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Data integration with diverse data: aerospace industry insights from a systematic literature review

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Abstract

Data Integration (DI) is a technical framework that facilitates the integration of different data sources into a unified system. Often, organizational data is spread across various files, databases, and personal computers, resulting in data silos and difficulties in accessing vital organizational knowledge. The solution rests in the development of Information Systems capable of handling diverse data from multiple heterogeneous sources. This study presents a systematic literature review on data integration approaches, specifically focusing on the aerospace industry. We conducted a literature search on IEEE Xplore database with keywords 'data integration aerospace' for articles published between January 2000 and December 2022 to discover aerospace industry insights on data integration with diverse data. Four (4) distinct aerospace-specific data categories and three (3) data integration types were discovered. The findings of this research offer insights on data integration in the aerospace domain with the results suggesting limited research on cloud-based integration.

Keywords: data integration, aerospace industry, decision support systems, big data, diverse data

Introduction

Many organizations continuously accumulate enormous amounts of structured, semi-structured and unstructured data. Managing these data requires an Information System (IS) capable of handling multiple heterogeneous data sources and producing a high-level of data prioritization according to the frequency of use and domain-specific understanding. Data Integration assists with establishing a digital infrastructure by connecting sources of information into a unified system.

Li & Zhong (2010) define Data Integration as a state when data from different sources, including software systems, is linked together conceptually and physically in a database. The other distinct definition is provided by Salem et al. (2013); the authors stated that data integration is the process of consolidating data from heterogeneous and distributed sources into a unified repository and providing the user with a unified view of these data.

DI allows organizations to access a multitude of data quickly for analytical and other purposes to generate previously unavailable insights with new understandings. As such it becomes an essential element in establishing an effective data-driven Decision Support Systems (DSS). Codd et al. (1993) emphasized the effectiveness of DSS in having easy and rapid access to large amounts of accurate, well-organized multi-dimensional data. These information systems utilize information, models, and data manipulation tools to help make decisions (Phillips-Wren et al., 2004), support the effectiveness of decision-making events (Barr & Sharda, 1997), and provide strategic and competitive industry advantages. Furthermore, data driven DSS assists management, operations, and other divisions of the organization to effectively make important decisions quickly and dynamically, which would typically require significant amounts of time and energy if performed manually (Kim et al., 2007).

Prior research in the aerospace domain reveals a multitude of data challenges described by Yung & Watton (2012) as follows: (1) lack of data exposure and access; (2) lack of cross-mission area information exchange and sharing; (3) lack of data integration and data analytics; (4) lack of data understanding under mission context. The authors stated that the current approach to data sharing is not enough to support decision making and without fusing disparate data sources and “connecting the dots” across seemingly unrelated events, we will be left without actionable information. For instance, Yeung & McGregor (2018) reference multiple adaptive-assist equipment used during different stages of spaceflight to help the crew member adjust to the drastic change in gravitational environment. These equipment and devices collect a wide range of physiological and mechanical data that can be integrated and utilized for real-time physiological health monitoring and other areas such as aircraft operations.

Therefore, in this paper, we conduct a systematic literature review to explore Data Integration approaches and techniques in the aerospace domain that focus on handling diverse and multi-dimensional data. Furthermore, we provide other researchers and industry leaders with a detailed description of aerospace domain-specific data. This paper is organized into sections, defining the research methodology, a summary of the findings, and the discussion.

Methodology

Research Questions

The primary objective of this research is to identify a variety of Data Integration approaches and techniques, models, applications, and practical solutions with a focus on the aerospace industry and handling industry-specific data. Based on these objectives, we formulated the following research questions:

RQ1. *What approaches, techniques, and models are proposed for data integration?*

RQ2. *What types of data are discussed in the existing research?*

RQ3. *What are the industry applications for Data Integration implementations?*

Search Process

The scientific literature search was conducted using IEEE online database. Interest in exploration of technical DI aspects led us to limit the research efforts to IEEE Xplore digital library, which provides access to research materials from Institute of Electrical and Electronics Engineers and Institution of Engineering and Technology, covering literature related to engineering, computer science, and communications.

We performed our literature search on the following phrase ‘data integration aerospace’. The search results were inclusive to conferences and journals, filtered by years 2000 to 2022, in the English language, with full-text available for review.

Furthermore, we utilized a publication topic filter to avoid irrelevant articles and limited our findings to “data integration” and “aerospace computing”. Table 1 details the search process.

Table 1: Search process

Steps in the Search Process	Count
General search term	236
Filter: conferences and journals	218
Filter: years 2000-2022	210
Filter: publication topic	69

We selected "data integration" with quotation marks to group words that appear together exactly as typed. This is done to avoid being irrelevant to "data integration" research. After performing the first round of search, the total number of articles was 236. Next, we limited our search results to articles published in conferences and journals and filtered by year of publication between 2000 and 2022, resulting in the selection of 210 articles. Finally, we used a filter to select studies with topics on data integration and aerospace computing, which aided the final selection of 69 articles.

Selection Process

The PRISMA Model (Page et al., 2020) was implemented to structure this systematic literature review. Figure 1 represents the search process based on the PRISMA approach.

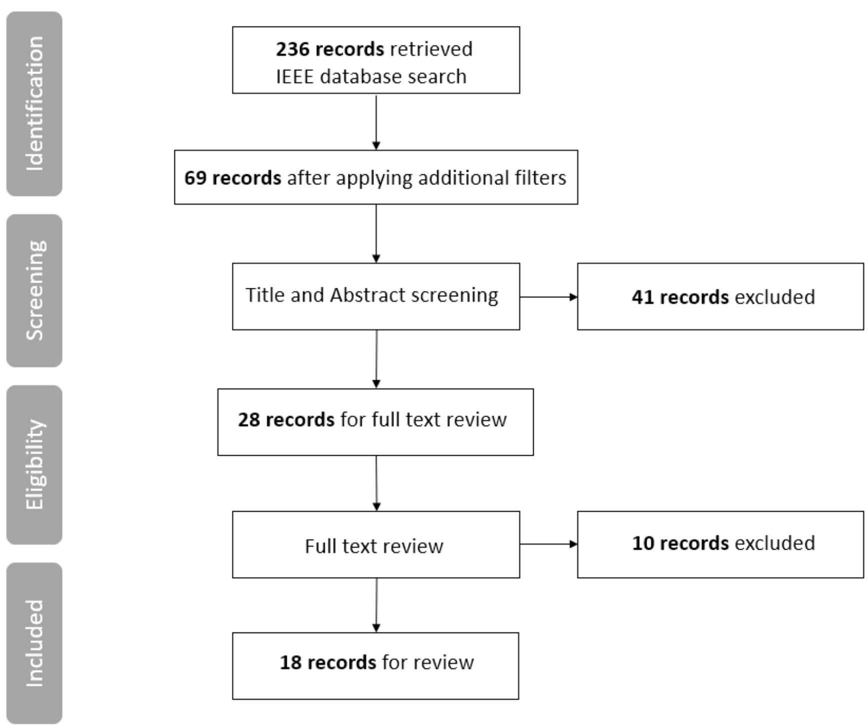

Figure 1: Selection procedure

During the search process, we excluded 51 irrelevant studies that did not provide meaningful research on data integration topics and did not specifically address the aerospace industry. During the title review, we closely examined each articles' title and its publishers. Conference or publisher specific details aided in the selection process by offering an insight on data integration topic in aerospace industry. For instance, articles that do not explicitly mention aerospace application in their title, may still be relevant to our research if published under IEEE Aerospace Conference or National Aerospace and Electronics Conference.

The total number of selected articles after the title review was 39. Next, we reviewed abstracts of the selected studies in search of articles with a primary focus on integrating domain-specific heterogeneous data from various sources, which resulted in the selection of 28 articles. The full-text review allowed us to identify research that discusses different aspects of data integration, frameworks, and integration techniques. The final step resulted in the selection of 18 articles.

Profile of the Selected Studies

The selected research studies were reviewed in relation to the research questions. Table 2 presents a summary of our review results sorted alphabetically by Publication.

Table 2: Article summary in relation to the research questions

Publication	DI Solution	Type of Data	Application	Category
Bachmann et al. (2009)	Generic design	Various types of data containing engineering knowledge	Manufacturing, aircraft automation	Engineering
Eito-Brun & Amescua-Seco (2018)	Generic design, XML based transformation	Text data, quality, and verification reports	Management, reporting automation	Engineering
Gandhi et al. (2021)	Distributed architecture	Sensor data	Space control and space security	Mission
Han & Li (2016)	Integration framework for design and process data	Text, images: Engineering data	Design and process data	Engineering
Kirk D. Borne. (n.d.)	eScience paradigm, data-driven science	Reference to data streams, data from multiple sources	Scientific and operational decision making	Other
Maluf & Tran (2008)	Generic design: "Schema-less" data integration approach on NETMARK with XML	Reference to semi-structured and unstructured data	Multiple applications	Other
Maluf et al. (2007)	Schema-less object-relational database management system (NETMARK)	Various types of data	Knowledge management	Other
Ortiz et al. (2008)	Integrated Airplane Health Management (IAHM) system based on generic design	Various types of in-flight and maintenance data	Maintenance and flight data	Aviation

Publication	DI Solution	Type of Data	Application	Category
Popov (2004)	Collaborative integrative system IMPRAS	Reference to various types of data	Mission planning	Mission
Popov (2005)	Distributed approach	Mission data: video, audio recording data	Mission planning	Mission
Popov (2006)	Process-based: Integrated Workflow package	Reference to mission planning data	Software integration	Mission
Prysyazhnyuk & McGregor (2021)	Cloud-based adaptive framework	Psychological data, medical history, sensor data	Psychological health monitoring in space	Medical
Rong (2013)	Generic design, Heterogeneous Navigation Database Management System	Various types of navigation data	Civil aviation	Aviation
Snider & Rice (2016)	Generic design, based on MS SQL server	Sensor data	Psychological health monitoring	Medical
Solomon & Crawford (2021)	Cloud-based data integration	Reference to various types of air traffic data	Civil aviation	Aviation
Xiong et al. (2012)	DI based on information grid approach	Various types of public service data	Civil aviation	Aviation
Yeung & McGregor (2018)	Cloud-based, Artemis platform	Reference to various types of psychological data, sensor data	Psychological health monitoring in space	Medical
Yuan & Watton (2012)	Push-pull event processing DI framework	Sensor data, mission specific data	Space control and space security	Mission

Results

This research provides significant insight into the current academic research in the aerospace domain. First, most of the recent research discusses DI solutions that handle real-time data from heterogeneous sources. Data-driven information systems with advanced real-time decision-making capabilities are becoming more relevant in a variety of applications. According to Lopes & Oliveira (2015) data can be complex: heterogeneously structured, originated from several different sources, represented through various standards, provided via distinct formats and with meaning changing over time. As a result, it is essential to consider these conditions in the development of DI framework.

Summary of Aerospace Industry Data

Our DI research discovered the following primary data categories in relation to aerospace industry data: (1) medical (health), (2) mission, (3) engineering, (4) aviation, and (5) other (unspecified) data. Some of the research papers did not reference any specific data type, these are marked as “Other” under proposed data classification. In other cases, the researchers provided specific descriptions of data types, for example, psychological health records or medical sensor readings, which were categorized under "Medical" type. Figure 2 represents the count of papers for each aerospace-specific data category colored by the types of DI approaches, followed by a description for each data category.

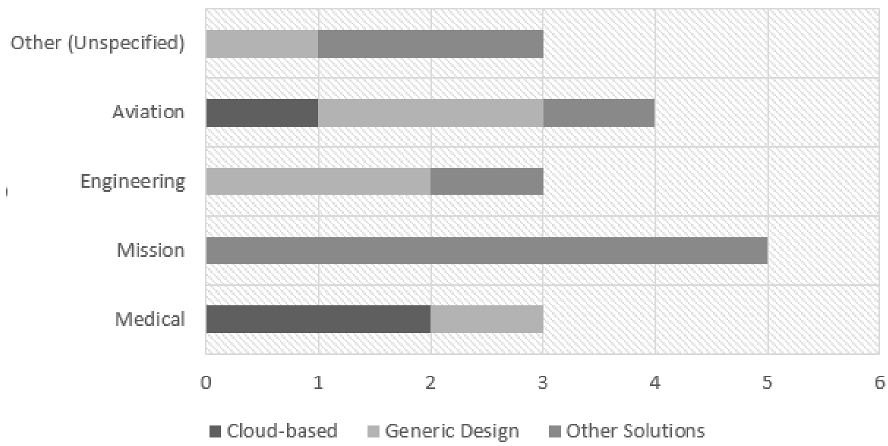

Figure 2: Aerospace domain data categories

Engineering Data

Many aerospace companies heavily rely on engineering data to support various organizational processes and activities, producing a large number of documents, containing various types of drawings, design solutions, manuals, video documents, technical standards and other types of unstructured and semi-structured data. Han & Li (2016) described it as information, containing design information, properties of parts & components, model properties, model structures, relationship between the models and components, relationship between parts and components and documentation, engineering change properties, baseline content, validity attributes, etc. Liu et al. (2008) stated that engineering processes are highly creative and knowledge intensive and comprise activities such as design, engineering analysis, manufacturing, and performance evaluation.

Several studies show that engineers spend as much as two-thirds of their time communicating to get input to their work and output results from their work, and one-third of their time searching for and accessing design information with about 80% of explicit knowledge found in documents. Quick access to engineering data is crucial as it provides engineers and managers with an essential knowledge to support multiple organizational activities. Bachmann et al. (2009) discuss DI focused on engineering knowledge from fields as diverse as aerodynamics, aeroelasticity, engine building, environmental impact assessment, material science and structural issues, whereas Han & Li (2016) focused on a specific type of spacecraft design data (CAT images and documents). References to various types of data, a variety of databases, and datasets suggest that most DI solutions are focused on data from several heterogeneous sources, represented through various standards, provided via distinct formats, and changing over time.

Medical Data

Previous research efforts indicated the importance of health-related data during deep space exploration missions (NASA) and dynamic flights (Aviation). Prysyazhnyuk & McGregor (2021) stated that environmental threats are characterized by increased exposure to galactic cosmic rays, extreme temperature variations, remoteness from Earth, isolation, and lack of gravitational force, which affect physical, mental, and social well-being of the crew. Limited technological and computational resources and delays in communication create additional implications in space exploration. Yeung & McGregor (2018) emphasized that without on-call access to an Earth-based doctor during communication black outs, there is a critical requirement for an autonomous health monitoring platform onboard the spacecraft to provide medical support for the mission crew with capability to integrate sensor data, medical history, psychological reports, etc. and provide timely medical decision support. Snider & Rice (2016) stated that psychological hazard conditions as defined as any abnormal physical symptom, injury or medical condition that occurs during dynamic flight, have increased by over 400% from FY 2010 to FY 2015 in Naval aviation, which indicates a necessity in the development of a health monitoring solution. As such, medical data integration has become an important part of DI research.

Mission Data

Mission-specific data is analyzed in Popov's research relative to International Space Station (ISS). Popov (2005) indicated that mission planning is a core component of what is being termed as space mission preparation and support. ISS Mission Operations Directorate manual states that the Integrated Planning System (IPS) was established to provide data on resources available, identify conflicts in resource allocation, and distribute Station's resources. This system consists of a collection of software applications for planning and analyzing Space Station Operations. The primary users of IPS are flight controllers and planners (Popov, 2004). Mission planning processes are not isolated and co-exist with software engineering, system engineering, and operation support between the highly structured/rule-based type and unstructured/ad-hoc type. Yung & Watton (2012) addressed lack of data understanding under mission contexts, which contributes into the data overload problem, stating that incorporating mission context into system solution will make the system "smarter" and more responsive to mission threats and changing missions.

Aviation Data

Our research discovered references to multiple types of aviation data, including public service, aircraft, and navigation data. Solomon & Crawford (2021) stated that aeronautical data used for tactical decision-making is now seen as crucial to the decision-making process in Air Traffic Management. Integration of global and localized datasets into a digital aviation data platform enhances the capabilities of the solutions. It opens the possibilities of leveraging big data analytics and microservices to compute trajectory predictions, demand capacity balancing, arrival and departure sequencing, airspace delay, among others, in real-time to achieve operator-driven mission objectives. Xiong et al. (2012) stated that the public service data in civil aviation mainly originates from manufacturing units, including aero surveillance authorities, airline companies and airports. This data is different in structure and shape and dispersed in different systems, including air traffic control centers, airline companies, airports, etc.

Ortiz et al. (2008) focused their research on aircraft system health management, referring to aircraft data as data that comes from flight recorders, maintenance reports, logistics, and mission-readiness reporting systems, consisting of the aircraft's system operational conditions or maintenance and repair actions. The authors indicated that crucial information regarding flight condition and situational parameters are often disregarded because of accessibility issues or what can be an overwhelming volume of time-series data that is collected from modem onboard aircraft data recorders. Rong (2013) identified multiple data sources for navigation systems, consisting of PDF format data, executable and own excel format data, etc. that needed to be integrated into the navigation central database, which includes heterogeneous data source management module and central data management module.

Data Integration Approaches

In this section we discuss the Data Integration approaches discovered in academic literature in relation to the aerospace domain. These DI approaches are classified into the following categories: (1) Generic (Uniform) Design, (2) Cloud-based, (3) Other. Figure 3 represents the different types of DI as they related to the aerospace-specific data.

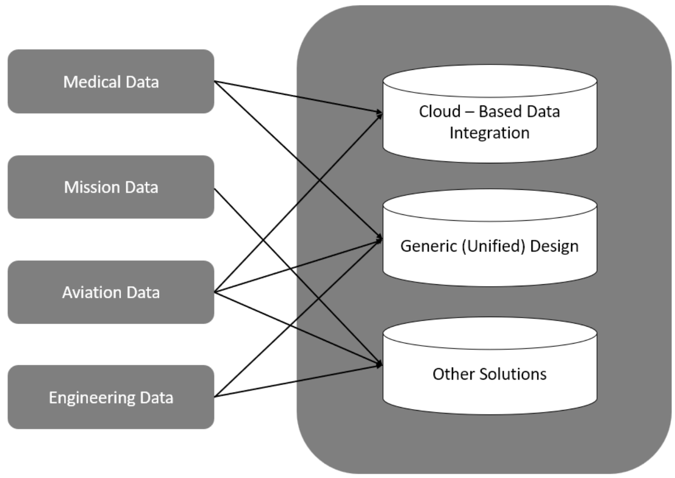

Figure 3: Aerospace Data in relation to Data Integration

Generic (Uniform) Design

Generic design is based on a concept of creating a unified data format, for instance, developing a common database schema, to support data integration from heterogeneous sources. Bachmann et al. (2009) proposed utilization of generic design that is independent of any details related to data formats and software integration frameworks. This approach focuses on application domain, enabling easy transition between, as well as adaptation to any other framework to be used in the future. It is based on a concept of creating a standard for an extensible data format, originally designed for use in the preliminary design phase of single aircraft optimization, but also suitable for other areas loosely connected with aviation.

Eito-Brun & Amescua-Seco (2018) proposed a technical solution created to collect and integrate data from heterogeneous tools with use of XML to support data exchange, integration, editing, and implementation of interfaces to gather data from external tools. The authors describe these interfaces as small software programs that retrieve data, transforming it to XML structure. Snider & Rice (2016) proposed utilization of SQL Server database table and use of Microsoft's extract, transform and load tool, SQL Server Integration. Ortiz et al. (2008) suggested to develop a common database schema to effectively store and retrieve data across an arbitrary aircraft platform for each of the otherwise disparate data sources (flight and maintenance data), which helps maintainers and engineers make more informed decisions for aircraft health management.

Cloud-based Approach

Prysyazhnyuk & McGregor (2021) proposed a cloud-based health monitoring framework based on the Artemis and Artemis Cloud platforms by integrating multi-source, multi-type data. This platform provides in-depth adaptation-based assessment and identifies issues, which have been known to impact human health in space. Yeung & McGregor (2018) proposed a health analytics platform for real-time physiological monitoring based on medical support and countermeasure equipment data integration. The solution is centered around collecting physiological data from astronauts onboard the International Space Station to enable predictive and diagnostic analytic provisions.

Solomon & Crawford (2021) focused on integrating global and localized aviation datasets into a digital platform to leverage big data analytics and microservices to compute trajectory predictions, demand capacity balancing, arrival and departure sequencing, airspace delay, among others, in real-time to achieve operator driven mission decisions with help of cloud and hybrid cloud solutions. Furthermore, cloud-based implementations provide a cost-effective model for data integration applications. Most cloud computing services implement "pay-as-you-go" model, allowing users to pay only for resources that are needed and used. A consumer can provision additional computing resources as needed without human interaction with the service provider (Al-Gumaei et al., 2018). Additionally, cloud resources can be rapidly expanded on demand. These attributes contribute to cost reduction, however cloud-based challenges may appear in terms of latency, sensitive data security, and integration with IoT and big data.

Other Approaches

Our research revealed a multitude of additional DI solutions that could not be classified under previously described categories. For instance, Gandhi et al. (2021) discussed a distributed approach for Mission and Maritime Surveillance (MMS), presenting a platform for managing various sensors and integrating sensor data. MMS system can ingest real-time data produced by sensors and share that data with other systems. An event-driven approach was proposed by Yung & Watton (2012) with push-pull data integration based on an Event-Driven Architecture. The centerpiece of the framework is an Event-Driven Data Integration Environment (EDDIE) that serves as a broker between mission-specific data needs and various data providers. This framework leverages the emerging Event-Driven Architecture and Complex Event Processing, providing on-demand "pull" of relevant data by an end user and the event-driven "push" of time-sensitive information to support decision making.

Discussion

The findings of this study indicate that the majority of the selected research is focused on effectively handling and integrating diverse, multi-dimensional data. Furthermore, we have discovered three primary data integration types based on the technical aspects and methods of DI. Among the various approaches explored, we observed that one of the most accepted methods is centered around unifying data formats and structures. For instance, the use of a common database schema has been identified as an effective means of integrating heterogeneous data sources. However, we found limited industry research on cloud-based DI, which offers additional research opportunities associated with cloud-based implementations.

In this paper, we make a valuable contribution to the aerospace industry research and information systems science by not only identifying and describing the specific types and sources of aerospace data but also by developing a data classification based on the types of data discovered through our research efforts.

Our literature search was limited to IEEE Xplore digital library and resulting conclusions were derived from our limited selection process. By addressing these limitations and conducting further research, we can enhance our knowledge of data integration and its potential applications within the aerospace industry.

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