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Review

A Review of an Ontology-Based Digital Twin to Enable Condition-Based Maintenance for Aircraft Operations

Darren B. Macer [1,*], Ian K. Jennions [1] and Nicolas P. Avdelidis [2]

[1] IVHM Centre, Faculty of Engineering and Applied Sciences, Cranfield University, Bedford MK43 0AL, UK; i.jennions@cranfield.ac.uk
[2] Department of Aeronautics and Astronautics, School of Engineering, University of Southampton, Southampton SO17 1BJ, UK; n.p.avdelidis@soton.ac.uk
* Correspondence: darren.b.macer@cranfield.ac.uk

Abstract

The concept of digital twins has been studied for over two decades and the core tenet lies in it being a "digital representation of a connected physical object". Utilization of digital twins promises to enable superior decision-making, enhanced operational understanding and future predictions to enable levels of Condition Based Maintenance (CBM) through Integrated Vehicle Health Management (IVHM) which exceeds existing capabilities. Digital twins are being embraced by many industries, including aviation, and are often depicted as electronic images of an asset of interest. However, in a less visually appealing manner, they can also be described simply as a collection of data in an organized and easily accessible format from across the lifecycle which describes a feature that addresses a specific use case. This review demonstrates how the creation and maintenance of digital twins will play a critical role in enhancing IVHM to enable CBM within the aerospace industry. Through a literature review, this paper demonstrates the need for digital twins, of a sufficient level of fidelity, to facilitate the transition to being condition based through deeper levels of operational and component understanding. It emphasizes how detailed knowledge, represented through ontologies, regarding component design, manufacturing, and operational history aid in achieving the desired fidelity levels. By synthesizing insights from various industries with a focus on aerospace applications, this paper aims to provide a comprehensive understanding, focused on the aviation industry, of digital twin definitions, their creation processes, fidelity measurement, and their implications for CBM, while acknowledging the limitations of the current research landscape.

Keywords: condition based maintenance; digital twin; fidelity; integrated vehicle health management; ontology

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1. Introduction

While there are many nuances and abstractions of the definition of a digital twin, the central idea that has almost universal agreement is that a digital twin is a "digital representation of a physical object". This implies that if an object exists in the physical world, it can be represented digitally, creating a digital twin. Conversely, if an object has not yet been manufactured or if a prediction is being made about the future state of an existing object, it cannot possess a digital twin. For items that are intended to exist in the future, whether they are defined by a digital model, a drawing or in an anticipated state represented by a simulation, there can be no digital twin available, as their physical counterpart does not yet exist. The level to which a physical object can be digitally represented depends on its level of complexity and connectivity in design, manufacturing, and operation. For example, a classic wooden pencil may be automatically monitored during its production to ensure quality control, and records may even exist regarding the box it was shipped in and where it was shipped. However, once the pencil has been purchased by an end user, that portion of the pencil's lifecycle will be unknown to anyone other than the user. An example at the other end of the spectrum could be a component, such as an engine, attached to an aircraft which is manufactured and operated in a heavily regulated environment. The engine would not only have detailed manufacturing and assembly records, but data from the aircraft and operational environment that would allow the engine to be digitally represented, forming a digital twin. Unlike the pencil, the engine, and the aircraft it is attached to, are required to be monitored during operation to ensure regulatory compliance, improved levels of safety or reliability, and enable the various support and service offerings that exist. These support and service offerings can all be enhanced by the utilization of a digital twin. Like electricity, a digital twin does not achieve its potential unless it is powering something. As industry continues to strive for efficiency and optimization of processes and operations, a detailed understanding of an asset provides a solid foundation; it is from this foundation that predictions, simulations, or analysis can be based. A digital twin, of sufficient fidelity and updated at a sufficient frequency, will provide the foundational intelligence upon which optimization and advanced services can be built.

Existing research has focused on the areas of utilizing a digital twin for a point solution, describing their intended use, developing frameworks for digital twins, or separately considering the fidelity of a digital twin. It has lacked both the extent of what is required for a specific use case and the relationship between the fidelity of a digital twin and its ability to achieve that use case. This study intends to provide a comprehensive understanding and overview of existing approaches and the major components within the areas of digital twin definition, creation, maintenance, and its ability to enable and deliver a measurable improvement to the concept of CBM. Within the aviation industry it is accepted that reactive maintenance is approximately double the cost of scheduled maintenance. This aligned with the projected shortage of aircraft mechanics has resulted in the industry's desire to move away from a fixed interval for maintenance actions to conducting maintenance based on the known condition of a component, or Condition Based Maintenance. This will require discovering a method to link CBM requirements to measurable levels of digital twin fidelity and capability, both desired and actual, and then validating that those levels are achieved and meet the initial requirements.

As the subject of digital twins is wide ranging and far reaching, the introduction will provide background information of digital twin concepts salient to the subject of How the Fidelity of a Digital Twin Impacts the Ability to Deliver CBM for aircraft operations. Figure 1 shows the 3 areas addressed within the introduction; An overview of digital twins' history, use case dependance, role, application and scale, along with the different aspects of maintaining a digital twin over its lifecycle. Adoption within the industry is also covered by discussing barriers to implementation and various collaborations across the industry.

1.1. Digital Twins

These have been a topic of interest for many years, evolving within both academic and industrial domains. As an example, being used for analyzing travel behavior, a digital twin is defined as "a virtual representation, or replica of a physical system or process that accurately mimics its real-world counterpart," [1]. In the aerospace sector, a digital twin is referred to as a virtual representation of a "connected asset" [2]. Despite the different subjects, they share a core theme: a digital representation of a physical asset, system, or process.

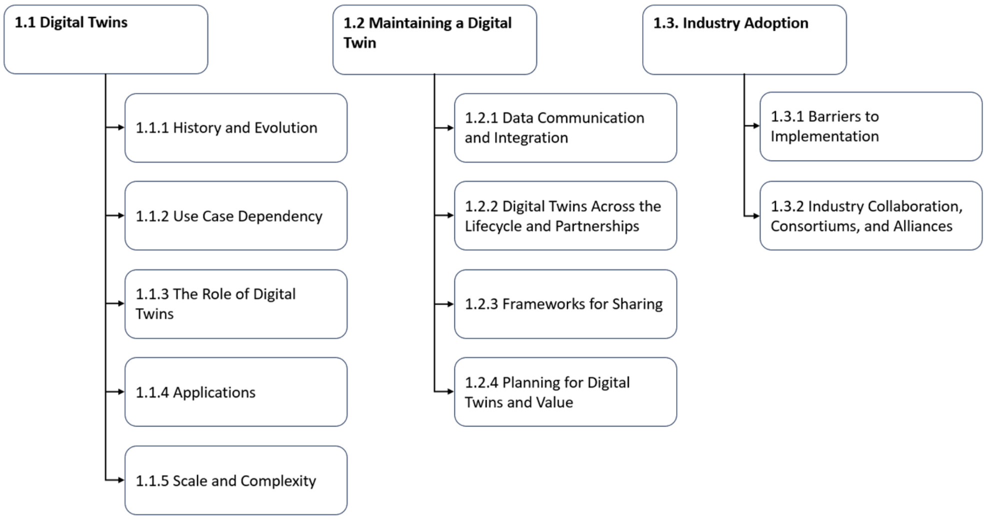

Figure 1. Overview of Introduction.

1.1.1. History and Evolution

The concept of digital twins originated from a collaboration between NASA and the University of Michigan in 2003, evolving from the content of a course focused on the Lifecyle Management of a Product, or PLM. In the white paper "Digital Twin: Manufacturing Excellence through Virtual Factory Replication," the idea of products existing in both physical and virtual spaces was born, with a connection between them for data and information [3].

Expanded definitions within the industry further refined the concept of a digital twin. NASA and the US Air Force describe a digital twin as "an integrated metaphysics, multi-scale, probabilistic simulation of an as-built vehicle or system that uses the best available physics models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin." [4]. A more specific definition is offered, stating that a digital twin possesses full knowledge of how the aircraft has been operated [5]. The connection between the physical and the digital is a fundamental aspect of the twinning process allowing the twin to be the represent the physical.

1.1.2. Use Case Dependency

While the definition of a digital twin may seem straightforward, its complexity is highly dependent on specific use cases, or the specific goal or question it is expected to answer. These can range from simple representations to intricate systems involving multiple components. At the simple end of the spectrum could be the ability to digitally represent, or understand, how many times each aircraft in my fleet has landed at a specific airport. Expanding upon the fact that an operator may want to know how long an Auxiliary Power Unit (APU) has been operated for and in what environments, such as moisture, temperature, particulates over its lifetime. At the extreme end of the spectrum, for a critical item, a complete representation of all lifetime experiences, including detailed manufacturing steps of all sub-components, operation and maintenance actions may be required. However, there is no strict definition regarding the scale, properties, or complexity of a physical asset, which can vary from a single component to a system of systems [6]. Regardless of scale or complexity, a digital twin must be tailored to meet the requirements of its intended use case [7]. To fulfill this need, a digital twin can either be monolithic, representing the entire physical system, or consist of multiple sub-digital twins [8].

The trend of increasing complexity and varying definitions of digital twins is occurring within industry, which depends on the individual or industry describing them [9]. This requires consideration of the relationship between the digital twin and its intended use case to determine the necessary level of complexity. Consequently, the initial concept of a digital twin as a digital or virtual representation of a physical asset, system, or process has evolved to include the requirement of being adequate for achieving a desired use case. It is understood that digital twins can represent many different physical items and enable many areas, aiding production systems, optimizing factories or other industrial aspects, however relative to enabling CBM, through health management, this paper adopts the following definition:

> *"A Digital Twin is a digital, or virtual, representation of a connected physical asset, system, or process sufficient to achieve a desired use case."*

The digital representation could be a model of how a specific system is operating, such as the current condition of an air conditioning pack, it could be an image of the actual state of an aircraft section taken from a drone and updated from the last inspection, or it could be the cumulative count of the extend of thermal cycles of an electrical component over its life. These are all different methods of representing a physical item digitally.

1.1.3. The Role of Digital Twins

The real value of a digital twin can be described as delivering actionable information that replaces wasted resources [10] and can benefit manufacturers and users through improved logistics and on-site activities [11]. The wind turbine industry is investing in digital twin technologies to reduce costs and enhance reliability [12]. At the GE Digital User Conference, the value of digital twins is connected to tangible business outcomes [13]. The value of digital twins can be categorized into four key areas: operations management, cost reduction, business model innovation, and product improvement [14]. Digital twins can perform many roles from improving understanding to enhancing business outcomes, but to be viable they must add value and achieve their desired use case. In the area of health management, the main value of digital twins lies in the understanding and monitoring they bring to items of interest and the downstream capabilities and services they provide, rather than the twins themselves. Digital twins enhance decision-making by providing valuable information that minimizes waste and assists users in recalling detailed information throughout an asset's lifecycle.

1.1.4. Applications

As Digital twins have progressed from academia to industry, they have expanded into many areas [14], documents 18 different industry sectors where digital twin applications are referenced in the literature. Many of these applications extend beyond conventional mechanical items, even encompassing biological subjects. While not explicitly mentioning the term "digital twin", patient-centered care is being enabled by the integration of Electronic Medical Records, Electronic Health Records, and Personal Health Records to provide a comprehensive view of patients [15]. Many other areas are being explored focusing on individuals, considering digital twins of workers, including their personal details, health status, and position [11], digital twins of pilots to optimize flight tests [2] and the creation and use of digital twins of hearts to aid in precision cardiology [16].

Beyond mechanical components and processes, a multi-agent approach for developing a digital twin of wheat is being explored to understand plant development and enhance overall yield [17]. In the realm of infrastructure, a digital twin is being utilized to determine the Remaining Useful Life (RUL) of cable joints in the electrical power grid of the Netherlands, facilitating the transition from a centralized to a decentralized system [18].

The concept of digital twins extends beyond traditional engineering, manufacturing, and Product Lifecycle Management (PLM) applications into diverse fields such as healthcare, agriculture, and infrastructure, demonstrating their versatility and broad relevance.

1.1.5. Scale and Complexity

Digital twins can vary significantly in scale, ranging from atomic-level representations to large systems. Digital twins can be referred to at the atomic level [19], or discussed at the micro-atomic level [10]. Various factors can contribute to digital twins, from manufacturing defects at the beginning of the lifecycle to operational fleet experience [4] and considering all life behaviors and structural deflections to predict aircraft structure life [5]. At the opposite end of the scale, frameworks are proposed to enable digital twins in smart cities [20]. The concept is extended to the national level, creating a digital twin of the United Kingdom [21]. It is evident that digital twins can range in focus from very small to very large, and the need to determine the appropriate size and level of detail for each component part, which may also have its own digital twin, becomes crucial.

For instance, consider an aircraft composed of multiple structural and system components; one digital twin could represent the hydraulic system, which consists of various subsystems and actuated parts, such as the main landing gear actuation. Each actuator comprises numerous parts. The fabrication process for each part is performed by a machine operated by an individual, and each piece of material has undergone various processes since its creation, making it unique. At each step in this process, there exists the opportunity to create a digital twin at different levels of scale and complexity. The use case should guide the requirements and fidelity of the digital twin as the overall system will not require the same level.

1.2. Maintaining a Digital Twin

The creation and utilization of digital twins are desired across multiple industries and applications, with the concept of a digital representation of a connected physical instance remaining central. The link between the physical and digital must be established through the flow of data. To create a digital twin, data regarding the construction of items of interest is essential. As the physical item is operated, maintained, or repaired, the continuous flow of data is critical to maintaining the digital twin alongside its physical counterpart.

1.2.1. Data Communication and Integration

The primary purpose of the digital twin can be described to serve as a single source of truth for information from its physical asset [22]. This is achieved by establishing a trusted and repeatable linkage between the physical object and its digital twin. The concept of data for the digital twin will ideally encompass all information about the physical system; however the volume of data could be substantial [23]. The connection between the physical and the virtual through authoritative digital threads is foundational to the development and implementation of a digital twin [24]. Some applications require two-way communication between physical and digital entities, referring to the act of "twinning," where changes to the physical result in changes to the digital, and vice versa [25]. A key aspect of a digital twin is communication between the physical and digital entities, allowing changes in one to be reflected in the other, thus maintaining the digital twin with its physical counterpart.

1.2.2. Digital Twins Across the Lifecycle and Partnerships

Digital twins require cooperation, data sharing, and collaboration for effective creation and maintenance. Creating and maintaining a digital twin relies on access to data, and it is crucial to know when and how to utilize digital twins throughout an asset's lifecycle, as this may need to be sourced from multiple channels and continuously updated [26].

Digital twins are expected to exist across various lifecycle phases: Design/Development, Manufacturing/Deployment, Use/Modification, and Recycling/Retirement [27]. For complex assets like aircraft, these phases are interconnected, involving various manufacturers, suppliers, and maintenance organizations.

Managing digital twins becomes complex when multiple entities contribute to the lifecycle of a physical item, highlighting the need for effective data sharing. This complexity can lead to individual digital twins of specific components being created by different companies over small portions of their lifecycle. Integrating these individual digital twins into a connected structure is essential for maximizing the benefits of digital twins in complex systems [28,29].

The challenges of accessing data across the lifecycle could be achieved through co-ownership of digital twins to address data sharing and intellectual property concerns [14]. Capturing all physical environment data can pose significant challenges in data sharing among individuals and organizations [30]. With the industry's trend toward component pools, where components move between aircraft, operators, and Maintenance, Repair, and Overhaul (MRO) organizations, the process of obtaining all relevant data will become more complicated [31].

A common theme in creating and maintaining digital twins is the necessity of obtaining and updating data from multiple sources. Collaboration among stakeholders such as manufacturers, suppliers, and maintenance organizations, is crucial, as typically no single entity possesses all the data needed for a complete digital twin.

1.2.3. Frameworks for Sharing

The complexity of digital twins and the various entities within the value chain that contribute to their development, and the introduction of a "Twin Sharing Framework" to enable collaboration are explored by [11]. Ref. [32] proposes a lifecycle digital twin collaboration framework to ensure that a digital twin instance is shared across manufacturing and operational phases. They suggest two key enabling technologies: a generic ontology modeling approach and an identification and resolution system to facilitate data sharing. The use of a knowledge graph and value network to connect various digital twins from different stakeholders, creating a unified value chain is proposed by [33].

1.2.4. Planning for Digital Twins and Value

The evaluation of requirements of digital twins, through use cases, can ensure consistency and should involve collaboration between digital twin experts and subject matter experts to clearly define and document use cases [34,35]. These requirements should be fully understood based on the digital twin's purpose before allocating resources [36]. Ad hoc or poorly planned approaches to creating digital twins can fail due to insufficient data to create or maintain them. This lack of proper problem framing has resulted in poorly validated models and inadequate data [37]. Addressing digital twin requirements early in the design process helps designers understand use cases and available data. The value of the digital twin should be a key focus from the outset of the system's development. Digital twins should not be treated as add-ons; they need to be considered during the initial design phase and relate to specific use cases to ensure the digital twin is correctly scoped.

1.3. Industry Adoption

Despite significant advancements in academic research, the adoption of digital twins in corporate settings has been slower than anticipated. The transition from theory to practice has not progressed as swiftly as expected, despite the potential for substantial value. This slow uptake can be attributed to a lack of comprehension regarding the benefits of digital twins [14]. Additionally, a low awareness of the interrelationships among the various components of a digital twin can contribute to limited adoption [38].

1.3.1. Barriers to Implementation

Several barriers hinder the widespread adoption of digital twins, including a lack of awareness regarding the relationships among digital twin components, insufficient trust, and a tendency for companies to develop isolated point solutions rather than integrated systems. This lack of trust can be considered a significant obstacle and an area where defined frameworks and industry standards can address this issue [39]. These challenges can lead to implementation difficulties and impede the broader adoption of digital twins throughout their lifecycle.

1.3.2. Industry Collaboration, Consortiums, and Alliances

Early effort to document and unify major aerospace OEMs in this domain was undertaken [40], followed by the formation of a "Digital Twin Consortium" [41]. This consortium's mission is to bring companies together to collaborate on digital twin initiatives. The concept of industry alignment in the digital space is further exemplified by Airbus's announcement in 2025 of an aviation digital alliance with Delta TechOps, GE Aerospace, Liebherr and Collins Aerospace [42], aimed at leveraging their combined expertise in aircraft systems, airline and maintenance operations, digital analytics, and operational data.

The aviation industry has recognized both the benefits and challenges associated with digital twin adoption, leading to the establishment of consortiums and partnerships aimed at standardization and fostering a common understanding to advance digital twin initiatives.

2. Problem Statement

The aviation industry is increasingly adopting Condition-Based Maintenance (CBM) strategies to enhance operational reliability, control costs, and improve aircraft availability by transitioning from unscheduled to scheduled maintenance based on component condition rather than fixed time intervals. This shift necessitates the development of capabilities that leverage engineering expertise and data science techniques to deliver servicing, diagnostic, and predictive alerts, enabling proactive measures to prevent component failures. However, the successful implementation of CBM is contingent upon accurate Integrated Vehicle Health Management (IVHM) capabilities, which must operate not only at the aircraft level but also at the component and failure mode levels.

Despite the potential benefits of digital twins in enhancing CBM accuracy through personalized alerts based on real-world component experiences, the specific requirements for the fidelity of digital twins to support particular use cases remain inadequately explored. Existing digital twins are often developed post-design and production, relying on data and resources available to the organization, which may not align with the rigorous demands of regulatory compliance and operational reliability.

Moreover, a significant barrier to the widespread adoption of digital twins in the aviation sector is the availability and quality of data throughout the asset lifecycle. Companies must ascertain whether existing data is sufficient to create a digital twin of the desired fidelity to meet their intended use case. This challenge necessitates strategic alliances, agreements, or data rights access across the operational lifecycle of the asset. However, there is currently no clear, defined, or measurable approach to determine the appropriate actions required to enhance data sources or resolution, nor to assess the necessary levels of domain knowledge and data fusion methods.

The lack of a comprehensive understanding of the relationship between IVHM, digital twins, and their impact on operational reliability and availability metrics, combined with the challenges of data availability and fidelity requirements, presents significant gaps in the literature and practical implementation of CBM in the aviation industry. Addressing these shortcomings is essential for realizing the full potential of digital twins in supporting effective CBM strategies.

2.1. Applying a Digital Twin to Enable CBM

An ecosystem to produce a digital twin of sufficient resolution to achieve a CBM need is depicted in Figure 2. It illustrates various aspects and capabilities to understand the business needs, understand digital twin requirements, ensure sufficient data, models, and IVHM capacities exist to deliver on the requirements. Figure 2 illustrates the approach to a digital twin ecosystem which can enable a CBM business need to be realized by fully understanding the use case. This will drive the requirements of the digital twin to enable the desired outcome. The required level of fidelity of a digital twin will not be constant across all components of an aircraft and it is anticipated that varying levels of fidelity will exist from one part to the next. A digital twin of a rivet attaching a secondary structure bracket will be significantly lower fidelity than a flight and safety critical component.

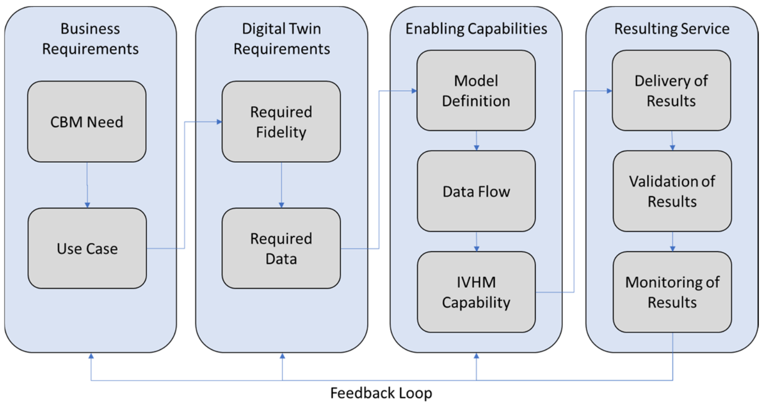

Figure 2. Potential Ecosystem of a digital twin enabled business requirement.

2.2. Define Business Requirements

This initial task will be to determine the business requirements of a CBM need, addressing items such as anticipated maintenance burden, frequency and difficulty of tasks which will result in a use case.

2.3. Digital Twin Requirements

After understanding the initial need, the digital twin requirements must be obtained to inform the required fidelity and the data needed to achieve that fidelity. This step must consider how detailed the data needs to be, how it will be defined, the resolution or frequency, the data sources that are needed to digitally represent the physical item.

2.4. Enabling Capabilities

With the business and Digital Twin requirements defined, the various capabilities to achieve the use case must be designed, developed, or utilized to develop a system that will deliver on the initial requirements. This will include if sufficient models exist to define the digital twin, are the data streams sufficient to create or maintain the digital twin and is the IVHM capability accurate enough to achieve the defined use case.

2.5. Resulting Service

Once a digital twin is created and maintained at the intended level, it will ultimately enable a service which meets the initial use case and business requirements.

2.6. Feedback Loop

The delivered results of the service need to be monitored for accuracy and their ability to achieve the initial requirements. Any unacceptable deviations from these requirements will require an update to the business or digital twin requirements or the underlying enabling capabilities.

3. Scope and Structure

3.1. Scope

The focus of this review is the aviation industry and specifically how digital twins can enable regulatory approved condition based maintenance through deeper understanding of relevant features and operational history. To achieve this understanding efforts from outside the aviation industry will be included as a comparable, complex system of systems also exists in the building, power generation and maritime industries.

This review focuses on understanding what a digital twin is and how it is created and maintained. It will also recognize the importance domain knowledge, ontologies, and the role data play in realizing the fidelity of a digital twin and ultimately is ability to achieve a desired need. To achieve the goal of a Digital Twin enabled CBM program the link between digital twins and their ability to enhance levels of IVHM and the subsequent effect on aircraft maintenance will be considered.

While the creation and maintenance of digital twins, along with measuring fidelity, will be considered within this study, their method of delivery to downstream customers and their deployment within services will not be addressed. The use of AI technology in the creation of digital twins will not be considered within this study as it is focused on the fundamental aspects for the creation of a digital twin.

3.2. Structure

The objective and overall motivation of this work is to apply an academic approach to solving an industry-relevant question regarding how to deliver superior levels of CBM using individualized understanding of assets through digital twins. This industry-driven need has influenced the literature review to include industry publications to understand how these techniques are being discussed and applied. This industry-related scope was achieved through publications from institutions such as SAE, IEEE and AIAA, and conference papers by those sponsored organizations and others such as the Prognostics and Health Management (PHM) Society. These conference papers have also provided the segue to academia through SCOPUS.

A graphical representation of the review can be seen in Figure 3. The subject areas that drove the research are based on the interaction between digital twins and CBM/IVHM, and the data required to enable the creation and maintenance at a level required to achieve a desired aim. The research resulted in five major elements, highlighted in Figure 3 and their focus areas.

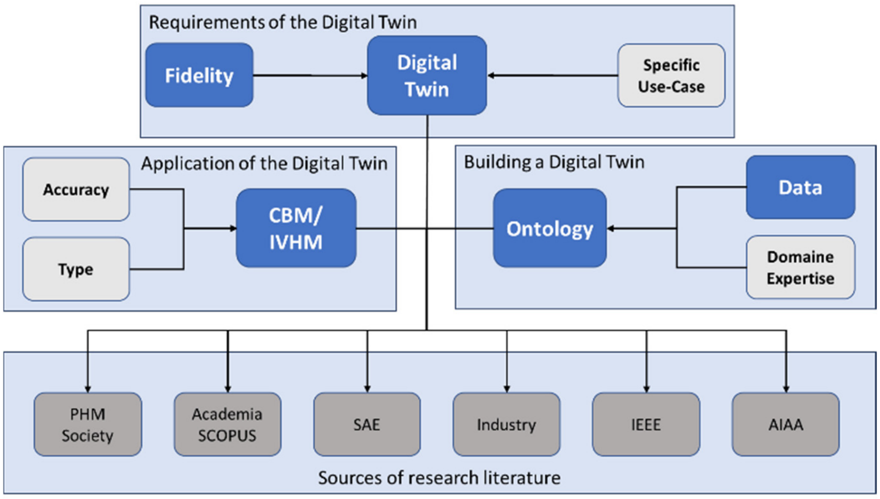

Figure 3. Focus areas and research sources.

1. Digital Twin—Details in Section 4.
2. Ontology—Details in Section 5
3. Fidelity—Details in Section 6
4. CBM/IVHM—Details in Section 7
5. Data—Details in Section 8

Initial searches were based on the combination of keywords of the areas identified in Figure 3; Data, CBM/IVHM, Digital Twin, Fidelity, and Ontology. These combinations were applied to each of the sources of research literature. These searches resulted in over 30,000 papers, necessitating the need to apply filtering beyond searches for the individual elements as defined below:

Initially, date filters were applied to the searches of the various elements based on the levels of research, effort, and movement of research within the areas. The date cut off for CBM/IVHM, Data, and Fidelity elements were set to 10 years, for digital twin definition. For Ontology the date cut-off was reduced to the last four years. Exceptions to these date cutoffs were applied based upon the investigation of references from initial or referenced papers.

Further filtering was also applied to reduce papers that only addressed a single element related to data, ontology or resolution as these elements exist outside of the subject of digital twins and CBM/IVHM. The application of these filters further reduced the number of papers to 3199.

Papers were then reviewed for relevancy and applicability by title. More detailed filtering was completed by reviewing the abstract for detailed paper content, followed by examining the conclusions for additional understanding and results, then reading the paper for deep understanding, resulting in 211 papers. Finally, relevant citations, and where the paper had been cited, were further reviewed for relevancy.

As the literature review continued it became apparent that the focus is the intersection of digital twin, ontology and IVHM/CBM and the interaction between all three is the potential to optimize maintenance for aircraft operation, with only four papers addressing all three areas.

Due to the interdependence between the five focus areas, depicted in Figure 3, an overlap between the papers was expected and few focused on an individual area. Figure 4 shows the distribution of papers used for this review and their focus area, both by number and percentage of overall papers referenced. The subject of digital twins was the largest based on being the main focus of this paper. Ontology and fidelity are the second main areas due to the importance of ontologies in defining digital twins and the desire to understand fidelity relating to digital twins. Figure 5 depicts the number of focused areas covered by each paper and the year the paper was published. The increase in more than one area being covered by a single paper in the most recent years illustrates the increased linkages between the subject areas, with two papers covering four areas and one all five. These aspects will be further explored, in detail, regarding the current state of the art and approaches from both academia and industry.

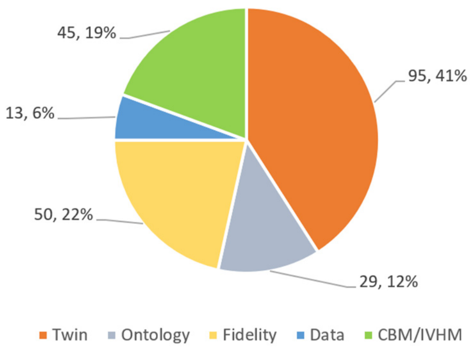

Figure 4. Number of publications addressing each focus area.

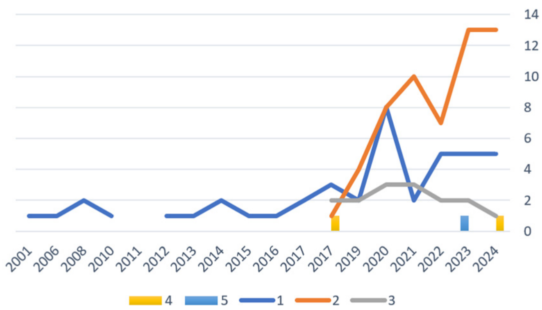

Figure 5. Number of focus areas covered in each paper.

4. Digital Twins

Digital twins are being considered and researched across Industry 4.0 from many sectors. While focused on aviation, this section draws on papers from across various parts of the industry to address component parts of a digital twin methods of measuring maturity of digital twins and frameworks to create digital twins. Figure 6 illustrates the industry sectors that have contributed to this section.

Digital twins require data to create and maintain them, they also enable various support and services activities, all of which are enabled by core and component parts. This section dissects the concept of the digital twin into its component parts, discussing how maturity is considered and measured, and how frameworks are created to enable digital twins.

4.1. Component Parts of a Digital Twin

As digital twins have become more popular, their key components have been identified and defined to improve understanding and focus. While these components can function independently, some are essential for creating and maintaining a comprehensive digital twin. For instance, data acquisition and storage for analytics and insights are important but do not alone define a digital twin. Just as data is important to enable a digital twin, the services built upon it are important but not necessary for a digital twin to exist. The value of a digital twin is to be able to interrogate and understand the physical, at scale and throughout the lifecycle. To enable this, it needs to persist and be enabled by a suite of capabilities.

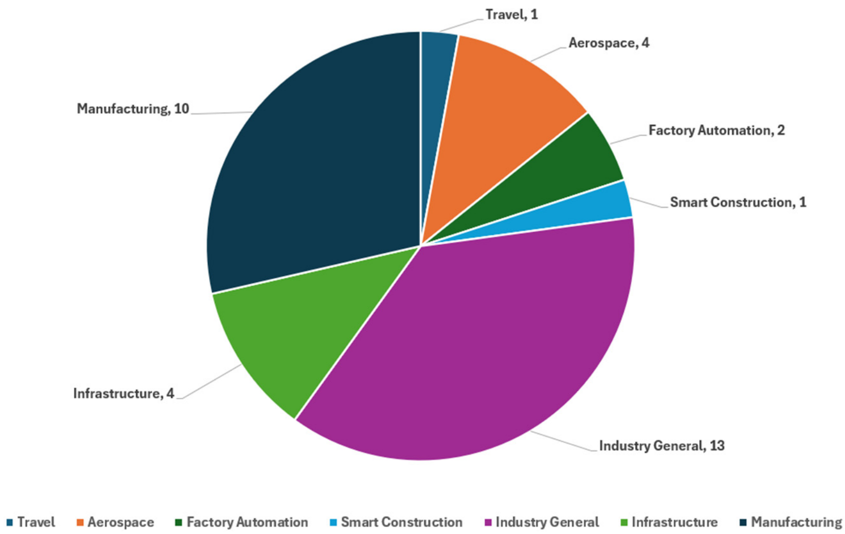

Figure 6. Contributing Industry sectors.

The many components of digital twins have been explored. Ref. [14] identified nine dimensions, while [22] outlined ten features, including Data Link, Security, and Artificial Intelligence, to create a framework for comparing digital twins. Ref. [43] proposed "function modules" as central capabilities that unify the operation of digital twins, a concept supported by many others.

The various capabilities to enable digital twins are summarized in Table 1, which can be categorized into three areas by function of the capability and dimensions: data management, core functionality, and delivery. These capabilities, along with security, which in any data related environment is a necessity and therefore considered part of doing business, are essential for maintaining a digital twin alongside its physical counterpart.

Within the Data Management category, all papers considered data acquisition or connection an essential element of a digital twin, most listed data storage/processing. Within the delivery category, many considered services a component part, while some cited the need for a user-interface to interact with a digital twin.

While not all capabilities are desired by each application, many are common and alignment around these areas is occurring. Under Data Management the digital twin is not only created but also maintained alongside its physical counterpart throughout its lifecycle, necessitating consistent and reliable access to data. This requirement is underscored by the processes of data acquisition, connection, and storage, which are prevalent in most studies. The importance of "data synchronization," particularly highlighting the "data exchange" dimension and the need to maintain synchronization between the physical and digital entities must be considered [35,44].

The concept of digitally tracking a physical component's experiences throughout its lifecycle, is addressed by the role of "Domain Ontology" for effective data and model management [32]. Ontology management is vital for ensuring model consistency, as is the importance of agreed-upon ontologies for fostering trust and facilitating the sharing of digital twins [45,46].

Digital Twin Models (DTMs) are essential for ensuring accurate representation, validation, and adaptability throughout the lifecycle of a digital twin. They encompass four main dimensions: geometry, physics, behavior, and rules. DTMs are considered critical for the successful application of digital twins [47], along with the information model as the backbone of digital twin representation, providing necessary input and output requirements [8]. Various modeling approaches can be employed, but the selected model must yield results that are equivalent to measured quantities. Appropriate model type, and selection, is critical and needs to be both accurate and validated, whether they are data-driven or physics-based [48]. As digital twins evolve, their models must adapt to new capabilities and changing circumstances to maintain relevance and accuracy. This could be addressed by different models throughout the lifecycle [49] or by updating existing models with new insights [50]. Validation of digital twin models is critical to ensure they are believable, actionable, and accurate, especially when transitioning from providing advice to enabling data-driven decision-making. The validation of these models, especially as digital twins increasingly play a role in automation and engineering operations, is critical [51].

System configuration and streamlined runtime for a digital twin-based enabled capabilities can be achieved by consolidating core functions into “Function Modules” [43]. The concept of function modules serves as a centralized capability to ensure harmonious operation, a notion echoed by other researchers [52,53]. Delivery of insights from a digital twin is enabled by services which integrate various services around the digital twin to provide valuable business insights [54]. Boeing utilizes a “Digital Value Chain”, which begins with data and is empowered by the digital twin, ultimately leads to insights and data-driven decisions [46]. Additional details and examples of the various dimensions of the component parts of the digital twin are detailed in Table 1.

To create and maintain digital twins, and enable the various capabilities, multiple technologies are needed. Various efforts have been undertaken to collect and collate these efforts; Ref. [14] listed 40 technologies, ref. [55] refers to 29 key technologies in their review of smart manufacturing, whereas [47] lists 25 technologies and 33 tools in their review of digital twin modeling. Ref. [27] Provides a digital twin support technology matrix that contains 46 support technologies spread across six dimensions of the digital twin. These lists range from individual sensor types to IBM Watson and from spreadsheets to neural networks.

A digital twin is not always a deliverable itself but does enable analytics and data driven decision-making, making it part of a digital value chain enabling downstream services. As digital twins have gained popularity, essential components have been identified to enhance understanding; while some can function independently, others are crucial for creating and maintaining a comprehensive digital twin, such as data acquisition and storage.

As the component parts of digital twins continue to coalesce and interact, a vast array of tools and technologies are required to enable them. As digital twins have begun to be implemented across industries, the process of implementation and execution has resulted in thinking about them as component pieces which, when assembled, produce business value.

4.2. Digital Twin Maturity

As digital twins have transitioned from research to implementation, the focus has extended to their level of maturity and how to compare them with each other. A lack of systematic methods for evaluating the functionalities and capabilities of digital twins has resulted in confusion and hindered adoption [27]. Since 2021, various methods have been created to describe and measure the maturity of digital twins [1,27,29,39,44,52]. All have defined various maturity levels by which to measure individual digital twins. Each suggests that higher maturity correlates with greater value but has not proposed a method to quantify these levels.

Table 1. Examples of digital twin component parts.

Function	Dimension	Use	Activities/ Examples
Data Management	Data Acquisition and Connection [6,8,14,19,22,30,32,35,43–45,52,56–59]	The collection and transmission of data which describes both the physical and digital asset, its operation, condition and environment	- Data acquisition - Data addressing - Transport of information between heterogeneous systems - Transport of data between network layers - Physical to physical data exchange - Physical to virtual data exchange - Virtual to virtual data exchange
	Data Storage and Processing [6,14,19,22,30,32,43,44,52,56–59]	The ability to make the required data available in an efficient and optimised manner	- Data cleaning - Data optimisation - Data Fusion
Core Functions	Ontologies [19,32,43,45,56,57]	The instructions and definition to correctly integrate the data into a digital twin	- Ontology management - Ontology access - DT Ontological definition
	Models [6,14,30,32,35,44,45,52,56–59]	The ability to programmatically store and execute the information and process required for the creation and maintenance of a digital twin	- Virtualisation of physical assets and processes - DT model creation - DT validation - DT model interaction
	Function Modules [8,14,19,22,43,44,52,56,59]	Core technology to enable creation and maintenance of a digital twin	- Enabling technologies
Delivery	Services [6,14,19,22,30,32,44,45,52,56,57,59]	The ability to deliver create and deliver insights through the interrogation and use of the digital twin	- Predictive simulation - Monitoring and analysis - Health Management - Optimisation - Analytic Services
	User Interface/Collaboration [6,14,22,32,52,56,58,59]	Provides an appropriate and intuitive method of interacting with the twin	- Training of human operators - Monitoring human-machine interaction
Security and Privacy [14,22,32]		Ensures that all aspects and functions are completed in a secure way that protects data, IP and privacy	- Protecting against data tampering - Authentication issues - Data and model trustworthiness - Protecting against cyber-physical threats

Several studies [28,34,53,60] have introduced frameworks to describe, quantify, and compare digital twins. These frameworks provide a repeatable method for defining maturity based on initial dimensions. Each method identifies contributing features, or attributes, and assigns a value. These can then be future assigned importance weightings resulting in a maturity score for a digital twin.

For example, ref. [28] identified ten dimensions to consider when implementing digital twins in the commercial aerospace OEM industry. For nine of these dimensions, they define four levels of maturity, while the tenth has three levels. Each dimension and maturity level includes guidance on what is needed to reach that level, allowing for objective comparisons of digital twins created by different companies. The dimensions considered are 1. Lifecycle integration, 2. Level of DT individualization, 3 Data collection frequency, 4. Analytical capability, 5. Decision implementation, 6. Model update frequency, 7. Modelling scope, 8. Stage of implementation, 9. Operational Data accessibility, and 10 Business level affected.

Moving from scoring companies that their digital twin implementation to the twins themselves, ref. [34] identified seven components of a digital twin and assessed each with two to six attributes. They developed a method to calculate maturity by scoring each dimension, allowing for the comparison of multiple digital twins' maturity levels.

These studies have resulted in various approaches to categories digital twins and compare them to each other by defining dimensions, categories, rubrics and levels. These provide descriptive attributes and guidance resulting is methods to quantify levels of maturity from basic to "ideal". As the understanding of digital twin maturity has developed, it continued to align with the original definitions and components of a digital twin. Key aspects of the features include having a model, processing capabilities, data input, a lifecycle, and the ability to connect with other services and digital twins. These factors can be quantified to assess how complete a digital twin is and measure its maturity. Overall, there is a growing consensus on the dimensions and attributes of digital twins, and methods for measuring maturity are being established.

4.3. Digital Twin Framework

As we move from the description of a digital twin, its component parts and the importance of the various models within the digital twin, the consideration becomes how to integrate them.

An approach to enable this complex integration of multiple nodes, capabilities, and relationships can be though using property graphs and ontologies to facilitate the required sharing and coordination [56]. A collaboration framework which supports lifecycle sharing of digital twins is an area that needs to be considered [32]. Their framework includes four key elements: a generic digital twin model, a lifecycle ontology, data collection technology, and a distributed collaboration system. This framework relies on a cloud-based digital twin server that collects and shares data from manufacturers, integrators, and users.

To enable digital twin sharing between companies within the smart construction industry a framework which fosters collaboration throughout an asset's lifecycle has been implemented [11], with full integration representing the highest maturity level. These higher maturity levels require effective linking and interaction between digital twins and models. Ref. [36] proposes a framework based on the 4R's: Representation, Replication, Reality, and Relational, where each element builds on the previous one, increasing capability and complexity.

With complex machines spanning large portions of an assets' lifecycle and being represented by digital twins the need for cooperation and collaboration is clear. This is being recognized within industry and the concept of structured frameworks is being employed in some areas. To successfully implement digital twins, there must be more common frameworks, or at lease agreements, and standards in place.

5. Ontologies

The creation of a digital twin requires the connection of many different pieces of data, models and capabilities in a structured, trusted, and repeatable manner. An ontology allows for the codification of knowledge in a standard and repeatable method, defining relationships and instructions to integrate data to create a digital twin. When employing a digital twin to enable a regulatory approved CBM program not only does a defined level of "correctness" need to be achieved but also maintained. Through the utilization of ontologies and the structure enabled by them, the potential exists to create a high quality digital twin, based upon the combined knowledge and expertise of multiple companies from across an asset's lifecycle. This organization can be completed using ontologies [56]. When considering ontologies and their relationship to digital twins, there are five main areas to be considered: how they are defined, how ontologies are used in the creation of digital twins, how domain expertise influences the creation of an ontology, the necessity of sharing ontologies across the lifecycle, and how standards can assist in using ontologies.

5.1. Definition of Ontologies

Originating from philosophy, they are used to describe the characteristics of objects and their relationships between them. Their main goal is to capture knowledge from related fields and provide a common understanding to facilitate knowledge sharing [45]. This knowledge can be broken down into units and relationships, allowing it to be recorded consistently for reuse. By formalizing domain knowledge, ontologies give the user of an ontology the confidence that a level of "correctness" can be expected from the domain knowledge.

Ontologies are used to improve knowledge representation in digital twins, making complex knowledge understandable for both machines and humans [61]. They formally describe a specific domain by listing relevant concepts and their relationships [62] and can be considered to describe collections of classes and properties that represent facts about a domain [21]. Ontologies can be used to help formalize a company's knowledge and ensure data exchange between different systems [25] and be used as frameworks which consist of defined classes, relationships, and properties [2].

Ontologies can be described as a formal specification that model's entities, relationships, and attributes in a way that both machines and humans can understand and describe how they can align with graph and knowledge base models to create a Universal digital twin [56]. Ontologies allow knowledge to be structured so that both humans and machines can interact with data from physical objects. By defining relationships and semantics, any entity with access can represent domain knowledge in a standard way that can be used across different groups. For example, Figure 7 illustrates a simple ontology describing a flight from one airport to another. It includes details about the aircraft, such as type, registry, and airline, which are relatively stable. While aircraft ownership may change infrequently, flights occur regularly. Each flight has a flight number and defined relationships, such as "departs from" or "arrives at" an airport. Additional relationships describe the locations of the airports, and the aircraft involved.

While this ontology is basic and limited in its attributes and relationships, it provides a consistent framework for describing a flight. This ontology has been created by the author and codifies my domain knowledge within that space and for an intended purpose. The values in the nodes can change, but provided the relationships remain the same, multiple flights can be defined, stored, and compared by anyone that has the ontology and data to populate it. By utilizing an approved ontology, a repeatable product can be achieved.

5.2. Ontologies to Enable the Digital Twin

Using an ontological approach to define the component parts of an event and their relationships provides a consistent method for representing physical events with data. Ontologies can help identify various domains and layers involved in creating digital twins, particularly in describing physical components and their attributes [61].

Utilizing a digital twin for a specific asset enhances business value by quantifying knowledge and leveraging models, rather than depending solely on individual expertise, particularly as systems grow increasingly complex [24]. This approach is especially pertinent in the aviation sector, where multiple teams, and companies, collaborate in the design, development, and operation of intricate systems. To effectively manage these complexities, it is essential to comprehend the interconnections and interactions among various components, establish frameworks for knowledge sharing, and distill documentation from human insights.

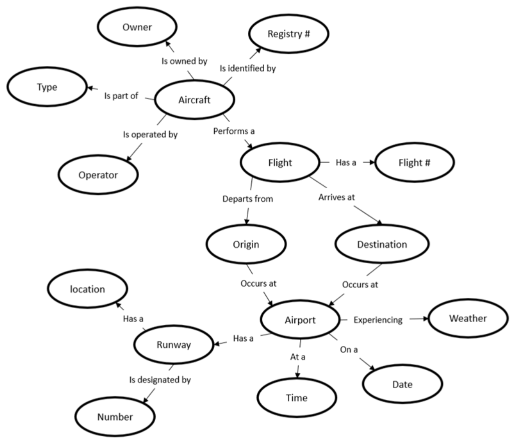

Figure 7. Example ontology to define a flight.

A Digital Twin Ontology (DTO) is proposed by [19], focused on describing digital twins and their dynamic physical counterparts. They also suggest a Data Conversion Ontology (DCO) to address data integration issues and siloed data. The importance of ontologies for managing digital twin data and integrating it into PLM is highlighted by [45]. They provide an example of a "lifecycle data evolution model," arguing that without it, digital twin technology cannot reach its full potential. They also propose an "ontology-based digital twin management architecture" to manage data throughout the asset's lifecycle. Ontologies can be used to represent both static and dynamic information as demonstrated in the creation of an ontology-based digital twin for machine tool modeling, where the ontology represents both static and dynamic information [57]. While each of the authors discuss the ontologies slightly differently it is clear that the ability to digitally represent a physical entity and create a digital twin depends on effectively integrating data. This integration requires a relational and semantic approach, which can be achieved using ontologies. The simple ontology depicted in Figure 7 illustrates a method for describing a physical event, in this case a flight from one location to another. By applying a source of data to the relevant nodes in the ontology a digital representation of the flight can be created and maintained, creating a digital twin via an ontology.

5.3. Domain Expertise

The concept of trust in digital twins was discussed in Section 1.3.1, emphasizing the need for digital twins to be reliable and accurate, having an expected level of "correctness" [20,22,39]. Ontologies help define and organize knowledge through semantic representation and relationships and can serve as a "roadmap" that connects data from an asset's operations to create a digital twin. By developing these ontologies, domain knowledge can be integrated into the digital twin, ensuring a consistent and trustworthy final product. The importance of domain expertise in creating ontologies and the content within them is highlighted by [63], who suggest involving both ontology and domain experts, as well as end users, in the ontology creation process to ensure accurate and trustworthy representations. The potential for domain experts to share ontologies can enhance understanding across different enterprises through a unified ontology [32].

Domain-specific assets can be considered as essential for automating digital twin modeling, and ontologies are needed to describe various aspects of production systems and products [25]. They suggest a method to achieve this by involving domain experts to ensure the correct ontologies are created or used for specific digital twin needs. A lifecycle evolution model can provide a logical and comprehensive definition of a digital twin at different design stages, highlighting the importance of an ontological approach for detail and accuracy [45]. The expertise needed to define, create, or maintain an ontology is not limited to one entity and companies can gain a competitive advantage by integrating their processes and sharing common vocabulary and data models [64]. They found that using ontologies helps reuse knowledge, maintain consistency, resolve semantic ambiguities, and integrate different systems.

An ontology allows for the codification of knowledge in a standard and repeatable method and provides relationships and instructions to integrate data into a digital twin. The creation of the ontologies, and the resultant "quality" of the digital twin produced, are dependent upon the knowledge and expertise of the ontology creators. When considering using a digital twin to enable CBM the need for accuracy will require the codification of domain knowledge. This requirement will be enhanced when a regulatory approved program is desired. While some ontologies may only require a single person to develop, others may require deep domain from multiple people, or companies to contribute to a unified ontology.

5.4. Sharing Ontologies and Linking

Just as physical assets have a lifecycle and are managed by different entities throughout that lifecycle, their digital twins also exist in various forms throughout their lifecycle. Ontologies are used in Building Information Modeling to manage complexity and large amounts of data generated by multiple stakeholders [65]. These ontologies are a knowledge base developed by experts, detailing how different elements within a system relate to each other. As assets become more complex, and ontologies grow in scale, managing a single ontology can become overwhelming. Modularization can simplify management by structuring them into modules, such as manufacturing, context, and condition monitoring [66].

Complexity can lead to the duplication of ontologies in the same area and documenting requirements systematically for comparison across projects is recommended to prevent duplication [64]. They advocate for pairing ontology and domain experts and end users to ensure accurate requirements are captured from the start. With multiple ontologies being created, whether within a company or shared across companies, it is crucial to consider how to link these ontologies. This can be achieved by layered ontologies, using a top-level ontology to describe core concepts and lower-level ontologies for more detailed descriptions [67]. Demonstrating this in the building industry, a "Building Topology Ontology" with sub-ontologies for specific areas, is proposed [68]. They introduce a "Semantic Digital Twin" to integrate various information sources using semantic technologies like ontologies and knowledge graphs.

The use of knowledge graphs has been used to connect ontologies and lead to comprehensive digital twin implementations and graph technology used to connect ontologies and digital twins, aligning with the complex relationships described by ontologies [21,56].

The complexity of assets throughout their lifecycle cannot be captured by a single ontology due to varying detail levels and distributed domain expertise. Therefore, multiple ontologies are necessary to describe a physical item across its entire lifecycle. To ensure consistency and interoperability of digital twins, identifying, cataloging, and linking these ontologies within companies and across the industry is essential. The use of graph technology has been successfully used to effectively facilitate this linking.

5.5. Industry Standards

The need to share and link ontologies arises from the complexity of assets. As the details of a physical asset increase, so do the complexity of its digital twin and the way it is described using ontologies. With multiple organizations, companies, industries, or even countries involved in providing data and expertise, some level of interoperability or standards is necessary. For example, NASA created the Air Traffic Management (ATM)

Ontology to connect various aviation data models and enable cross-data source querying, serving as a foundation for integrating data from multiple sources [69].

The need for a universal approach to standardizing and sharing ontologies exists within different industries. Within the area of digital twins for machine tools it is suggested that creating a basic ontology for monitoring machine tools and using a dictionary of important terms from textbooks, professional dictionaries, and international standards to enhance reusability [57]. Similarly, the call for a common taxonomy of parts and an ontology for parts is required within the aviation industry [24]. The need for common industry standards for an ontology-based approach to condition monitoring is desired to help implementation [66].

In the building industry, a system ontology is being developed to represent the various interconnected systems within a building. The use of ontologies to aid the integration of digital twins and representation of building service systems for automatic energy control, is expected to improve energy efficiency [70]. Sharing is essential for ontology-based digital twins to succeed throughout their lifecycle and to establish trust and accuracy. This need is recognized and advocated within the building industry. Examples of common approaches are emerging, such as Building Information Modeling efforts around the TUBES ontology and NASA's public ATM ontologies.

Although ontologies originated in philosophy to describe characteristics of items, their value in creating and maintaining digital twins is clear. They help codify domain expertise from one or more companies into a digital description of a physical item. Table 2 outlines the key aspects and contributions of ontologies in enabling the creation, maintenance, and use of digital twins.

An ontology can be used to form the backbone of a digital twin. It provides a standardized method of defining the various elements that are used to digitally describe its physical object. It codifies the domain knowledge from various contributors, these may be within an individual company, or from many entities within an industry, and links them together in a standardized and repeatable method.

Thorough the use of ontologies, a physical item can be described, through data, by populating the various nodes at a frequency that is determined by a use case. Ontologies can be created, and the domain knowledge codified, in preparation of a digital twin being required. For example an ontology of an maintenance check may include the facility, the maintenance personal, the tools, the environment within the building and inventory of all parts help that the facility, but if the use case requires a digital twin of how many aircraft were maintained over a period of time, what type of maintenance was performed, how many task cards were loaded and how many resulted in findings, only a portion of an ontology would be required. Using standard ontologies, the ability to create shared digital twins will become a reality. This, however, will require the industry groups to contribute and agree to standard ontologies. With these agreed upon standard ontologies digital twins can be created at a sufficient level to enable CBM decisions to be made based on their insights.

Table 2. Key aspects of ontologies to enable digital twins.

Focus area	Key Aspects	Papers
Ontology Definition	• Enable the codification of knowledge for both humans and machines in a standard and repeatable method. • Involves semantic definition and the establishment of defined relationships. • Companies can represent domain knowledge and expertise. • Knowledge is formatted for utilisation across multiple groups.	[24,25,45,56,61,62]
Use to Crate a digital twin	• Provides relationships and instructions for integrating data into a digital twin. • Successful digital twin creation relies on correct data integration. • Ontologies can achieve the necessary relational and semantic integration. • The creation of ontologies affects the quality of the resulting digital twin	[19,24,25,32,43,45,49,61]
In Codifying domain expertise	• Companies can represent domain knowledge and expertise. • Expertise of the creator may affect the quality of the digital twin as domain expertise may not exist in a single company. • Sharing helps achieve the necessary level of trust and correctness.	[25,32,45,62,63]
Sharing and Linking Ontologies	• Sharing is required as domain expertise not residing within a single company. • The need for sharing is essential for ontology-based digital twins across the lifecycle. • Multiple ontologies are necessary to address asset complexities and level of detail required. • Linking ontologies is essential for consistency and interoperability of digital twins. • Linking ontologies have been achieved using graph technology	[21,25,46,49,56,63–68,71]
The need for standards	• There is a growing expectation for sharing within the industry • Standards are an essential part of ontology creation to enable sharing • Examples of common approaches include NASA and BIM/TUBES	[24,43,65,66,69]

6. Fidelity

The need to quantify the level of how closely a digital twin represents its physical component can be described by many means. For example, does it look the same? Is it updated regularly? But the need to describe that likeness also exists, which can be defined by its level of fidelity. Within this section there are five main areas covering fidelity; how fidelity, resolution and detail interact, how fidelity is described, how fidelity is defined in relation to digital twins, what methods are employed to measure fidelity, and the various approaches to add a value to fidelity.

6.1. Fidelity, Resolution and Detail

The "content" of a digital twin should be determined, or shaped by, the desired use cases [9]. When we talk about the "content" of a digital twin, we can think about its completeness and quality, which can be described using the terms "fidelity," "resolution," and "detail." The Cambridge Dictionary defines these terms as follows:

- Fidelity: The degree to which the detail and quality of an original is copied accurately.
- Resolution: The ability of a device to show things clearly and in detail, which can be low or high.
- Detail: The inclusion of all information or parts about something

While fidelity is important for accurately representing a physical object, resolution, how distinguishable the various details are, and detail, how much the reproduction matches the original, are also crucial. Together, these three factors describe the quality of the representation. Although many methods exist to assess the completeness and quality of a reproduction, "fidelity" is commonly used to describe how well a digital twin represents its physical counterpart. Therefore, in this paper, fidelity will be used to indicate the degree to which the digital twin reflects the physical object.

6.2. How Fidelity Is Described

Fidelity is a crucial factor that affects the effectiveness and advantages of digital twins, as it determines how accurately a digital twin represents its physical counterpart. The concept of high-fidelity physical models can be considered, by some, a necessity for digital twins [4]; for others fidelity significantly influences the benefits derived from digital twins [38]. Regardless of its use, the level of fidelity is a key element, being described as the level of detail and realism in the virtual representation [35]. who point out that the lack of clear methods for quantifying fidelity has led to varied interpretations and misunderstandings. Taking a more generic approach [26] considers fidelity should be a "reasonable" estimation.

The concept of measuring and quantifying fidelity presents challenges, with various interpretations and scales discussed in the literature. Fidelity can be described as the extent to which digital twin measurements align with true observations [72]. Fidelity is considered a core theme of digital twins and can be defined as a highly accurate replication of the physical entity [30]. Expanding beyond highly accurate fidelity can become a major cost driver for digital twins and affects their capabilities and introduce a category above "ultra-high fidelity," termed "Fully Consistent," indicating that the digital representation perfectly aligns with the physical world [73].

Increasing levels of fidelity can lead to increased computational and operational costs and achieving high fidelity may not always be practical or necessary. Considering these factors when determining fidelity is important to control costs and models should be sufficiently accurate without excessive complexity [48]. Modeling physical reality requires some level of abstraction, and the appropriate fidelity level should depend on the use case and associated computational costs [74]. There is a trade-off between fidelity and computational expenses.

Balancing fidelity with computational costs and complexity is essential, with the idea of "suitable fidelity" tailored to specific use cases, which can be completed by evaluating components based on their importance and balancing accuracy with modeling effort [75].

Fidelity can be a double-edged sword, where high fidelity can enhance accuracy but may also deter the use of digital twins due to high costs or complexity [61]. Pursuing high fidelity can lead to unnecessary complexity and advocate for finding a balance between fidelity, consistency, and cost [76]. The balance between model fidelity and simplification to manage data size effectively is something that needs to be considered during the planning for digital twins [47].

This balancing of fidelity introduces the approach of different models of the same physical entity existing at varying levels of fidelity, providing flexibility based on need requirements. Matching levels of fidelity to use cases can result in using different fidelity levels throughout the lifecycle [77] and is expected that fidelity levels will vary based on use, need, and precision at different system levels [78]. This can be achieved by using "multi-fidelity" digital twins, where multiple models of one physical item exist at different fidelity levels, allowing selections based on specific use cases [79]. The use of varying complexity and fidelity based on the use case provides the ability to control costs and ensure explainability and acceptance of digital twins.

A digital twin can be considered more authentic if it captures detailed characteristics of the physical object, enhancing the richness of its representation. This authenticity can add to the acceptance of digital twins. While the term "Digital Twin" implies some level of similarity, not all parts need to be identical [37]. There is an expectation of completeness and consistency between the digital and physical twins, and higher fidelity may indicate a more credible digital twin. The concept of "authenticity" can be considered a measure of fidelity, focusing on how well the digital twin captures fine details and characteristics of the original [34].

The concept and need for a desired level of fidelity should be considered early in the design and development phases, including planning for data collection and model parameters. Sensor data collection should be planned during the design phase to determine the necessary level of representation and frequency [23] to ensure a complete picture. Also, consideration of fidelity early in the design process, along with identifying model parameters and ensuring sufficient data for updates [48] will ensure an accurate representation can be achieved.

Fidelity is crucial for the effectiveness of digital twins, as it determines how accurately a digital twin represents its physical counterpart, influencing the benefits derived from its use. However, there is a lack of clear methods for quantifying fidelity, leading to varied interpretations and challenges in measuring how well digital twin measurements align with true observations. Defining the level of fidelity is important as increasing it can lead to higher computational and operational costs, making it essential to balance accuracy with complexity and ensure models are sufficiently accurate without unnecessary complexity. This can also be addressed by utilizing "multi-fidelity" digital twins allows for different models of the same physical entity at varying fidelity levels, providing flexibility based on specific use cases and controlling costs. To further ensure costs are controlled the desired level of fidelity should be considered early in the design and development phases, including planning for data collection and model parameters to ensure an accurate representation of the physical object. The level of fidelity should be matched to the intended use of the digital twin.

6.3. How Fidelity Is Defined

While acknowledging that fidelity of a digital twin may change over the lifecycle of the physical item, it needs to be based on key use cases and how well the digital replica reflects the parameters, accuracy, and level of abstraction of the data exchanged between the physical and digital entities [72].

The complexity of a digital twin can be defined by the precision of its outputs [36] who propose a framework with two key requirements, "representation" and "replication", addressing how closely the digital twin matches the physical object. They introduce the concepts of "detail" (the complexity of variables in the digital twin) and "dynamic" complexity (how these variables change over time).

The frequency at which digital twins are updated is important, a digital twin can become inaccurate if it is isolated from real-time data from its physical twin [19,35,76]. This time lag can be described by the term "twinning," which refers to the point at which the physical and digital twins are considered equal, and they measure the "twinning rate" as the frequency of updates [30]. Gaps in operational data flow an also reduce effectiveness of the digital twin with may require a certain flow be maintained to ensure the level of desired fidelity [74].

The concept that a digital twin can lag its physical asset can be a concern depending upon the use case, this relationship between updates and fidelity is influenced by the timing of data collection [28]. For example, if flight data is updated immediately after a flight, the digital twin will be more accurate than if updates are delayed. They also emphasize that the rate of data collection must meet the digital twin's requirements; for instance, if the model expects data at 10 Hz but only receives it at 1 Hz, the update rate will result in insufficient fidelity for the use case.

It is not just the speed at which data is received that can define the digital twin, the quality of information needed to represent an object with the types of data collected must also be considered, along with the challenges of determining the necessary data types, sources, and frequencies for effective decision-making [71,80].

Moving beyond just data itself, data granularity can be divided into three areas: attribute granularity (how object attributes are described), object granularity (how the object is broken down into components), and services granularity (data provided by services) [45]. Fidelity can be described as consisting of three main components: data, models, and parameters [73]. The accuracy of the data directly affects the fidelity of the digital twin. The models form the foundation of the digital twin, and both the number and accuracy of parameters also influence fidelity. The concept of models is broken down further by [81] in their work on digital twin-driven prognostics they define a "Virtual Equipment Model" as a high-fidelity representation of physical equipment, consisting of four parts: geometric, physics, behavior, and rule models. This comprehensive approach creates a complete digital twin.

One common defining factor for establishing fidelity is the data that flows from the physical to the digital. Various aspects of data, including its type, the items being sensed, and the rate of data recording and ingestion, all play a role. Five main attributes to fidelity in digital twins are:

- The amount of data from the physical object.
- The type of data collected.
- The accuracy of the digital representation compared to the physical object.
- The degradation of the digital twin and its fidelity can occur over time based on data updates.
- The combination of data, models, and parameters.

6.4. The Measurement of Fidelity

Moving from describing or defining fidelity to measuring can be addressed by either passing tests or obtaining levels. The "Grieves test," while binary can be used to determine if someone can distinguish between a physical object and its virtual counterpart, if the difference cannot be detected, the virtual object is considered "virtualized" [82].

While many may advocate for the highest fidelity, it can be viewed on a scale from abstract (low) to precise (high), with medium in the middle [30]. This can be achieved by defining targets to measure how well the physical and digital twins match, expressed as a percentage of actual features [77]. The comparison between physical and virtual models, can be achieved using "tolerance corridors" to measure acceptability between the two and the measure between the physical and the digital tolerance corridors used to determine a level of acceptability [3].

A systems engineering approach can be used to define digital twin fidelity levels in manufacturing through a "Digital Twin Fidelity Requirements Model" (DT-FRM). This model breaks down requirements into variables, assigns priorities, and results in a fidelity matrix categorizing fidelity as high, medium, or low [83]. There is a relationship between potential savings and digital twin fidelity, which can be described with digital twin benefit curves illustrating the relationship between value, benefits, or costs and the level of effort required [38]. These curves were refined through expert interviews, showing optimal fidelity exists between minimum and maximum levels.

Ultimately, a digital twin's objective is to provide an accurate representation of the physical object. It can be considered binary: it either contains sufficient information to fulfill its intended purpose, or it does not. This can lead to a more descriptive approach to quantifying fidelity levels, ranging from low to ultra-high, allowing for comparisons between different digital twins and setting expectations for their capabilities. There is a desire to measure fidelity as a relationship between potential savings and digital twin fidelity, illustrated by digital twin benefit curves that show the optimal fidelity level exists between minimum and maximum thresholds, refined through expert insights.

6.5. Adding a Value to Fidelity

Measuring the fidelity of a digital twin is much more complex than simply counting the pixels in an image. With the increasing use and expectations of digital twins, their ability to accurately represent physical objects is becoming a key differentiator. Fidelity can be described as how well a digital twin reproduces the actual state and behavior of its physical counterpart.

An approach to model fidelity can include three key attributes: data, models, and parameters. By adding values to these attributes, the fidelity of a digital twin can be defined, allowing for the comparison of one digital twin to another using specific codes [73]. To quantify a digital twin's representation, a basic approach can be where the digital representation is based on the attributes and operations of the physical instance [8]. They propose aligning variables and inputs from the physical twin with the digital twin's attributes, then mapping the outputs to the operations, demonstrated through modeling robot arms. They also suggest that as complexity increases, additional models and semantic relationships should be considered to enable cooperative systems within the digital twin context.

Expanding from this approach, ref. [84] introduces a Digital Twin Fidelity Calculation Method (DT-FCM) that estimates savings and costs to determine "optimum" fidelity. This optimum fidelity is quantified using a normalized scale from 0 to 1 across four dimensions: tolerance, frequency, latency, and level of integration. As the importance of fidelity in digital twins grows, so does the need to quantify it, leading to the development of frameworks. Two main approaches have emerged: measuring the difference (or delta) between the digital and physical twins or assigning values to key features that define the digital twin.

Efforts to quantify fidelity show that it can exist along a scale and that fidelity is linked to the digital twin's ability to meet its intended use case. It is easier to describe fidelity than to define it, easier to define it than to measure it, and easier to measure it than to quantify it. Table 3 summarizes the key points and contributors related to digital twin fidelity.

Table 3. Descriptors of digital twin fidelity.

	Fidelity Is, or Can, Be:	Papers
Describe	• Important to the digital twin • How close to reality is the twin • It is not fixed, ranges from low to ultra-high, even "fully constant" • The twin will never match the physical • Will evolve across the lifecycle • Higher fidelity will result in higher costs • Should be matched to the use case	[1,4,20,23,26,30,33–35,37,38,47,48,52,72–79]
Define	• Determined by the amount of data from the physical • Determined by the type of data from the physical • How close the digital represents the physical • Degrades with time since update • A combination of multiple contributors, such as data, models and parameters	[1,19,26,28,30,35,45,71–74,76,80,81]
Measure	• A binary test, it does, or does not achieve its aim • A descriptive scale from very low to ultra-high • The percent of likeness between digital and physical • Plotted on a chart to interact with other features	[3,10,30,73,77,81,82,84]
Quantify	• A numerical difference between measured parameters from the physical and digital • A value added to important features	[8,73,79,84]

Fidelity significantly influences the usefulness and success of a digital twin. A digital twin that does not accurately reflect its physical counterpart will have limited practical application. While higher fidelity is generally preferred, it comes with associated costs. Maintaining high fidelity throughout the lifecycle of the physical twin can be challenging, and at times, lower fidelity may be accepted.

As mentioned in the introduction, the responsibility for data is shared across multiple companies throughout the lifecycle, which can lead to challenges such as down sampling or aggregating. The further the digital twin is from the physical object in terms of time and data filtering, the lower its fidelity will be.

There is a clear link between a digital twin's fidelity and its ability to achieve its intended purpose. The fidelity of a digital twin is rooted in its capacity to represent its physical counterpart accurately. Data is essential for a digital twin; without a continuous flow of data the digital twin cannot be defined or maintained. As this review continues, fidelity of a digital twin will be described as "the ability to digitally represent the physical twin at the required level of detail and resolution to achieve a desired outcome". Ultimately, the measure of fidelity will depend on the digital twin's success in achieving its intended results.

7. Condition Based Maintenance

To operate an aircraft in a safe and efficient manner, maintenance is a necessity. While there are many different approaches to maintenance, no method is suitable for every maintenance action.

7.1. Maintenance Approaches in Aviation

Aircraft maintenance has evolved significantly over the years, the main goal of maintenance is to ensure that aircraft are safe and airworthy, ref. [85] also note that maintenance programs improve reliability. Airlines For America (A4A), previously known as the Air Transport Association (ATA), in their publication [86], describes the objectives of scheduled maintenance in four parts:

1. Ensure realization of the inherent safety and reliability levels of the aircraft.
2. Restore safety and reliability to their inherent levels when deterioration has occurred.
3. Obtain the information necessary for design improvement of those items whose inherent reliability proves inadequate.
4. Accomplish these goals at a minimum total cost, including maintenance costs and costs of resulting failures.

Maintenance strategy falls into two main types based on failure occurrence: corrective maintenance, which occurs after a fault, and proactive maintenance, which aims to detect or correct potential failures before they happen [87]. On the proactive maintenance side continued evolution occurred to preventative (the current health of the asset), predictive (what could happen), and prescriptive (action when the fault occurs) and outline the data needed for these strategies and link predictive and prescriptive maintenance to CBM [88]. CBM and its constituent technologies, IVHM, Condition Health Monitoring, Aircraft Health Management, Prognostics and Health Management and Structural Health Management all help prevent unscheduled maintenance [89].

Figure 8 illustrates the different maintenance approaches. Reactive maintenance is unscheduled and occurs when an operator must respond to a fault that has already happened. In this approach, maintenance personnel typically fix the issue by adjusting or replacing faulty parts. In contrast, scheduled maintenance is proactive, where maintenance actions are taken before anticipated issues arise.

When scheduling maintenance, decisions can be based on component condition or a predetermined schedule. If a schedule is chosen, maintenance occurs based on operating hours or cycles. This proactive approach aims to prevent operational disruptions by addressing potential issues before they escalate. Preventative actions include inspection tasks to check for defects and rectification to fix any identified issues. If no defects are found during an inspection, another inspection is scheduled for the next predefined interval.

While this method effectively detects and corrects defects before they become critical, it can create additional maintenance burdens if inspections are performed without finding any issues. On the other hand, condition based maintenance focuses on using data to determine the current or predicted condition of components, allowing maintenance to be scheduled at the optimal time before a failure occurs. However, it is important to avoid scheduling maintenance too early, which could lead to unnecessary removal of components before their operational life is fully utilized.

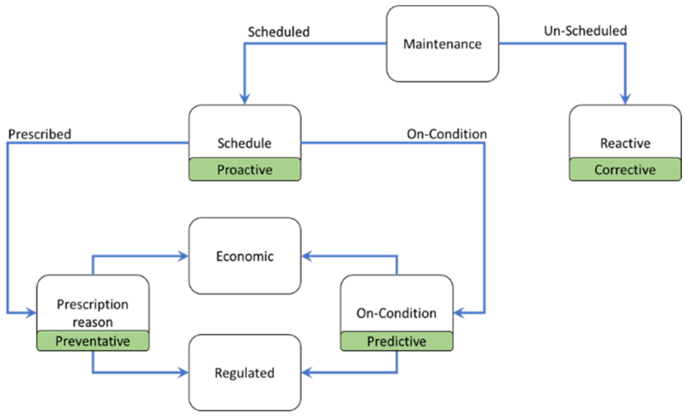

Figure 8. Graphical Representation of Maintenance Approaches.

7.2. The Move to Condition Based

The industry's interest in moving to a CBM approach aims to reduce unscheduled maintenance, lower costs, and improve operational reliability [89]. A balance is needed between predictive maintenance and corrective or preventative maintenance, as removing components too early can waste usable component time, while waiting too long can lead to unexpected maintenance issues [87].

CBM is a maintenance philosophy, enabled by IVHM technology and capabilities. In their overview of IVHM technologies, ARP 6803, ref. [80] state that the motivation for implementing an IVHM system includes enhancing safety, increasing availability, improving mission effectiveness, and reducing operational and maintenance costs. IVHM is defined as the ability of a system to assess the health of its components and integrate that information within the context of available resources and operational demands. ARP 6275 [90] lists the benefits of implementing an IVHM program including fuel savings, fewer mission aborts, increased efficiency, and better identification of faulty components.

The US Department of Defense (DoD) explains that the shift to CBM is intended to lower lifecycle ownership costs [91] and define Condition Based Maintenance Plus (CBM+) as maintenance performed based on evidence from Reliability Centered Maintenance (RCM) analysis and other enabling technologies. The goal of CBM, according to the DoD, is to conduct maintenance based on the actual condition of a component rather than a fixed schedule, moving from a reactive approach to a proactive and predictive one, which increases asset availability.

Selecting the optimal maintenance strategy is essential, as no single approach suits all aircraft components; a balance between predictive and corrective/preventative maintenance is necessary to avoid wasting usable component time or facing unexpected issues. The industry's move towards a CBM approach aims to reduce unscheduled maintenance, lower costs, and enhance operational reliability by performing maintenance based on demonstrated need. This is enabled by the implementation and utilization of IVHM.

7.3. Regulatory Approval

Regardless of whether maintenance is scheduled, preventative, or predictive, requirements can be by operators for economic reasons, or regulators through the maintenance schedule per the MSG-3 process or life limits, on components, set during design or certification.

Implementing a CBM program for economic reasons still requires regulatory-approved practices, but it does not need regulatory approval to start. The intent of CBM is to conduct maintenance based on the actual condition of a component, using data to assess its current state. Historically, data and predictive maintenance have been used mainly for economic purposes rather than for regulated scheduled maintenance. Prior to the release of Advisory Circular(AC) 43-218 [92] and Issue Paper(IP) 180 [93], all regulated inspections on aircraft had to be performed by a mechanic, physically at the aircraft. These documents allowed for the use of data for certain, preapproved, inspections.

These capabilities and regulatory acceptance will facilitate the shift from fixed schedules based on hours or cycles to a condition-based maintenance approach [94]. To support this transition, IP 180 [93] and AC 43-218 [92] require that data used in a condition-based maintenance program must accurately represent the system and its level of degradation.

While CBM has been commonly used for non-regulated tasks, such as soft time and run-to-failure components, regulators have now accepted the use of data to assess the condition of components under regulated maintenance schedules. This acceptance and the subsequent issuance of guidance have paved the way for the industry to implement CBM for scheduled maintenance tasks but requires an accurate understanding of the condition of the component.

7.4. Importance of Accuracy

For regulatory-approved tasks, both regulators and the industry expect a clear understanding of a component's current condition enrolled in a CBM program. While no system is perfect, and "false alarms" can be expected from an IVHM system [90], and some inaccuracies may be acceptable for economic items, regulatory actions require a higher level of accuracy.

To gain acceptance of CBM programs in aviation, accuracy must be prioritized, algorithms may produce false positives or negatives, which may reduce acceptance, this will require improved accuracy and predictive capabilities of health management models [89]. Further hampering acceptance are the complexities of real-world applications and the challenges of creating accurate RUL predictions has resulted in the use of "black box" models which do not provide the interpretability required and methods to improve "opacity" are needed to assist with acceptance [95].

While flight or safety critical components will certainly require high accuracy, limited accuracy may be acceptable for inexpensive or non-critical [96], as such accuracy does not need to be a fixed constant.

While predicting the future state, or RUL, of a component is uncertain, ensuring an acceptable level of accuracy regarding its current condition is essential for building confidence in the system. While nonregulated inspection tasks can accept lower accuracy, regulated tasks demand higher accuracy. Although there are many benefits to implementing a CBM program, the value diminishes with each incorrect assessment of a component's condition, such as misclassifying a healthy component as degraded or failing to detect a faulty one.

7.5. How CBM Is Being Measured

Accuracy is crucial to successfully implement CBM. Diagnostic and prognostic metrics for aerospace propulsion health management exist and can be categorized into cost benefits, computational performance, and algorithm/system performance [97] and core metrics which include accuracy, precision, coverage, timeliness, confidence, robustness, and convergence. An analytical approach can be used to create a "health index" producing a value between 0 and 1, indicating time to failure and providing a RUL value for an individual component. If required these values from individual assets can then be combined to create a band representing the overall fleet [98].

While no IVHM system can be 100% accurate, it is essential to consider false positives and negatives in decision-making [80] and the performance of any alerts. The need to minimize false negatives in critical systems, without increasing false positives, must be considered as it can lead to unnecessary maintenance [89] and increased overhaul costs. With increased understanding and detail afforded by digital twin based predictive maintenance the true positive detection rates can be improved [99].

Consistent metrics for assessing a CBM program is important as it must perform better than an interval based program and not result in removal of health components. The No Fault Found (NFF) rate should be lower in a CBM program compared to an interval-based one [89]. Additional metrics for evaluating prognostic techniques, addressing the concepts of false positives and negatives exist; the ratio of Mean Time Between Failure (MTBF) to Mean Time Between Unit Removal (MTBUR) and prognostics can reduce this ratio by allowing components to operate longer [100]. As CBM becomes more prevalent and includes more tasks, measuring the accuracy of CBM algorithms will become increasingly important.

The industry has developed or adopted various measures that, when combined, provide a good indication of the effectiveness of predictive or CBM programs. These measures are summarized in Table 4. For CBM to be effective, it must accurately assess the current condition and predict future conditions. Incorrectly indicating a degraded condition can lead to unnecessary repairs, while failing to detect an actual issue can undermine the benefits of a CBM system. While the traditional measures of true and false positives or negatives are important to consider for individual predictions, they will not have the ability to measure the performance of a CBM system. The effectiveness of a successful CBM can be better demonstrated by a reduced rate of NFF, indicating component degradation is adequately calculated and alerted to, optimizing RUL. The ratio between MTBF and MTBUR has the potential to provide accurate indications of the effectiveness of a CBM program by quantifying the interaction between missed opportunities, indicated by failures, and proactive removals.

7.6. The Role of Digital Twins in CBM

CBM is a key application of digital twins in support and services, and accuracy is an important portion of the implementation [24]. A digital twin can provide more accurate and personalized alerts by understanding the actual experiences of components, they can be considered as essential for effective IVHM systems [31]. For example, a heat exchanger in an aircraft's air conditioning system may be cleaned based on a set schedule. However, if the aircraft operates in a clean environment, less maintenance may be required compared to one in a polluted area.

Digital twins can be considered essential for various maintenance strategies, including reactive, predictive, prescriptive, and CBM and their accuracy can be linked to their level of fidelity [52]. A complete understanding of components and systems, their configuration and lifetime experiences, through data, from across the lifecycle better enables CBM [89,96].

The utilization of digital twins for health management requires proper initialization and calibration [72] and prediction quality can be linked to the level to which digital twins are created and maintained [99]. The use of digital twins to enable a higher level of CBM is being achieved across many industries and can measure and detect discrepancies in behavior during an asset's operational phase [26]. This can be achieved through various methods; a model-based health management approach, where the digital model is compared to operational data to assess system performance [101], or by "Deep Digital Twins," using deep learning from operational data for detection, diagnostics, and prognostics [102].

Table 4. Common measures for predictive alerting.

Measure	Description	Reason for importance	Result
True Positive	Predicted true and is true	If the predicted or determined condition of a part is known to be correct, it allows the confidence for the part to remain operational for as long as possible	Maximum operational life
True Negative	Predicted false and is false	If a part is predicted to be operational and is operational	Normal operation
False Positive	Predicted true and is false	If a part is predicted, or determined to be degraded to a point that it must be removed only to find that it is still acceptable	Unnecessary work
False Negative	Predicted false and is true	If a part is predicted to be good and fails in operation an unscheduled event will result	Unscheduled event
No Fault Found Rate	The rate at which a removed component is inspected, and no fault is detected	Is a measure of how accurate the initial prediction is and if it is confirmed by inspection during overhaul or repair	Increased costs if high
MTBF/MTBUR Ratio	The ratio between the MTBF of a component and the mean time between proactive removals of the same part	The ratio between how long a component lasts before failure and how long it is operational before a proactive removal	Reduced costs and improved operational time

Moving beyond using digital twins for CBM, efforts are being focused on how to improve the level to which they can be used such as using digital twins as tools for predicting RUL by combining data-driven analytics with physics-based models [103], or how digital twins can be used in IVHM to monitor RUL and component degradation [78]. Predicting individual asset performance cannot be achieved using fleet averages and a collaborative approach, using a distributed digital twin architecture can better achieve the levels required [104]. They also explore different deployment methods for digital twins, whether at the data source (edge) or in a centralized location.

Complex machines and systems require detailed understanding of their current and past operation with which to accurately predict future conditions and calculate RUL. This deep understanding of configuration, operational conditions, lifetime experiences. The comprehensive understanding of individual components and current performance afforded by digital twins which will enable enhanced accuracy and personalized alerts enabling wider acceptance and adoption of CBM.

8. Data to Enable the Digital Twin for CBM

Digital twins can be created from domain knowledge, codified through ontologies, and are critical to providing the desired level of accuracy for regulatory approved CBM. However, the digital twins cannot reach their full potential without data which is essential for the creation and maintenance of a digital twin both to exist and persist.

8.1. Data from Across the Lifecycle

Digital Threads connect physical assets to their digital twins, facilitating continuous data, and is the foundation for digital twins by continuously adding data to these threads enhances the definition and scope of the digital twins [24].

Effective digital twins require real-time access to data throughout their lifecycle and will need to overcome the challenges of data sharing among organizations [58]. Data from across the lifecycle is necessary not only for setting up a digital twin but also for its ongoing evolution and updates [52]. Without data throughout the asset's lifecycle, the digital twin cannot accurately reflect its performance [105].

Various data types are essential for accuracy of digital twins. Planning for data across the lifecycle is important and the different data types, sources, and labeling early in the design phase must be considered, including creating "metadata" for digital twins [68].

Access to data, and of the required quality, is not always easily available the quality of data needs to be considered in the ability for a digital twin to enable for in-service support and maintenance [106]. Data scarcity, quality, and complexity are all challenges in using digital twins for predictive maintenance, this can be addressed through industry collaboration to create data models and standards for digital twins [78].

Data from across the asset's lifecycle is essential for continuous updates reflecting the physical asset's performance and is the focus of many as they address maintaining digital twins. Digital Threads connect physical assets to their digital twins, enabling continuous data flow that enhances the definition and scope of the digital twins throughout their lifecycle.

8.2. Data Quality

For data, and digital twins, to be accepted for regulatory maintenance or inspections, the data must be of high quality, equivalent to what a mechanic would provide during an inspection. The importance of data quality is emphasized in the FAA's guidance for regulated CBM programs [92], which highlights the need for proper data transmission, standards, and sampling rates.

Data quality is a key part of a digital twin maturity model [34], dividing it into four areas:

- Accuracy: Does the data accurately represent what is being measured?
- Completeness: Is there enough data available for the intended use?
- Consistency: Is the same data always represented in the same way?
- Uniqueness: Is there any unnecessary duplication of data?

The theme is continued by the creation of a framework for defining information quality based on data attributes [71] identifying six dimensions:

- Timeliness: Is the data available promptly after an event?
- Credibility: Can the information be trusted?
- Reliability: Is the data precise, correct, and detailed enough?
- Interpretability: Is the data easy to understand and consistently labeled?
- Operability: How quickly can users' access and retrieve the data?
- Sufficiency: Is there enough data to complete the required task?

The quality of data is crucial for a digital twin to accurately represent its physical counterpart. High-quality data directly impacts the quality of the digital twin created. Measuring data quality using attributes like accuracy, completeness, and credibility, are essential for a digital twin, especially when used for monitoring or decision-making related to regulated actions like maintenance.

8.3. Data Updates

The timing of data updates must be considered, as some aspects of a digital twin may require near real-time updates, especially if degradation occurs quickly, such as on a flight-by-flight basis [74]. In contrast, other applications, like fatigue monitoring, can handle longer intervals between updates.

Information and data can be improved at various stages of the lifecycle and need not be static [76]. Early in a program, there may be few operational aircraft, resulting in low-fidelity models. However, as time and technology advances, the fidelity of these models will improve [5]. This concept also applies to data gathering, sensing, and transmission, as new sensors may be added to address gaps in monitoring components or detecting failure modes. Potential negative effects on operational decisions can result from slow, or missing, updating frequency. If updates are not timely, then digital twins are not up to date limiting effectiveness [76]. Data interruptions will result in digital twin failing to update and become inaccurate [35].

A data link between the physical and digital worlds is essential for creating a digital twin. However, the further the digital twin is from the physical object in terms of time, the less accurately it can represent the physical object. Updating a digital twin with near-real-time data can be challenging and expensive to compute and labor intensive, and risks making the digital twin outdated for time critical applications. If the data flow stops then the digital twin starts to become outdated and depending upon the use case can be ineffective until the data begins to flow again.

8.4. Fusing Data to Create a More Complete Picture

Different types of data are used in predictive maintenance with digital twins containing historical information, technical data, maintenance reports, manufacturing reports, and operator and asset features, the fusion of this data is essential for creating effective digital twins [103]. This data must be fused with both sensors and offline contextual data, such as photos, maintenance logs, and expert opinions, to be combined for a complete creation of the digital twin [74].

Fusing data helps create a more detailed picture of an item of interest. The healthcare industry has shown that combining multiple data sources leads to better evaluations, enhances context and improves image resolution [107,108]. Data fusion can be required as insights from a single data source often will not tell a complete picture, underlying the importance of image fusion techniques to integrate complementary information [109].

Within the smart factory environment, the need to fuse multiple sources of data exist and is enabled through a digital twin-based framework for integrating big data [59]. Information available can be greatly enriched using a data model of complex equipment using data from physical assets, digital sources, domain knowledge, and service models [110].

A single type of data, regardless of how detailed or accurate, rarely tells the whole story or contains sufficient context for a full understanding of a situation. It requires linking data from different systems, formats, and times, which is central to the concept of a digital twin. Various industries are working to combine data from single events to enhance understanding and provide context. This effort is crucial for interpreting individual events that may not be fully understood otherwise.

8.5. Data Types for Aviation

When defining what a digital twin is and how to create and maintain it, identifying the types of data involved are crucial for improving accuracy in CBM applications. The acquisition, flow, and processing of data are essential to ensure that the digital twin accurately reflects the physical twin for specific use cases. The data production (in the context of the aircraft lifecycle and digital data) is addressed in AIR 7501 [110], detailing the various contributors and activities that generate data within the aerospace ecosystem, providing a comprehensive list of different data types. Although there is a significant amount of data related to the manufacture, operation, and maintenance of aircraft throughout their lifecycle, the relevant data for creating and maintaining an operational digital twin for CBM is summarized in Table 5.

Table 5. Data to enable a digital twin for a CBM program.

Producing Stakeholder	Producing Event	Produced Artefact
Manufacturer	Deliver	Instruction for Continued Airworthiness As Delivered Configuration
Supplier	Overhaul	Overhaul shop reports
Supplier	Deliver	Instruction for Continued Airworthiness As Delivered Configuration
Regulator	Regulations	Advisory Circulars Airworthiness Directives Maintenance Review Board Report
Operator	Fly	Aircraft data (Faults, ACMS, QAR) Logbook write ups Operational deviations
Operator	Maintain	Inspections completed Inspection results Component removal/installation Inspection results As flying configuration As maintained configuration Overhaul shop reports Maintenance program
Maintainer	Maintain	Inspections completed Inspection results Component removal/installation Inspection results As maintained configuration Overhaul shop reports

This data includes information generated during manufacturing, operation, and maintenance but does not account for the environment in which the aircraft operates, or the personnel involved in its operation and maintenance. Challenges and opportunities exist in implementing predictive maintenance for aircraft, and tools are needed for the required level of analytics and listing essential data types, such as pilot logs, ACMS reports, fuselage inspections, and component monitoring.

9. Summary

This paper has investigated and presented the state of the art, through a literature review, of four key areas essential for understanding the interaction between fidelity and the ability of a digital twin to enable a defined use case. It has also demonstrated the need to move from reactive to proactive maintenance in the aviation industry and how it will be enabled by digital twins. These areas are digital twins, fidelity, ontologies, data, and CBM. The key findings and validations are:

9.1. Digital Twins

Digital twins are essential components in the digital value chain, enabling analytics and data-driven decision-making that enhance downstream services across various industries. Importantly, these digital twins must be tailored to specific use cases to effectively address the unique requirements of each application. The complexity of modern machines requires collaboration among stakeholders to establish common standards and structured frameworks for successful implementation. As the industry evolves, fostering cooperation on these standards will be essential for maximizing the value of digital twins and enhancing their integration into operational processes tailored to specific use cases.

9.2. Fidelity

Fidelity is a critical for the effectiveness of digital twins, directly influencing their ability to accurately represent physical counterparts and deliver meaningful benefits. Key attributes such as data type, quantity, and accuracy play significant roles in establishing fidelity, along with the continuous data flow throughout the lifecycle of the digital twin. Ultimately, the success of a digital twin hinges on its fidelity, defined as the capacity to represent its physical counterpart at the necessary level of detail to achieve desired outcomes, thereby reinforcing the need for ongoing efforts to quantify and optimize fidelity in digital twin applications.

9.3. Ontologies

Ontologies serve as a foundational element in the development and maintenance of digital twins, enabling structured knowledge representation that facilitates interaction between humans and machines. By defining relationships and semantics, ontologies provide a standardized framework for integrating diverse data sources, which is essential for accurately representing physical entities. The complexity of assets throughout their lifecycle can require the use of multiple ontologies to capture varying levels of detail and domain expertise. This will require collaboration among industry stakeholders to establish common standards. The successful implementation of ontologies will enhance the quality and functionality of digital twins and promote interoperability across different systems and applications. As the industry moves towards the adoption of shared digital twins, the collective effort to develop and agree upon standard ontologies will be critical in realizing the full potential of this technology.

9.4. Data

The integration of data throughout the asset lifecycle is fundamental to the effective creation and maintenance of digital twins, as it ensures continuous updates that accurately reflect the states of physical assets. Digital Threads facilitates a seamless flow of high-quality data, which is essential for enhancing the definition and scope of digital twins. The quality of this data directly influences the reliability of the digital twin, particularly in contexts requiring regulatory compliance. Challenges related to data sharing and the need for real-time updates should be addressed early in the design phase to prevent the digital twin from becoming outdated, as any interruption in data flow can significantly diminish its effectiveness. As industries continue to advance in their use of digital twins, the focus on robust data management practices will be critical to realizing their full potential.

9.5. CBM

The industry's shift towards CBM represents a proactive strategy that leverages data to assess component conditions, to reduce unscheduled maintenance and associated costs. Regulatory acceptance of data-driven assessments for scheduled maintenance tasks requires accurate condition monitoring and predictions, as the effectiveness of CBM hinges on the precision of these evaluations. While predicting the RUL of components presents inherent uncertainties, maintaining a high level of accuracy in current condition assessments is essential for building confidence in maintenance systems. Ultimately, the integration of digital twins into maintenance practices enhances the understanding of component performance, facilitating improved accuracy and personalized alerts that support the broader adoption of CBM methodologies across the aviation industry.

Based on the findings, limitations in the current condition regarding the interaction between fidelity and the ability of digital twins to enable defined use cases in the aviation industry are:

9.6. Complexity of Implementation

The implementation of digital twins requires collaboration among various stakeholders to establish common standards and structured frameworks. The complexity of modern machines adds to the challenge of achieving successful implementation. This complexity is felt from the creation of ontologies, sharing of data and ownership of digital twins all which require sharing throughout the lifecycle

9.7. Consideration of Specific Use Cases

Digital twins must be specifically tailored to address the unique requirements of each application. This customization can be resource-intensive and may limit the scalability of solutions across different use cases. Without planning early in the design digital twins may not be sufficient to achieve a desired use case, this is common in the application of digital twins on existing platforms.

9.8. Fidelity Challenges

Achieving the necessary level of fidelity is critical, yet it is influenced by factors such as feature identification, data type, quantity, and accuracy. Understanding the link between the features necessary to create the digital twin and then ensuring a continuous data flow is essential. Any interruption can significantly diminish the effectiveness of the digital twin.

9.9. Regulatory Acceptance

The shift towards Condition-Based Maintenance (CBM) relies on regulatory acceptance of data-driven assessments. Achieving this acceptance necessitates accurate condition monitoring and predictions, which can be difficult to maintain.

These limitations highlight the challenges that need to be addressed to fully realize the potential of digital twins and their integration into proactive maintenance strategies in the aviation sector.

10. Conclusions

The need for IVHM, predictive maintenance, and CBM is increasing due to industry demands to reduce unscheduled maintenance. A comprehensive approach to maintenance will require moving to a regulatory-approved CBM process, where maintenance is based on the condition of components rather than a fixed schedule. Achieving the necessary accuracy will require individualized algorithms, alerts, and predictions, all supported by digital twins.

The relationship between the physical object and its digital representation, defined through data collection and engineering, determines the fidelity of the digital twin. Digital twins must have sufficient detail to meet their intended use case. Ontologies help codify domain expertise and integrate data into digital twins. The flow of data throughout the lifecycle is critical for creating and maintaining digital twins. There is a strong desire for improved health management to support CBM programs and predictive maintenance, which has been demonstrated in both academia and industry. However, there is currently a gap in defining, and measuring, the fidelity of a digital twin or prescribing the level required to achieve a defined outcome. For CBM to achieve its full potential digital twins are required and they must be of a level sufficient to achieve the aim, but too high of a fidelity could result in unacceptable costs to create and maintain the digital twin. A defined and measurable approach can result in an ability to understand desired and achievable levels of Digital Twin fidelity required to achieve a prescribed use case. The ability to quantify the fidelity of a Digital Twin for an intended task is an area that requires further study.

Additional research is required in this area specifically to address:

- How digital twins improve maintenance in the context of CBM/IVHM.
- How to design digital twins for IVHM/CBM.
- How to enable, and quantify, data management for digital twins through ontologies in the context of CBM.

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Abbreviations

The following abbreviations are used in this manuscript:

AC	Advisory Circular
A4A	Airlines For America
APU	Auxiliary Power Unit
ATA	Air Transport Association
ATM	Air Traffic Management
CBM	Condition Based Maintenance
CBM+	Condition Based Maintenance Plus
DCO	Data Conversion Ontology
DOD	Department of Defense
DT-FCM	Digital Twin Fidelity Calculation Method
DT-FRM	Digital Twin Fidelity Requirements Model
DTMs	Digital Twin Models
DTO	Digital Twin Ontology
IP	Issue Paper
IVHM	Integrated Vehicle Health Management
MRO	Maintenance, Repair, and Overhaul
MTBF	Mean Time Between Failure
MTBUR	Mean Time Between Unit Removal

NFF	No Fault Found
PHM	Prognostics and Health Management
PLM	Product Lifecycle Management
RCM	Reliability Centered Maintenance
RUL	Remaining Useful Life

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