accident occurs. It achieves this by evaluating all available safety operational data to identify risks based on historical or latent data from past accidents, incidents, or safety-related events. What distinguishes proactive SMS from its reactive counterpart is its use of aviation leading indicators to directly assess underlying factors and precursors, creating a framework for understanding future risk exposure, mitigations, and safety assurance. The objective of proactive SMS is to identify precursors, anomalies, and potential causal factors through data markers, system behaviors, passive sensors, and human performance modeling, with the goal of preventing unsafe conditions and hazardous operations. Examples of proactive SMS data programs include Line Operations Safety Audits (LOSA), Aviation Safety Action Program (ASAP), and Flight Operational Quality Assurance (FOQA) [14, 17, 64].

Predictive Safety Management

Predictive safety management focuses on recognizing potential risks in a given context and foresees the necessary risk-mitigation measures. Proactive safety management identifies root causes that can lead to hazard occurrence as well as drift in operational practices away from nominal patterns or procedural requirements [70]. Reactive safety management identifies the specific causal and contributory factors behind an incident or accident, both in the design and operational phases, and formulates measures to reduce the likelihood of those factors leading to a subsequent incident or accident. Contemporary SMSs combine reactive and proactive safety management, leading to data-informed approaches that systematically examine safety events and conditions more effectively in real-time or near real-time, based on actionable data. The challenge facing modern SMS is the significant growth in data volume and the increasing complexity and uncertainty surrounding the causal factors of contemporary safety. Predictive analytics builds on advanced methods for data-driven anomaly detection using ML/AI. Data-driven anomaly detection, coupled with domain expert feedback on the operational significance of the identified off-nominal conditions, can effectively identify operationally significant anomalies during operations and provide explanations for them. Precursor identification methods can be used by domain experts to identify precursors to known, undesirable safety events. These approaches enable effective teamwork between human domain experts and ML/AI to identify sequences of events that lead to anomalous operations and can lead to increasing trust in autonomous systems [e.g., 71-76]. Effective concepts and principles in human teaming with automation and autonomy, as well as human-system integration, will be important to achieving trust. NASA and collaborative partner research pose that ML/AI algorithms should be considered complementary and multiple algorithms will need to be integrated to use their respective strengths [e.g., 77-83].

Operators stand to gain from the advancement of technologies that can integrate and harmonize vast, diverse datasets from various sources. This approach facilitates a comprehensive system-wide risk assessment to aid in time safety risk management. Machine learning and artificial intelligence have the capacity to amalgamate and interpret complex data patterns that might otherwise seem insignificant. This improved speed, and the in-time ability to characterize system-wide risk identification, would supplement existing SMS processes that support safety risk management and assurance. Part of the building blocks for conceptualizing development of safety intelligence and continuous learning in IASMS involves considering systems for reactive, proactive, and predictive safety management. The IASMS SFCs provide for faster and more responsive protections and mitigations using proactive hazard identification and predictive safety indicators [2, 4-5, 55, 68-69]. These multiple channels provide critical understanding, analysis, and design of IASMS for monitoring, assessing, and mitigating risk.

Safety Intelligence and IASMS

The IASMS offers a unified approach for airlines to create a safety intelligence vision and learn from all operations. Learning from all operations aligns with the fundamental components of the ICAO SMS and presents new opportunities to enrich the pool of data available to various data repositories [7-8]. This data can be used to enhance risk management and safety assurance processes by providing valuable insights and lessons learned on how to mitigate risks in similar circumstances. Safety information and data sharing is promoted among all involved parties, spanning from the FAA and ASIAS to ICAO, the IATA, and other stakeholders.

Safety intelligence, especially predictive safety intelligence, is a pivotal component of the IASMS and its implications for various aspects of the NAS. Current Part 121 air carriers can evaluate the benefits and limitations of IASMS as part of the business case for complying with SMS components [55, 68-69]. This encompasses the identification and prioritization of applications and improvements to predictive analytics and prototype data decision dashboards. Such capabilities empower human safety intelligence and continuous learning from all operations, thereby enhancing compliance with SMS components. This approach bridges IASMS with safety policy and safety promotion, fostering more effective advancement of organizational continuous learning strategies aimed at proactive and predictive safety intelligence. New emergent operators and those that may be required to have SMS in the future (e.g., Part 135 [e.g., 84]) can utilize tailorable and scalable SFCs and architectures that enable better interoperability across all actors and stakeholders.

In-Time Predictive Safety Management

Safety intelligence is built upon predictive analytics. Predictive safety management focuses on recognizing potential risks in their native contexts and foreseeing the necessary risk-mitigation measures [see 14, 17-18, 69]. The growing demand for digital data in predictive analytics and ML/AI is not limited to enabling new operations; it is a vital element of transforming the future aviation system safely. Each existing air carrier with its established SMS will need to adapt safety business strategy to harness the anticipated surge in data volume, using an architecture designed to facilitate access and data aggregation. These strategies will also seek to capitalize on opportunities presented by novel data analytical methods and innovative approaches to system safety thinking.

Safety intelligence is intrinsic to the IASMS architecture, featuring SFCs that integrate risk mitigation into design and operational safety assurance. Furthermore, to meet airworthiness standards for Part 25 transport category aircraft, learning from all operations and safety intelligence serve as a lens to assess and validate designed risk mitigation controls, identify relevant changes to operational procedures and training, and enhance the dissemination of SMS information and safety culture that are intended to be extensible to other operational domains (e.g., AAM) and aircraft (e.g., Part 23). The SFCs that evolve with the IASMS architecture will introduce primarily automated sources of information, offering options for assessment and mitigation within the framework of risk management and safety assurance. As part of the foundational elements for the development of safety intelligence and continuous learning, ICAO SMS provisions include: (a) Proactive safety activities for collecting safety information and data; (b) Proactive methods for hazard identification; (c) Predictive safety indicators focused on processes and activities to enhance and maintain safety; and (d) Predictive analysis based on current operations.

Data-driven anomaly detection, coupled with domain expert feedback on the operational significance of the identified off-nominal conditions, can effectively identify operationally significant anomalies during operations and provide explanations for them. Precursor identification methods can be used by domain experts to identify precursors to known, undesirable safety events. These approaches enable effective teamwork between human domain experts and ML/AI to identify sequences of events that lead to anomalous operations and can lead to increasing trust in autonomous systems [71-76]. Effective concepts and principles in human teaming with automation and autonomy, as well as human-system integration, will be important to achieving trust. Research poses that ML/AI algorithms should be considered complementary and multiple algorithms will need to be integrated to use their respective strengths. Analytic techniques derived from R&D current investments in AAM, or other emergent operations may be extensible to Part 121 air carriers, such as with data-driven anomaly detection [e.g., 2, 77-83, 85].

FAA SMS incorporates three types of thinking about safety described as reactive, proactive, and predictive thinking. As practiced by most airlines, today's SMS represents reactive safety systems. Some SMS methods like LOSA and ASAP are considered to represent human contributions to safety as proactive safety systems. Predictive safety involves methods in advanced data analytics. ICAO in development of the currently pending Amendment 2 to Annex 19, emphasizes development of safety intelligence in order to maintain and continuously improve the effectiveness of safety programs [14, 17]. Guidance is expected that will provide strategy for development of safety intelligence [14, 17, 55].

Interoperability of IASMS

NASA has published a volume of papers outlining IASMS for different operations domains. The papers include UAM/AAM [e.g., 2]; vertiports and vertiplexes [86], space launch and reentry [e.g., 87]; upper Class E [e.g., 88]; Part 135 business and on-demand charter [e.g., 84]; and Part 121 commercial cargo and airline operations [e.g., 69]. In work papers include IASMS for Part 139 airports, original equipment manufacturers, maintenance repair organizations, natural disaster response and ambulatory helicopter operations, ATM/ANSP, autonomous cargo, military operations, international IASMS and Part 129, Part 91, and IASMS data sharing and cybersecurity.

D. IASMS/SMS Needs and Challenges

The National Academies identified key challenges and high priority research needs for IASMS [4] that focus on data completeness and quality, how to fuse data across siloed safety systems, new safety portals and architectures, development of in-time data analytical methods, and identifying new actionable data types. The needs and challenges enumerated above reflect ultimately to make the safety system of tomorrow a more adaptive and resilient safety system. To date, the NASA System-Wide Safety project has shown:

- Methods to improve risk management and safety assurance processes by proactively identifying risks and causal factors before an accident/incident occurs.
- Integrated risk assessment capabilities to monitor and assess NAS operations based on advanced data analytics methods and predictive model development.
- Machine Learning Analytics Tools, in collaboration with our partners, that identify and characterize operational risks, monitor, and integrate data, evaluate risk mitigation strategies, and determine causal and contributing factors.
- System architectures and system engineering (including MBSE) model generation.
- Generation of various IASMS roadmaps, in collaboration with partners, such as the Verification and Validation 2045 and IASMS 2045 roadmaps.
- Development and test validation of new SFCs for emerging operational domains, such as sUAS disaster response and AAM.
- Progress on verification and validation methods and new ways to certify autonomous safety systems.
- Publications on specific applications of IASMS for future NAS operations, to include commercial space launch, AAM, Upper-Class E, vertiports/vertiplexes, and Part 135.

V. Multi-Agent Adaptive and Resilient Safety System

The human represents the only true adaptive agent in the modern air transportation system. People exhibit adaptive decision-making and agile performance every day in the NAS accounting for substantial part of why the current system is considered ultrasafe. Another part of the reason commercial aviation is safe is because it is also resilient.

Adaptability concerns the ability to learn flexibly, efficiently, and continuously and apply that meta-skill knowledge to new situations; it involves agility to manage under new conditions. Resilience is a related concept that describes a system capable of 'bouncing back' and/or reversion to a previous, more positive state, after experiencing some system safety disturbance or failure [89]. As defined by the Flight Safety Foundation, resilience is, "the ability to successfully adapt and respond positively to difficulties or other adverse conditions" [7-8, 90]. Resilience can also be conceptualized as a "graceful and expected degradation with planned and achievable recovery such that no component in the air transportation system including people drives the 'health' of the overall system…" [91]. A degradation of NAS system capabilities occurs every day at varying levels of severity. Taking a human factors viewpoint on sociotechnical resilient and adaptive systems, they can be characterized [91]:

- Systems and people that –
    - Know what to do – addresses the actual
    - Know what to look for – addresses the critical
    - Know what to expect – addresses the potential
    - Know what has happened – addresses the factual, learning from past and predicting the future

- What they look like –
    - Appropriate information provided to human to enable and ensure awareness of above
    - Clearly defined and communicated roles and authority levels (including back-ups)
    - Supported communication among agents
    - Flexible function allocation among humans and automated agents

Through resiliency, the safety system can sustain essential operations, under expected nominal but also unexpected off-nominal situations (e.g., rare "black swan" events [92-94]). Organizational and system resilience largely depends on an organization having an empowered, learning and just culture as well as policies, procedures, and safety nets that provide support to what humans do very well everyday – they are adaptive and resilient to changing situations and apply knowledge-based decision making and problem-solving to unknown and/or new risks, threats, and hazards to that particular operation or that confronting safety persons.

The expected introduction of new advanced automated/autonomous systems and sub-systems, along with forecasted volume of accessible data in the future, may consequently necessitate new ways of safety management. Automation and autonomy can be seen as existing along a continuum. Given calls for advancing and/or introducing both types of technical capabilities, they are stated together throughout present paper. It is recognized that future advanced types of more highly capable automation, increasingly autonomous systems, and autonomy each have their own human factors challenges [see [95] for conceptual framework]. There are also many common ones as well [e.g., 96], including those discussed here that are applicable to entire spectrum of automation to autonomy. Where appropriate, human factor challenges unique to automation and/or autonomy are expressed. For example, Kaber [95] argued that there are unique requirements of design for autonomy that include: (a) agent viability in a target context, (b) agent self-governance in goal formulation and fulfilment of roles, and (c) independence in defined tasks performance. Generally, however, the vast majority of human factors research and design challenges are relevant although it may take different form in how they are researched and practically implemented in human-system design. For example, Endsley [96] concluded that levels of automation literature can serve as foundation and key aspect of autonomy design. Concerns for new human roles and responsibilities, how to properly design the human-system interfaces, system interdependencies and organizational factors, new cognitive and attentional demands, new forms of error and ways of information processing, human-system coordination and how to "team" human and machines together, human-system integration, and other significant human factors research needs and design challenges discussed here are applicable across the range of advanced automation, increasingly autonomous systems, and autonomy.

One change may be much more capable data safety surveillance systems that possess monitor-assess-mitigate-assure multi-agent adaptive resiliency. Such change, and others, may bring with them unforeseen challenges and concerns for the human operator, who currently is primary source of safety in the NAS - the human roles may be different with possibly shared responsibilities between humans, SFCs, and highly complex data analysis systems for safety. Consider, for example, the NASA Aeronautics Research Mission Directorate (ARMD) Strategic Implementation Plan [51-52] that calls for:

- Introduction of an IASMS that continuously monitors the NAS – and sub-elements within the NAS – to collect data on the status of all elements and operators within the NAS. The IASMS will accommodate new operations and new capabilities as they are introduced into the system, detecting new risks as they emerge.
- Beyond 2045, adaptive in-time safety threat management will incorporate increasingly autonomous human-machine decision support to enable proactive and predictive mitigation of risk in complex operations and support NAS-wide safety assurance.

To enable this future safety perspective, research by NASA and others focus on safety intelligence through highly automated ML/AI-enabled IASMS for dynamic and shared human-automation hazard mitigation strategies. However, ample evidence exists today as to how highly capable systems break down in unexpected ways. Consider the Qantas Flight QF32 uncontained engine failure and the resultant significant number of electronic centralized aircraft monitoring (ECAM) alerts that overwhelmed the flight crew and resulted in their ignoring the ECAM checklist and other synoptics; the flight crew did what they are trained to do which is fly the plane. However, this example, among many, highlights that technology is a tool and, although future safety systems are being posited to have autonomous mitigation functions, ultimately the system is designed by a human. Self-learning and adaptation may characterize these systems but, at present, this capability has not yet been shown with the level of integrity required for safety-critical operations (up to 10^{-7}). If technology is able to meet this augury, the future NAS safety systems may have many adaptable agents all responsible for shared safety – a potential human factors problem involved in multi-agent coordination and accountability. If it is not able to achieve this technological readiness level [e.g., 97-98], the system may be even more reliant on the human for safety assurance, which may require an increased human readiness level [e.g., 99]. Either way, considering the human factor in future safety systems, like the IASMS, is of upmost importance requiring contemporary and ultramodern advances in our understanding of human contributions to safety today, and how to ensure that design includes the human as indispensable, to yield the imagined NAS of tomorrow.

VI. Human Factors Challenges

ICAO has underscored that the incorporation of human factors is an essential component of safety management. It is vital for comprehending, recognizing, and mitigating risks while enhancing the human role in ensuring organizational safety. It revolves around understanding how human behavior relates to safety and risk. The development of a safety culture is an inherent outcome of the human presence within the aviation system [100]. Significant human factors challenges confront aviation today, and future changes may bring with them new and/or additional problems.

Historically, design of safety systems reflected more what technology was capable of doing at design time with remainder of tasks being off-loaded/given to humans, to include supervisory control monitoring responsibilities of the overall system; sometimes termed "function allocation by substitution" [101]. Particularly in the case of automation in aviation, too often the human has been/is placed in situations (e.g., dark, noisy, high vibration flight decks environments) and given tasks that from evolutionary perspective, and supported by a wealth of research, that they are not well-suited for. For example, humans are not good at vigilance [102] but aviation operators (e.g., pilots, controllers) are placed in the role to watch computer displays waiting for times when they *may* have to intervene, sometimes under conditions of duress (e.g., autopilot fails or disengages; poor weather; etc.). Consider that today, pilots typically hand-fly only an estimated 2-7 minutes of the flight with the remainder communicating with air traffic control or dispatch, supervising the automation/systems, and, most importantly, *anticipating* those 2-7 minutes when they may have to jump in. Unfortunately, this has resulted in new risks introduced into the modern NAS (e.g., "mode unawareness" and "automation surprise" were not common terms prior to introduction of modern flight deck automation systems) [e.g., 103-105]. Moreover, systems evolve over time to become ever more capable, with added and/or expanded functionality, that can tax the human ability to interpret, understand, and act on data and actions recommended by such systems (e.g., ML/AI techniques are opaque with hidden layers and non-deterministic paths to solution convergence). The increase in ML/AI-based safety SFCs and safety systems (including future SMS/IASMS) may acerbate this problem as well as extend them to other operators, such as future safety data analysts/scientist or multi-vehicle control (m:N) fleet managers.

Billings [106] wrote about these concerns with advanced automation where clumsy automation design results in issues of complexity, brittleness, opacity, literalism, and increased training requirements as well as many human-system interaction issues (e.g., data overload, skill degradation, high monitoring requirements, coordination challenges, and trust/overreliance on opaque but seemingly highly reliable automated system) [106]. In the same way that Billings advocated for a human-centered automation philosophy providing a set of principles and guidelines to effect it in practice, a human-centric in-time integrated SMS is also needed which addresses new safety system technology introductions. The design goal should be a symbiosis between them so that humans and machines work together better; a paradigm shift offered by human-machine/-automation/-autonomy teaming. The opportunity to do so is the present, early in design lifecycle of such systems like IASMS starting with identifying principal human factor design considerations and challenges; to fail to do so risks repeat of the mistakes of the past as aviation accidents and incidents too often evince.

The next sections describe key human factor design considerations and challenge needs requiring more research and, where available, possible solution paths critical to ensuring the safety of the future air transportation system. The needs are discussed grouped into the following: (a) new human roles and responsibilities, (b) new information and cognitive requirements, (c) human-system interaction and coordination, (d) human-system integration/human-machine teaming, and (e) system interdependencies/organizational factors.

A. New Human Roles and Responsibilities

The air transportation system of the future is envisioned to usher in new ways of air travel, airspace management, and operational use that is posited to necessitate new human roles. For example, AAM concepts of operations involve a progression from the highly capable pilots of today to those who would operate simpler vehicles with one (m) human pilot operating multiple (N) number of vehicles (i.e., m:N) responsible for operational monitoring and contingency management. The result will be operations where pilot simplified vehicle operations (SVO) and m:N remote vehicle operations (RVO) will shift the air taxi operator role from today's active pilot-in-command to supervisory control monitor of advanced automated, increasingly autonomous, and autonomous vehicles [107-108]. SVO has been defined as, "the use of automation to reduce the number of skills a pilot or operator of an aircraft must acquire to achieve the required level of operational safety" [109, p. 2]. RVO is characterized as a type of operation where "aircraft are remotely controlled by some combination of one or more humans piloting a single aircraft or operating/managing many aircraft, with varying degrees of automation support" [110, p. 1]. The concept of RVO encompasses scenarios where a single pilot remotely controls a single aircraft, multiple pilots remotely manage a single aircraft, or multiple pilots remotely operate multiple aircraft. Within the m:N operational paradigm envisioned in AAM, fewer human operators are needed to simultaneously manage a number of aircraft, with the support of higher levels of automation and/or autonomy. Responsibility for safety is expected to be shared between complex, highly intercoupled safety system SFCs and humans that fundamentally changes how safety is managed in the NAS. How roles are assigned between people and these autonomous and automated agents are key human factors challenges that will fundamentally define how operations are conducted in the future. This may require fresh and novel design paradigms for future vehicle, operator, and airspace safety systems (e.g., human-autonomy/-machine teaming, discussed in later section).

Woods [112] discussed how technology may change human roles. Historically, as technological advances have been introduced, they have transformed human-system interaction in many new ways that have had positive benefits but also resulted in some situations that have shown deleterious impact on ability of humans to perform optimally. For example, there may be new or changed tasks (e.g., operating sequences) and new or increased cognitive and attentional demands placed on the human operator. Technology change may also increase the burden and complexities with potential for human error. New system capabilities increase the integration and coupling across many sub-systems which subsequently may increase the opaqueness of system operation challenging human ability to understand and act on volume and complexity of big data in a manner that is in-time. Consequently, there will be ever increasing reliance on automated/autonomous system safety SFCs.

A critical question is what the proper roles and responsibilities of the human in future aviation safety systems, like IASMS, should be. It is a premise of IASMS that design of such systems must preserve the function of humans as safety primary, while enabling the full potential of support safety systems can offer. The risk is that, if roles are not adequately considered that truly account for proper function allocation (perhaps even dynamic function allocation), there may be increased propensity for people to "misuse, disuse, and abuse" technology [111]. These include overreliance and inappropriate trust and complacency, cognitive and decision overhead associated with use or disuse of technology, and system designers that do "left-over" assignments to humans that technology cannot yet perform. The resultant 'intelligent' systems can exhibit as strong, silent, clumsy, and difficult to direct: (a) strong when they can act autonomously; (b) silent when they provide poor feedback about their tasking and intent; (c) clumsy when they interrupt during high tempo and/or high safety critical situations adding new cognitive burdens; and (d) difficult to direct when the operator mental overhead challenges the human "partner" to monitor and direct technology and the concomitant attentional/decision-making burdens associated. Systems with these characteristics are seemingly proper for design (particularly for uninformed calls to remove the human entirely in attempt to increase safety) but, in effect, can also create new problems and new ways of system failure [112].

Today, the human functions as both a controller and manager of sociotechnical systems-of-systems that range from directed manual control, to various management modes (e.g., management by delegation, consent, and exception) and limited cases of fully automated operations. Paradoxically, technology introduction has been justified on basis that it reduces workload, attentional/cognitive demands, training needs, and "human error" yet may instead increase them; that is, strong, silent, clumsy, and difficult to direct [112]. Although it has been often cited that 70% of nonfatal and 80% of fatal accidents in aviation are caused by human error [113-115], the statistics are misleading (e.g., not single causal events) and don't reflect the "deep structure" and context, the base rate of how often humans contribute to safety, and the effects of automation/technology that contribute to human error due to poor interfaces and ineffective human-system design [e.g., 116]. It is incumbent for system designers to recognize the perils of engineering for best technology as end-goal, when technology is used simply because it can be rather than because it should or needs to be. Instead, it is critical to recognize and consider the holistic nature of sociotechnical systems, including people and interaction with technology, that may reduce safety resulting from poor human-technology fit [e.g., 103-105; 112].

The assignment of human roles is derived from the functions they undertake although optimal task delegation has historically not been adequately done. For example, Sheridan and Parasuraman's analysis of supervisory control revealed human functions, in highly automated task environments, include pre-planning, observing the system implementation of the plan, and taking action to abort or assume control as necessary [117]. Taking a wider view, Wickens [118-119] postulated that information is processed through human information processing (IP) stages of sensory processing, perception/working memory, decision-making, and action implementation that are extensible to automated/autonomous systems also. As technology and operations evolve, the roles of human operators will also likely change incrementally, at first, but eventually (as futurists argue for) dramatically as compared to today's human roles for safety management. However, research has shown that operator capability limits can constrain human performance and interaction with highly automated/autonomous systems, like those expected for future safety systems. Focusing back on in-time integrated safety management, theoretically, the IASMS adopts these IP stages and functions in terms of monitoring, evaluating, and mitigating to handle safety risks, while the human operator can be seen as perceiving, evaluating, and responding/taking action to mitigate risks based on the IP model. Through design consideration of how humans process information and various functions they and technology *should* perform, future safety systems can ensure that people are not relegated to roles ill-suited for what they *could* perform.

The challenge lies in optimal design of the interfaces for human-system interaction with increasingly complex and reliable highly automated/autonomous safety systems, as well as ensuring that information is at least minimally managed by humans to guarantee timely safety [e.g., 112, 120]. These challenges include decision support analytics, human automation/autonomy function allocation, and cognitive modeling of human-machine interaction that account for new information and cognitive requirements.

B. New Information and Cognitive Requirements

In the realm of future aviation, it is envisioned that humans will continue to play a pivotal role in ensuring safety through constant, in-time surveillance of operations and mitigating emerging risks. Yet, a significant challenge lies in the fact that the current certification and safety assurance protocols presume the presence of people (e.g., safety analysts, dispatchers, pilots, air traffic controllers, etc.) for operational safety. For instance, the shift from conventional vehicle handling to advanced automated/autonomous systems that are properly designed, adaptive, resilient, and capable would necessitate a phased implementation of autonomy. Taking an AAM example, this may involve a change progression, from today's type of piloting and operational flight management, to SVO and RVO type operations, including possible future highly automated vehicles with passengers who would be capable of acting during emergencies (with fail-safe control remote capability). Alternatively, it may involve fully autonomous aircraft, automatic traffic management systems, data analysis systems, or other systems where the human, still present in the system, functions and acts only under situations where the system is incapable (i.e., lacks resilience and adaptivity) – a role that human factors research has shown consistently is a very poor fit. These new vehicles, operations, and technologies may change the cognitive and attentional demands on the human operator through design decisions, intended to address "human error" by giving more authority to safety SFCs but significantly distance the human from the system, that may unintentionally reduce safety. A significant human factors challenge is to understand how cognitive and attentional demands may change, through early investments in human factors research, and develop solutions that may offer ways to possibly minimize the impacts of such designs.

New Cognitive and Attentional Demands

There exist several theoretical frameworks that posit the limited attentional capacity human operators have when interacting with automated, complex systems; this is particularly the case for systems that are strong, silent, clumsy, and difficult-to-direct. For example, Kahneman [121] posed attentional resources as a single unity pool of mental energy distributed across IP stages. In contrast, Wickens [118-119, 122] theorized that there exists a number of attentional resources that are allocated based on the task attentional demand. Yamani and Horrey [123] represent an attempt to integrate different frameworks (i.e., 118, 122, 124] where closed-loop resource allocation is influenced by situational, individual, and organizational factors. Other models, theories, and frameworks exist to account for human cognitive and perceptual/attentional limits and influences on human-system interaction and types of problem-solving/decision-making and potential for risk and error [e.g., see 121 for review]. Types and levels of human-system interaction are described later, but how system designers consider these human limitations has significant implications for design of safety SFCs and safety systems, as well as ways to ensure the human role is supported properly and appropriately particularly as safety systems (and their respective SFCs) become more complex, more integrated, and more capable.

Highly coupled systems breakdown in new and unexpected ways often due to misunderstanding or inability for people to monitor and assess highly complex safety systems and influence human decisions on how to act on actionable data with safety critical decision support systems. They can increase or introduce new knowledge demands (e.g., understanding complex system-of-systems operations), new attentional demands (e.g., overhead to intervene or even shut off these systems; ambiguity in probabilistic system detection of anomalous safety indicators), and ambiguity of who is accountable despite the human ultimately being responsible agent with ostensibly highly capable and reliable safety systems. A significant advance that may accelerate this concern involves forecasted increase in new data analytical SFCs that utilize ML/AI. The changes to operator roles and introduction of new technology may introduce new forms of human error as witnessed with past examples of increased automation that lead to "mode unawareness/confusion" and automation-induced errors [e.g., 106, 103-105, 112, 125-126].

New Forms of Error

There exists a large literature on research examining human error in high-criticality risk operations, such as aviation [e.g., 31, 127-129]. For example, Reason [31] provides the seminal book on random, systematic, and sporadic errors and etiological reasons behind mistakes, slips, and lapses. He also describes how these types of errors can be classified along skill-, rule-, and knowledge-based actions, based on the work of Rasmussen [130-131]. Although much has been written about human error in aviation, despite lack of consensus on what human error really is [e.g., 128-129, 132], the topic has undergone comprehensive examination, extensive discourse, and prolonged deliberation spanning over more than 50 years. Various ideas, models, and concepts have been put forth, carrying both theoretical and real-world practical ramifications. In today's world, which is becoming progressively automated, digitalized, and reliant on computers, and autonomous machinery and data analytic algorithms, the study of human error (and machine error) continues to be as relevant and widespread as it has ever been. Over the past half century, several 'new' views on human error have been put forth where these "perspectives can be seen to fit along a continuum between 'old view' [133] and the 'new view' of human error" [see 134]. The 'new' or, better said, 'newest' view on human error takes various names, such as "Safety-II" [e.g., 135], "Human and Organizational Performance" [e.g., 136-137], "Safety Differently" [132], and "Theory of Graceful Extensibility" [138]. These fall under the "resilience engineering" [e.g., 139-143] umbrella/banner grounded in concepts and principles, in part, from cognitive engineering [e.g., 144], Normal Accident Theory [145], and High Reliability Organizations [e.g., 146-147]. Although it has been questioned whether this is new system safety thinking [e.g., 148], Le Coze [128] concluded that, "value of these developments is clearly visible in their ability to engage with practices, methodologically but also critically" (p. 19).

Regardless of the debate on views of human error, [see 148], an important contribution is the emphasis on not "just what goes wrong" but also "what goes right" in operations underscoring the importance of human role in safety. As Woods [112] propounded, new technology brings new forms of interaction and, consequently, potential for new types of human error often because the human roles, as described above, are not accounted for properly in human-system design. Through better understanding of human contributions to safety, it can also better inform human factors design criteria to help assuage this potentiality. NASA [e.g., 149-153] has been researching how people influence safety positively every day in line operations and safety analysis, along with partners in FSF and others [e.g., 7-8, 154-155]. The objective is to not only explore how to quantify "productive safety," but also how this can inform "protective safety" by theoretically offering more data to mine than that offered by current reactive and proactive safety data sets. These are cases where they may point to indicators or precursors of latent risks and hazards that are shown evident through human operators evincing resilient performance and adaptivity. The goal here is to provide for the needed advance to predictive safety intelligence for in-time integrated safety management requiring big data made possible through new data types and new system safety thinking. Importantly, it requires acknowledgment by system designers about the limits of human expertise and the deep structure nature of human error and contributions to accidents and incidents that often are caused because of poor human-machine coordination and task assignment not well-suited for people that must use these safety systems and associated safety SFCs. For example, pilot who spend long periods monitoring glass flight deck displays for flight management system perturbations, or safety analysts looking across large volume data sets for emerging safety trends, etc. [116]. To a large degree, as concluded by [116, p. 5], errors are caused by four factors of:

a. Specific characteristics of the tasks performed;
b. Events in the environment in which tasks are performed;
c. Demands placed on human cognitive processes by task characteristics and environmental events; and
d. Social and organizational factors that influence how a representative sample of experts would typically operate in particular situations.

It is unrealistic to expect that humans (and machines) will never make any errors. Nor can it be expected that technology can design out human and machine imperfections. Furthermore, "… only humans can deal with unexpected and novel situations and only humans presently can make value judgments among competing options with advantages and disadvantages…." [116, p. 302]. The objective is to design the operational and safety systems to be resilient and adaptive to the technology/equipment failures, unexpected events, and error that inevitably occur; the argument that future systems will have machine capabilities that will assure errors will never occur is to deny the nature of sociotechnical systems and a long history of human and technical failure [see 116, p. 302]. Instead, solutions should focus on analyzing how characteristics of the system and the operating environment at large interact with cognitive vulnerabilities inherent to humans, and system technical breakdowns that do and will continue to occur – "… a topic requiring considerably more research and close collaboration between the research community and the airline industry." [116, p. 303]. As we look to future safety systems, it is apparent that technology will continue to transform the air transportation system – new vehicles and concepts of operation will spawn new automation/autonomy capabilities and new ways to look at safety (including data and how to analyze the data) based, in large part, on new ML/AI-based SFCs. How these new data types and advanced data analytics will be used (or misused, disused, and/or abused) [111] are major human factors R&D challenges.

New Data Types and Advanced Data Analytics

Increasingly complex aviation safety issues necessitate new analytic methods and tools to identify complex patterns and detect emergent risks. The objective is to rapidly discover patterns in data that may predict negative outcomes before the next safety event occurs. Air carriers would benefit from development of technologies that integrate and fuse large, disparate sets of data from multiple sources. The approach enables the execution of a system-wide risk assessment to help achieve in-time system-wide safety threat management. ML/AI fuses and interprets complex patterns in data that might otherwise appear as insignificant. This improved speed and characterization of system-wide risk identification would augment existing SMS processes supporting risk management and safety assurance. In-time integrated safety management and assurance will require new and/or better data and methods to address the forecasted substantial increase in the volume and complexity of data. Current safety management employs data analytics including application of machine learning, albeit in more limited and less sophisticated form than that expected for future SMSs/IASMSs and system safety SFCs. By employing advanced ML/AI in new safety SFCs and data analytics, it is possible to have operational conditions, both nominal and off-nominal, that can enable more extensive in-time safety notifications and responses in both traditional and emerging aircraft operations and ATM as part of a transformed future in-time integrated SMS enabled by safety intelligence. Specifically, there is need to move toward a more predictive SI capability through advances in ML/AI and other data analytical methods.

The use of ML/AI to improve aviation safety is not new. Application of ML/AI and other current and emerging data-driven approaches have already contributed to enhancing safety of flight operations (e.g., new runway overrun protection systems design to reduce/prevent runway excursions, veer-offs, and other undesired aircraft states that may present upon landing and roll-out. Increasingly complex aviation safety issues necessitate more robust safety intelligence built on new analytic methods and tools to identify complex patterns and detect emergent risks. ML/AI can fuse and interpret complex patterns in data that might otherwise appear as weak signals and not be recognized by the human subject matter expertise augmented with synthetic data and other novel approaches (e.g., safety system digital twins). NASA and other research have been tackling the problem by introducing ML/AI methods into complex, data-informed decision-making to help identify actionable data, recognize patterns, predict mitigation actions, yield new hidden safety insights, and assure safety. Because of the ever-increasing volume of disparate data, the path to predictive SMS is challenged by the need for data analytics that can evaluate and detect unknown vulnerabilities and discover precursors, anomalies, and other predictive indicators, as compared to more traditional safety metrics used (e.g., FOQA exceedances). These vulnerabilities are "needles in a haystack" that ML/AI methods are ideally suited to discover. The evolution to predictive SMS and the increasing complexity of operations will increase the volume, velocity, veracity, and variety of data produced and the need for ML to understand and act upon these data. With this growth of predictive safety intelligence comes the challenges of integrating new data streams that are not easy to access and failure to integrate useful technologies due to programmatic roadblocks. It also may create new ways of human-system information processing.

New Ways of Human-System Information Processing

Research has demonstrated the challenge humans have understanding the subset of ML/AI non-deterministic, "black box" methods that can lead to less than desired human-machine interaction including over-trust/overreliance and complacency due to the high cognitive overhead associated with these data analytical methods, particularly for safety sensitive/critical use [71-77]. ML/AI models of high complexity tend to challenge human interpretability and vice versa. Although there are efforts to develop data analytical approaches that do not rely on complex ML/AI models, they have not yet been shown to yield better predictive performance and efforts are ongoing to test alternative data analytical methods (e.g., multiclass anomaly detection with senor fusion based on Dempster-Shafer Theory [156]). It remains a significant human factors concern given the potential for "misuse, disuse, abuse" of such safety enabling SFCs. In particular, the implementation and growing capability of ML/AI-based systems (whether onboard vehicles or air traffic control safety systems, or data-driven SMSs) and availability of new and larger volumes of complex safety data/information will transform the cognitive/IP requirements necessary for human operators. The introduction of more and more capable automation, for example, has resulted in change of information requirements pilots need to fly the aircraft that have evolved from skill-based performance to those more resembling rule-based goal-oriented if-then-else type piloting and management. When faced with an unusual situation, with no checklist or procedure to rely on, pilots and other operators in the air transportation system have formulated mental models and utilize their expertise, experience, and training to apply knowledge-based thinking and problem-solving [130]. As systems increase in complexity and more technology is introduced, it can become more difficult to match operator mental models to designer conceptual models [e.g., 110]. This can, and has been shown, to result in ever more reliance on technology and heuristic-type decision-making and less on "thinking outside the box" type cognition and problem-solving ability; this is not easily resolved by training particularly as it continues to be reduced or alternate, less effective methods employed (e.g., computer-based training). For example, in aviation accidents of the past, it has been found that inadequate knowledge or experience was provided by training and/or guidance [see 116, p. 298].

One mitigation is to ensure the human remains involved that is more within-the-loop (with primary control of safety data and analyses supported by ML/AI-informed data analytics) than on-the-loop (supervisory control) or, more concerning but possibly likeliest given proposed concepts of operation, over-the-loop type human involvement (passive monitor and management-by-exception). NASA research has been exploring how to keep the human involved in critical safety decision making. One promising area involves data-driven anomaly detection, coupled with domain expert feedback on the operational significance of the identified off-nominal conditions, that may more effectively identify operationally significant anomalies during operations and provide explanations for them. Precursor identification methods can be used by domain experts to identify precursors to known, undesirable safety events informed by active learning approach. Human feedback could be an assessment of whether a statistical anomaly found by a data-driven anomaly detection algorithm is a safety issue or not. Human feedback could also be a description of the state of the system based on the nature of data collected or any subset of it. Such feedback allows for a higher-level representation of the system state which is easier for humans to understand and helps the explainability, explicability, observability, and verifiability of these methods. It helps enable effective teamwork between human domain experts and ML/AI, through active human engagement with the system, to identify sequences of events that lead to anomalous operations and can lead to increasing trust in highly automated/autonomous safety data systems and safety SFCs. An extension of the approach would be to provide intuitive informative basis for safety system recommendations or actions that foster explainability, interpretability, and trustworthiness.

New Training Needs

Effective training can also help ameliorate potential problems, such as those identified here, relative to it supporting opportunities for mental model fostering and application of knowledge-based problem-solving [e.g., 110, 157]. Existing guidance for development of operator training programs, such as FAA AC 120-114 and AC 61-138A, provides information and guidelines for development of Part 121 pilot training programs and checking under Title 14 of the Code of Federal Regulations (14 CFR) part 121 subparts N and O, including part 121 appendices E and F. AC 120-54A provides FAA guidance for approval of Advanced Qualification Program (AQP) that incorporates data-driven quality control processes for validating and maintaining the effectiveness of training curriculum. AQP provides an alternate method of qualifying and certifying airline pilots, flight engineers, flight attendants, aircraft dispatchers, instructors, evaluators, and other operations personnel subject to the training and evaluation requirements of 14 CFR parts 121 and 135 that may need to be incorporated in future training requirements for other traditional and emerging operators and SMS/IASMS safety data analysts/scientists [e.g., 158-159].

Changes will be required to address increasing autonomous systems in future aircraft, airline/air taxi, airports, ATM and other SMSs to include new training requirement specifications for emergent operators (e.g., notice of proposed rulemaking 88 FR 38946 electric air taxi and other powered-lift aircraft training [159]). Similarly, data scientists and analysts will need a new level of expertise with safety systems to understand performance requirements and limitations, interdependencies, and other considerations in operational and safety SFCs, to include SMS data system involved in future IASMS. Human decision makers will need to be trained to understand sophisticated ML/AI-based data analysis methods for their operation to gain knowledge and skill and understanding of how algorithms work on safety data [e.g., 71-77]. While it may not be necessary to train to the expert asymptotic level, minimal training should address sufficient understanding of system design and operations. Automated data processing and assessment systems will also need to be designed with appropriate transparency and capability to degraded levels of automation in the IASMS (and generally other safety vehicle and systems similar to capabilities exists today, e.g., Airbus alternate law, ability to select different Flight Management Modes, etc.).

The need is significant to revise how training is done for all safety personnel, to include not only pilots that must interact and "supervise" complex systems but also those managing data systems that monitor for safety events and identify actionable data indicating need for mitigation. Key research questions include how to train the SMS/IASMS scientist/analyst to level of sufficient awareness of underlying system operation necessary to foster trust in the system. There must also provide the ability to assess integrity and accuracy of resultant products of the safety system (e.g., mitigation action decision aiding) - this is a significant challenge for human factors. Research is needed on how to design these training curriculum and new procedures that support proper human-machine/-system interaction and coordination [e.g., 160]. Furthermore, training will include new "human interfaces and management of information" (HIMI) that will be vital to ensuring operator shared situation awareness that enable effective teaming between humans and machines. Through transparent and intuitive human-centric HIMI, safety personnel and SMS practitioners can maintain shared situation awareness and possibly anticipate how risk is monitored, assessed, and mitigated. Design of new interfaces and how humans will manage safety information will be critical human factors that must be addressed to ensure successful deployment of IASMS.

New Interfaces and Management of Information

The interface with safety data and information management is the key portal through which human operators maintain situation awareness and team with increasingly autonomous systems for safety assurance and in-time risk management. Traditional roles and responsibilities of line operators (e.g., pilots, dispatchers, controllers) and safety personnel may blend into hybrid positions or a single position for simultaneously managing multiple flights, as done today by these different professionals, but with significantly more trustworthy decision aids and assured autonomous SFCs. These changes in human roles will also have a direct effect on how information would be managed and the human interface to it. Today, there are examples of these challenges, such as pilots who successfully manage equipment malfunctions that occur in normal operations but insufficient system knowledge, flight crew procedure, or understanding of aircraft state may, and has been observed in safety data, to decrease their ability to respond to failure situations. This is a particular concern for failure situations which do not have procedures or checklists, or where the procedures or checklists do not completely apply, such as with knowledge-based problem-solving and decision-making. Another example from the flight deck is ample evidence that pilots sometimes rely too much on automated systems and may be reluctant to intervene, and auto-flight mode surprise and confusion errors can occur, for example programming and usage errors with the aircraft flight management system [103-105, 161].

One concern is the extent that human factors, human-computer interaction, and various safety organization (e.g., SAE, AIAA, RTCA, ICAO, etc.) published standards, guidance, and lessons learned are extensible to HIMI with highly complex, high criticality ML/AI-based safety systems as forecasted in future visions. For example, there exists numerous usability and software interface design guides [e.g., 162-163], including DOT/FAA AC 00-74, TC-16/56, and TC-08/15, that can help inform future HIMI. For safety assurance, extensibility will depend on applicability/generalizability of existing standards, or revisions to them to account for new ML/AI-based safety systems, with dependencies in trustworthy decision support, potential bias, operator proficiency [e.g., 164-167] as well as need for new types of verification and validation methods [168-171].

As the complexity of data visualization increases, the data architecture expands to accommodate operational and safety SFCs, where human pilots remotely oversee a group of coordinated vehicles or manage multiple vehicles with asynchronous missions in ecosystem in close proximity with traditional aircraft (with more capable automated, even autonomous operating and safety systems) and other emergent operators (e.g., package delivery). This data architecture also interfaces with a collaborative ATM system, involving other operators engaged in data exchange through common SFCs. Within this data architecture, various data types intersect with safety risk and risk mitigation, including current and forecasted weather, pilot-reported weather conditions, geographic information systems data (e.g., obstructions), airspace configuration (e.g., temporary flight restrictions), and corridor data (e.g., congestion and slot management). Data visualization serves as the gateway through which human pilots, fleet managers, dispatchers, air traffic controllers, third-party service providers, etc. develop and maintain situational awareness. The traditional image of a human pilot seated in the flight deck, primarily focused on aircraft controls, displays, and scanning the skies for other traffic, will evolve and is posited to continue to evolve over time. Instead, the future human operator may now be expected to engage with displays presenting a variety of data types (often with many layers of available information). For instance, the data visualization requirements for an AAM fleet manager differ from the current pilot's reliance on a Cockpit Display of Traffic Information (CDTI) which may also have a different information display in future. This evolution in data visualization is further expected to similarly change from the perspective of today's air traffic controller who relies on traditional "radar" or situation displays [e.g., 85, 172] to a more integrated, highly automated system with added capability afforded by ML/AI and new safety SFCs imbedded. Other operators and safety personnel, other than pilots or AAM fleet managers and controllers, will have similar needs to reduce mode/operation complexity and intuitive data visualizations [e.g., 120, 172-174]. For future SMS data analysts/scientists, this need includes integrated, easy-to-understand safety dashboards and data portals [e.g., 175-177]; ways to better visualize ML/AI-based automated data processing systems [e.g., Visual Analytics Pipeline; 173-174]; and decision support tools, methods, and techniques (along with ability to assure them) [e.g., 178-188] to foster optimal human-system interaction and coordination which are key enablers.

C. Human-System Interaction and Coordination

Cognitive engineering, or cognitive systems engineering, offers a promising approach to better understanding human interaction with complex systems, such as with future safety systems (e.g., IASMS). It is a multidisciplinary field concerned with analysis, design, and evaluation focused on improving the "fit" between people and systems and has intersections in human-system integration (discussed in next section). There are many theories and approaches of cognitive engineering that generally revolve around several common fundamental principles. The design of complex interactive systems adopts an ecological perspective, necessitating a simultaneous consideration of individuals, artifacts, human objectives, and the surrounding environment in which these objectives are pursued. In essence, design principles are derived from observing and comprehending the behavior of system users "in the wild"; that is, their real-world context (e.g., typical and atypical line operations, day-to-day SMS safety data analysis and assessment processes, etc.). Consequently, cognitive engineering places a strong emphasis on observation and comprehension focused on crafting a cognitive task analysis that captures the tasks of individuals and the information used within their specific work domain. This cognitive task analysis aims to portray how people perform tasks within their domain using the tools and concepts relevant to their field, whether it involves documents, aircraft, ML/AI data algorithm outputs, or interactions with other individuals and intelligent systems. Methods for systematically investigating user tasks, organizing the observations' outcomes, and leveraging this information to guide system design and evaluation have laid the foundation for the field of human-systems integration (HSI) within engineering [e.g., 189-191]. These will be indispensable to future human factors professionals that research and apply cognitive engineering, and other approaches, to design of future safety SFCs and safety data and operational systems.

Cognitive engineering's inherent systems-based approach dictates that a full understanding of the human user must encompass the context of their tasks, the tools at their disposal, and their work environment. More and better data, better system-wide access, and increased system complexity are moving the role of systems engineering away from people as the hardware and software forcing function on design decisions to that of more an interdisciplinary team collaboratively integrating hardware, software, and human as part of system design trade-off analyses and decisions. The value of the approach can be seen through example outside aviation - Centaur Chess where less capable computer programs teamed with human players who together can defeat Grandmaster-level software which has implications for human-automation/autonomy design [see [192]. In other words, cognitive engineering advocates for human(s) and machine(s) joint-cognitive system design [e.g., 193] where to "team" together results in work that is better and safer together. Such human-centric approach has driven the development of the growing field of cognitive modeling, which aims to capture both the impact of the specific domain and the computational aspects of human cognition that shape our responses to the environment. Task and cognitive user models can be utilized to improve the tools available to human factors/systems engineers that describe the tasks people do, expertise required, what decisions need to be made, and what information is required to make those decision while considering the capabilities of the human and the machine to optimize the interaction and coordination [e.g., 189-191]. As Woods [112] observed, design involves more than just hardware and software, but also recognizes that the property of the system shape practitioner cognition and performance/behavior. The forecasted increase in ML/AI and fully automated/autonomous safety and operational systems should be the signal cue to examine what cognitive and performance/behavioral effects it will have on human safety practitioners/analysts/operators that must interact with such future highly technologically driven systems and SFCs.

As the aviation system transforms, and different in-time system-wide safety assurance methods become more complex, integration of cognitive engineering with ML/AI raise range of concerns about HIMI. These concerns are framed as questions including the following:

1) Where are opportunities possible for new types of interactions and how might they reveal knowledge gaps in the design path for IASMS?
2) How should best practices be leveraged?
3) How should information be scaled for display and how should the human operator navigate through menus and other techniques for more details?
4) How should safety dashboards be tailored for information requirements of different users?
5) How should time critical information be pushed to the display even if interrupts whatever was being displayed at that time?
6) How much training and education should be required relative to the level of understanding needed of the underlying algorithms?

NASA has significant human factors research investments to address these and other questions starting with looking to past human-automation interaction research and exploring function allocation and how design decisions influence human-machine trust and influences on human-system interaction and coordination.

Human-Automation/-Autonomy Interaction

The literature on human-automation/-system interaction and human factors is substantial (e.g., 194]. The impressive body of research has shown that human-system interaction design decisions are a major factor in how these systems are used and can serve as a starting point for guidance that complement cognitive engineering and other approaches (e.g., human-machine teaming) to human-system design (see [195] for review). According to Dunbar [98], significant research has been conducted on human-automation interaction that can inform advances in automation/autonomous technology development; future systems (e.g., processes, teams, sets of functions or tasks) may represent the zenith of the Level of Automation (LOA) continuum (i.e., autonomous) without requiring much, if any, human intervention (and by extension, human no longer in safety critical decision role). Although this may not be yet on the horizon, there are proponents and calls that champion this end-goal. Although there is not consensus in the human factors field (and certainly outside it) [e.g., 95, 196], it is likely, as many others have argued, and many others have also argued against, that humans and highly automated/increasingly autonomous/automated agents will remain essential part of future safety systems [e.g., 197-198]. However, a sea change in thinking about humans and intersections with highly automated/autonomous technology in the future is needed predominated by how humans and these machines can better interact in team-like ways to achieve mission objectives. An important determinator of this view is whether future systems will, or even can, successfully achieve human-machine teaming (discussed in next section) which, as essential design requirement, ensures that the operator/safety analyst/etc. remains “in-the-loop” [e.g., 199] and has appropriate levels of system trust in human-involved safety critical-recommendations and/or decisions/actions (e.g., 195, 200]. This teaming will continue to be reliant on human-human trust, but also machine “trust” with layers of sentinels and other surveillance capabilities for conformance monitoring. How to foster and maintain human trust in machines are key human factors design challenges for shaping successful teaming in tomorrow’s safety critical human-machine joint-cognitive systems [112].

Human-Machine/-System Trust

A major theme of human-automation/-system interaction literature has been on the construct of trust and how to promote it in complex, highly automated systems [e.g., 201-224]. Such systems are expected to increase in number of complexities as technology breakthroughs occur and cost-benefit analyses propel introduction of advanced forms of automation and hybrid-to-full types of autonomous operations. Trust has been shown to be a major influence on whether operators trust the system and hence use it, over-rely on it and misuse it, lose trust and disuse it, and system designer who trusts the machine more than human (often without evidence or citing misleading statistics on human error incidence) and abuse it in design [e.g., 201-224]. The theories, models, and frameworks on human-system trust (e.g., with highly automated systems) are plentiful and offer mechanisms of action and potential methods to foster, increase, and maintain trust with safety critical decision systems. For example, Lee and See [210] developed a conceptual dynamic process model of human-automation trust formed from performance, process, and purpose information based on automation characteristics, appropriateness of trust, and contextual factors. More recent research has built upon and adapted earlier works in human-machine trust (e.g., concept of "dynamic learned trust") as the construct is better understood (e.g., 123, 203-204].

The management of safety risk across diverse operational domains necessitates a profound integration between humans and systems in order to optimize the utilization of the escalating quantity of performance, process, and purpose information exchange presented to humans – an important mechanism underlying trust. The IASMS is intended to analyze operational situations quickly and help inform decisions based on the accessible data through predictive or adaptive processes. As an illustration, flight deck-based technologies, such as ML/AI-based Aircraft Health Monitoring Systems, will preeminently identify and mitigate unfavorable aircraft conditions, such as excessive energy during approach, prior to the occurrence of safety incidents. This serves as example of an aircraft SFC that transmit data in-time to IASMS for analysis together with all other aircraft flying in the NAS of which many humans will need to understand and potentially act upon this data and any system assessments and mitigations of risk. It is the forecasted substantial increase in volume of data that presents the challenge for the human analyst to comprehend and assimilate; this is unlikely to be able to be performed without the assistance of sophisticated algorithms for big data analysis. Therefore, a crucial aspect of human factors engineering is to design these systems in a manner that enables the human analyst to grasp the safety-critical data and make informed decisions, which will continue to remain the human's responsibility (at least, for the foreseeable future). To put this into practice, however, necessitates the establishment of a shared framework for collaborative decision-making, supported by proper human factors research that informs the human-system design, where the system provides substantial support to the human analyst in providing safety intelligence and guiding decision-making. The trust of the human in the system, while avoiding over-reliance as well as other human factor design and implementation considerations, will be paramount to a successful re-imagined safe air transportation system. Promising areas to further help guide future research and design development efforts may be found through human-system integration and human-machine teaming.

D. Human-System Integration/Human-Machine Teaming

Human-System Integration/Model-Based Engineering Needs

Human factors challenges center around how to design such human-centric safety systems, that are envisioned to continue to become more automated/autonomous through expected breakthroughs and scientific/technological advances in ML/AI. How to engineer into systems the shared awareness and collaborative decision-making capabilities between humans and machines, while maintaining the primacy of the human as critical decision-maker but aided by ML/AI, will not be an easy one to achieve. It is especially critical to consider the psychology of people that must interact with, monitor and/or supervise systems, that reliably exhibit superior performance up to some possibly unseen limit, but of which humans are ultimately responsible and accountable for both their and system actions/decisions. Design of future safety systems, such as IASMS or on-board vehicle management systems, benefit from human-system integration methods and guidelines [e.g., 226]. This includes considering the need to revise current human-system architectures and design utilizing Model-Based System Engineering [e.g., 225-227], in concert with human-system integration, and through design philosophy of Human-Machine Teaming. These serve as paradigms for the design of the IASMS.

Human-Machine Teaming Needs

The advent of the term "human-machine teaming" (or alternatively, "human-autonomy teaming") is relatively recently gaining significant visibility over the past decade. Looking back to past frameworks and models for human-automation interaction (e.g., LOA), it is possible that there may not be sufficient guidance to address the many envisioned changes that may be ushered in with increasing prevalence of ML/AI and highly automated and increasingly autonomous to fully autonomous systems. A "new" concept [see 195] has emerged in response, described in present paper as "human-machine teaming" (e.g., see AIAA Human-Machine Teaming Technical Committee), to reflect a broader purview of concept applicability to human factors design. Although that premise may be questioned [e.g., 95] (see 195 for review], it is less academic argument than practical need that may drive research and search for implementable solutions that are trustworthy and explainable. There is need for better HMT theories and more human factors research is necessary particularly for how to translate HMT concepts and principles into practical guidance and ways to measure design success (i.e., how do you know if you achieved human-machine teaming?). Fortunately, there has been recent significant increases in studies published on HMT [see 195]. HMT can be defined as, "… a distinguishable set of two or more agents (human and machine) that interact dynamically, interdependently, and adaptively toward a common goal/objective/mission" [228, p. 2 (adapted from [229] definition of human teams). According to Shively et al.'s [230] conceptual model of HMT, there exists three types of superordinate design principles: (a) bi-directional communication between human and automated/autonomous agent; (b) autonomous agent transparency; and (c) task/functional allocation assignment made at design time or run-time by a human/operator. Other researchers have also published HMT principles and design guidance that can be used to inform future safety systems, like IASMS, and safety SFCs. NASA has significant investments in HMT [e.g., 228, 231] that have applicability on how to design joint cognitive systems with trustworthy highly automated/autonomous safety systems, including IASMS.

Calibrated trust is an apex design goal for HMT, and there has been a growing number of research studies that examined trust in HMT [e.g., 222, 232-234]. Specifically, these works examined how the coordination of communication between the human operator and an autonomous agent influences the development of trust. Research has tended to focus on the coordination between people and automated/autonomous agents (see [95] for conceptual model that distinguished between the two); said another way, the research focuses on how to make automated/autonomous system team players [e.g., 112]. Essentially, as described by Woods [112], 'intelligent' machines create joint cognitive systems that distribute cognitive work across multiple agents. Furthermore, the design of future intelligent safety systems and SFCs is really the design of a team that coordinates between machine agents and safety practitioners and vehicle/system operators. It, however, has been shown in aviation (e.g., Maneuvering Characteristics Augmentation System) and other domains (e.g., anesthesiology) that automated/increasingly autonomous systems often fail to work together as team players if not design from that design goal perspective from onset [e.g., 106, 112].

Importantly, as there is an ever-increasing interest in automated ML/AI systems (including future SMS data analysis systems), the human factor challenge is how to engender trust with automated safety data systems [e.g., 71-77]. Through proper ways of visualizing the data (i.e., HIMI), such as that offered by Visual Analytics Pipeline and many other high potential methods, as well as taking a human-centric design approach for ML/AI application that are trusted, reliable, and safe [e,g,, 220] it supports design for intelligent human-system interaction and coordination; that is a laudable design goal and one advocated for by the IASMS concept of operation.

HMT offers promise as paradigm for addressing human factors challenges, but yet poses especially critical challenges. A particular concern involves trust miscalibration and ease that operators may distrust the automated/autonomous agent if undesired behavior is observed (or perceived) that may require supplemental operator/safety analyst training to reset the trust levels combined with recalibration of automated/autonomous systems within human tolerance boundaries. Efforts early in system design lifecycle and utilization of human factors test and evaluation methods can reduce this possibility and improve the human-system interaction and coordination. Team ab initio and recurrent training may help human operators and safety personnel become familiar with failure modes, ways to tailor HIMI by operator preference, bidirectional communication styles, and other system characteristics and latent and active operational functions, etc. that help develop a more accurate mental model. Although there is a large corpus on human teams and training design, there is relative dearth of research examining human and machine teams aimed at coordination, communication, and trust (e.g.,160, 232-238]. Therefore, human factors research is of significant need to address the relatively little research on above topics that examine specifically the unique challenges involved in human teaming with machines design involved in ML/AI-based highly complex automated/autonomous in-time integrated SMS and associated safety SFCs.

Another human factors challenge involves change over time from original design of safety critical systems. For example, consider the context of the FAA UTM and UAM ConOps [42-43]. This concept describes aircraft automation levels based on the level of pilot-in-charge engagement with UTM/UAM aircraft enabling systems. Levels of the evolution of aircraft automation consisting of the following:

- Human-Within-the-Loop (HWTL) - Human is always in direct control of the automation (i.e., systems).
- Human-on-the-Loop (HOTL) - Human has supervisory control of the automation (i.e., systems), and Human actively monitors the systems and can take full control when required or desired.
- Human-Over-the-Loop (HOVTL) - Human is informed, or engaged, by the automation (i.e., systems) to act. Human passively monitors the systems and is informed by automation if, and what, action is required, and human is engaged by the automation either for exceptions that are not reconcilable or as part of rule set escalation.

The UAM aircraft automation levels can be tied back to taxonomies of human-automation interaction LOAs. For example, HOVTL would represent, at minimum, Level 7 "executes automatically, then necessarily informs the human" or possibly "informs [human] after execution only if asked" [239]. Achieving each of these levels of HAT implies maturity paths for different defined IASMS SFCs. Each of the SFCs are posited to evolve differently, which may result in heterogeneous “readiness levels” that are achieved as breakthroughs are made and existing safety technologies are iteratively developed and implemented. A potential challenge is that design incompatibilities may develop between not only the system SFCs, but also the knowledge, skills, abilities, and experiences required for effective human performance by the safety analyst or, say the AAM fleet manager. Human factors research should also focus on how complex changes occur over time that may lead to drift into safety margins (or failure) as the system naturally evolves – these include not only change management of technology but also people and dynamic transformations that inevitably occur over time.

Despite current limitations and voiced reservations by some, through emphasis on concepts of teaming, joint human-intelligent systems, need for human-machine collaboration, and fostering of human-system trust, the burgeoning field complements design and training guidance [e.g., 240], derived from 50+ years of human-automation/-system interaction, towards optimal, dynamic allocation of functions to humans and machines [241]. Clarke [242], for example, provides specific instances where possible allocations may be optimal. It is by taking a systems perspective and looking across interdependencies and organizational factors that HMT may fully realize potential to facilitate the FAA and NASA visions for a realized future air transportation.

E. System Interdependencies/Organizational Factors

One way to address potential human factors gaps and issues is to consider system evolution and maturity across the design lifecycle when viewed through the lens of various design paradigms, such as HMT; cognitive systems engineering (e.g., use of cognitive artifacts); standards and guidance; and various tools, methods, and techniques available. Because the human is expected to remain within the safety decision loop of foreseeable future SMS and safety SFCs, it is paramount to design future aviation safety systems that can mutually support adaptability and resilience in both humans and machines as interconnected team players that together make up the organizational system, whether at airline or system-wide NAS. Today, people are the primary, and only adaptable, source of safety in aviation. However, it is envisioned that future autonomous SFCs may also be adaptable resulting in two adaptive and potentially conflicting monitor, assess, and mitigate safety roles and responsibilities. Therefore, better understanding is needed of both the human “SFCs” to anticipate, monitor for, respond to, and learn from safety events every day during line operations, as well as the corresponding IASMS automated SFCs that monitor, assess, mitigate, and assure against hazards and risks. This lens brings into focus the interdependencies of adaptability and resilience between people and automated/autonomous safety systems and safety SFCs. The scope should include better understanding of the human contributions to aviation safety that are helping to inform design of IASMS as a joint-cognitive system that exists within a larger ecosystem.

A final, but not exhaustive, human factors challenge described in this paper concerns how to step back to take in a broader system-wide perspective for air transportation system safety. The system already is very complex and is expected to grow in that complexity with increasing volume of operations and new entrants. New automated/autonomous technologies and better data analytical capabilities hold great promise for that needed growth to happen safely. However, as has been well argued before [e.g., 31-34], decisions do not only occur during design or in operation, but are products of continuous organizational pressures (e.g., resources, priorities, etc.) that have significant potential for deleterious impact. It is only through looking across the systems, beyond individual airline SMS or data systems (e.g., ASIAS), that safety operators, regulators, researchers/academia, industry (e.g., original equipment manufacturers), and safety organizations (e.g., IATA, ICAO, FSF) gain organizational trust. It further encourages acceptance of premise of humans as most critical component of an adaptive and resilient safety system. The entire perspective offered by present paper may not be shared with all stakeholders invested in the potential offered by the future NAS. However, it is hoped that some may be swayed by arguments made; or at least, will pause to consider these human factors challenges when confronted with their own safety system and SFCs design decisions.

VII. Conclusion

To transform SMS to the IASMS to help safely enable the future aviation vision, in-time integrated safety management will be a key need. Other technological and operational concepts will further transform the air transportation system of tomorrow, including new vehicles, new entrants, and new ways to assure safety. The paper focused on IASMS, designed not to replace current SMS but to evolve it and help ensure new technologies are introduced safely, that represents a tailorable and scalable solution to evolve SMS through monitor, assess, mitigate, and assure SFCs. The SFCs include capability for data/decision fusion and evaluate increasingly large, disparate sets of data to quickly (in-time) identify and mitigate risks and hazards in ever increasingly complex operations while integrating process changes to advance safety intelligence. Human factors, human-system integration, and how to effectively achieve HMT will be significant future design challenges. However, they also represent today's opportunities to help ensure that they are addressed early in the system design lifecycle; to do otherwise, risks repeating mistakes witnessed with past technology introduction and the changes it brought to human roles and responsibilities in safety critical systems. Too often, human factors provide useful inputs about a new design only after it is all but finished [127], which underscores need for sea change in how the profession collaborates with other disciplines and contributes new knowledge through participatory design.

In 2003, Meister [243] concluded, after more than 50 years of human factors research, that not much progress had been made. Technology and the changes it brought, and shall continue to bring, was the original impetus for human factors which started with aviation. The modern pace of innovation is not likely to slow anytime soon, and it is this inertia that has driven human-system design decisions and shall likely continue to do so. It is unfair to human factors to say it has failed for aviation, particularly when discipline is evaluated across the entire body of many successes. However, as Sidney Dekker sagely observed, "[i]f we in human factors and system safety keep doing what we have been doing, …we may become one of those systems that drift into failure. Pragmatics requires that we too adapt to better cope with the complexity of the world facing us now" [127, p. xv]. Written almost 20 years ago, these words still ring true today and serve as call to action for human factors profession.

As another new era dawns on yet another technological new horizon, there are significant challenges ahead. Moreover, there are opportunities for human factors to not only study how people use new forms of technology but, and most critically, also being able to apply that to practice of engineering and designing aviation safety products, processes, and systems. There have been undoubted successes for aviation human factors, but also too many missed opportunities to inform system design early resulting in less effective human factors solutions to poor human-system design. Part of the challenge has been changing perceptions on value of human factors contributions by other aviation engineering and science professions. It is of paramount importance that human factors assertively insert itself now into the epicentrum of technological "earthquakes" that are heralding many potential future benefits to society yet loom large in the upheaval it may bring if human factors field is unable to meet its profession responsibility. After all, this transformative future of aviation and air transportation system is, by definition, unwritten [244]; And all of us – human factors included – are the authors of that future.

The paper examined common and unique human factors and human-system interaction challenges involved in future in-time integrated safety management and safety SFC design. It described how design goal should be a symbiosis between humans and machines, so they are better by teaming and working together. An important human factor challenge concerns advances in ML/AI capability that may fundamentally transform human roles and responsibilities and have substantial human factors design implications, due to concerns of explainability, explicability, observability, and verifiability of these methods. NASA researchers and collaborative partners, along with many others, have been researching how to design these ML/AI methods to combat against potential human-system design challenges, as those described in present paper [76, 245-254]. However, human factors research is of significant need to examine specifically the unique design challenges surrounding human teaming with machines involved in ML/AI-based highly complex automated/autonomous in-time integrated safety management systems and associated operational and safety SFCs. One promising FAA-sponsored research project was awarded to develop guidance for the design, implementation, and evaluation of ML/AI specifically for ATM systems [255] but may be extensible to other operational applications (e.g., AAM m:N operations; traditional air operations, such as Part 121 and 135). Similar human factors research and development efforts are needed to address the many human factors design challenges, including those described here. Those discussed represent a long and common list, albeit not complete but well-known to human factors community, that include: (a) trust, (b) over-reliance/complacency, (c) human optimized data visualization, (d) training, (e) communication and dissemination of data and analyses, (f) situation awareness, (g) mental model formulation and maintenance, (h) saliency of indicators and knowledge of critical safety events, (i) accountability, (j) decision bias, (k) monitoring and supervisory control, (l) teaming, and (m) design paradigm implementation challenges and other potential human factors considerations and/or problems that must be confronted early in design lifecycle of such systems. The challenge is great, but so is the payoff, as the air transportation system looks to build a future "sky for all" that is also "safe for all".

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