drones

Review

A Review on the Construction, Modeling, and Consistency of Digital Twins for Advanced Air Mobility Applications

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Abstract: The advent of Advanced Air Mobility (AAM) presents a transformative solution to multi-modal transportation. However, coordinating missions, as well as monitoring and controlling multiple Unmanned Aerial Vehicles (multi-UAV systems), remains a significant challenge. The adoption of digital twin (DT) technology has the potential to provide a viable solution. This study synthesizes insights from 146 publications across the UAV, traditional aviation, and manufacturing domains, retrieved from major scientific databases such as Scopus, IEEE Xplore, and ScienceDirect. The aim is to comprehensively analyze advancements in cyber–physical systems (CPS) and DT technologies, with a particular focus on the key aspects of UAV-based DT construction, including framework architecture, geometric modeling, physical modeling, behavioral modeling, rule modeling, and cyber–physical consistent modeling approaches. Additionally, the application of DTs in AAM scenarios is analyzed, and key challenges are identified. Finally, we provide insights into research directions to enhance the robustness and applicability of future AAM-based DT.

Keywords: digital twin (DT); cyber–physical systems (CPS); advanced air mobility (AAM); urban air mobility (UAM); UAV (unmanned aerial vehicle); drone

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1. Introduction

Unmanned Aerial Vehicles (UAVs) are seeing exponential growth in use cases, including surveillance, search and rescue, target tracking, and logistics [1–5]. This has given rise to new air traffic concepts like Advanced Air Mobility (AAM) [6,7]. AAM systems enable next-generation aerial transportation, including remotely piloted, autonomous vehicles, while giving a renaissance to vertical take-off and landing (VTOL) aircraft. Similar to conventional air transport, AAM or Urban Air Mobility (UAM) [8,9] focuses both on passenger and cargo transport within urban areas, offering time-attractive, direct connections, especially in obstacle-rich (cities) or remote (mountainous areas) environments, by operating above-ground traffic. This has the potential to revolutionize modern economies by addressing urban congestion, enhancing logistics efficiency, reducing emissions, and minimizing infrastructure costs. The operational backbone of AAM relies on a large variety of special-purpose-built low-altitude UAVs performing complex missions in busy environments. To ensure safe and efficient operations, several technical challenges must be addressed, such as modeling such complex systems at design time, as well as conducting autonomous multiple UAVs' mission planning, execution, real-time monitoring, and control. These complex tasks require advanced software frameworks to keep the operational risk of the air transport system at current levels while enhancing AAM system reliability.

Digital twin (DT) technology [10], the cornerstone of Industry 4.0 and a key driver of intelligent systems, consists of a high-fidelity virtual mirror of the physical world [11] in a cyber–physical system (CPS). The DT integrates cutting-edge technologies such as the Internet of Things (IoT) [12–15], artificial intelligence, and big data analytics. It has been widely applied in fields such as aerospace, smart cities, and industrial manufacturing [16–21]. A DT decomposes complex system models into submodules, such as geometry, physical, behavioral, and rule models, and incorporates both historical data and real-time sensor inputs. This enables a DT to predict system behavior, optimize operational parameters, and simulate realistic environments [22,23]. In AAM, DT technology is expected to support mastering the challenges of complex low-altitude multi-UAV management. Firstly, by integrating environmental sensing with dynamic adaptation, DTs can monitor multi-UAV systems in real time. When discrepancies arise between actual UAV behavior and the mission plan, these inconsistencies can be promptly fed back to the behavioral model and execution layer for correction. Secondly, DT can be used to predict future UAV flight states and optimize their control using resilient strategies. Through conflict prediction, anomaly detection, trajectory deviation identification, and adherence mechanisms, DT is expected to prevent autonomous UAVs from violating flight rules, entering dangerous or flight-restricted zones, or colliding. Thirdly, DT can potentially simulate complex flight scenarios, including extreme weather conditions, so that a response strategy to such disruptive situations can be planned to help reduce delays in the transport system and energy consumption. Overall, DT has the potential to become a key technology in Unmanned Aircraft System Traffic Management (UTM), offering real-time monitoring, feedback control, predictive analytics, and advanced simulation capabilities. This can improve system reliability [24,25], reduce safety risks, and provide technical support for the implementation of AAM systems.

At present, the appropriate definition of the DT for the AAM system remains an open question. A future AAM-based DT should integrate not only UAVs but also supporting infrastructure such as airspace, vertiports, communication networks, and UTM. By integrating multiple UAV-based DTs into a larger, interconnected system, the AAM-based DT enables cooperative decision making, optimizes trajectory planning, and prevents airspace conflicts through shared situational awareness (coarse-grain level of AAM system). At the fine-grain level, each UAV has its own DT, mirroring its real-time operational state, mission objectives, and environmental interactions.

Although the current focus is on a fine-grain level of AAM-based DT, that is, UAV-based DT, it still faces many challenges. Key questions persist regarding the development of each sub-model within the UAV-based DT: How should these sub-models be systematically constructed? How can consistency be ensured across multiple UAV-based DTs operating concurrently? What strategies can be employed when inconsistencies arise—such as when the mission layer indicates that a UAV is still in flight, even though it has already landed, or when the control layer detects a deviation from the planned route that the mission layer fails to acknowledge and continues to execute the original plan? Moreover, there are a few DT systems specifically designed for scenarios where multiple UAVs collaborate. How to ensure safety and maintain consistency in such UAV-based DT systems remains a pressing question. These issues require further in-depth investigation and a review of existing literature to identify current solutions and future research directions.

Currently, some studies have explored UAV-based DTs with a focus on individual UAV states and behaviors. There are also results in aviation and manufacturing fields concerning how to construct DT models and maintain CPS consistency [26]. However, comprehensive reviews addressing these issues in the context of UAVs are still lacking. Therefore, this work begins from the fine-grain level of the AAM-based DT, i.e., UAV-based

DT, aiming to review the current research status of UAV-based DTs, summarize relevant experiences, and introduce them into the AAM context.

To systematically examine and analyze the research landscape, this study synthesizes studies from the aviation and manufacturing fields, reviewing the advancements in CPS and DT, the development of DT frameworks and models for UAVs, and their practical applications within the AAM sector. Based on this comprehensive analysis, we summarize the current challenges and provide research directions and recommendations for constructing future AAM-based DT.

This paper is structured as follows: Section 2 introduces the research methodology; Section 3 provides an overview of CPS and DT concepts and their development trends for UAVs, and gives a definition of UAV-based DT; Section 4 delves into UAV-based DT construction methods and modeling techniques; Section 5 discusses DT applications in the aviation and UAV sectors, while Section 6 highlights challenges and research gaps for UAV-based and AAM-based DT, offering future research directions; Finally, Section 7 presents the study's conclusions.

2. Research Methods

The literature screening process of this study was followed by the ideas of the Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) [27,28]. This review was conducted without a prior published or registered protocol. Data charting was conducted using a standardized Excel form. To ensure consistency, the reviewer applied the inclusion criteria carefully and reviewed any ambiguous cases with a second opinion when necessary. Our workflow is illustrated in Figure 1.

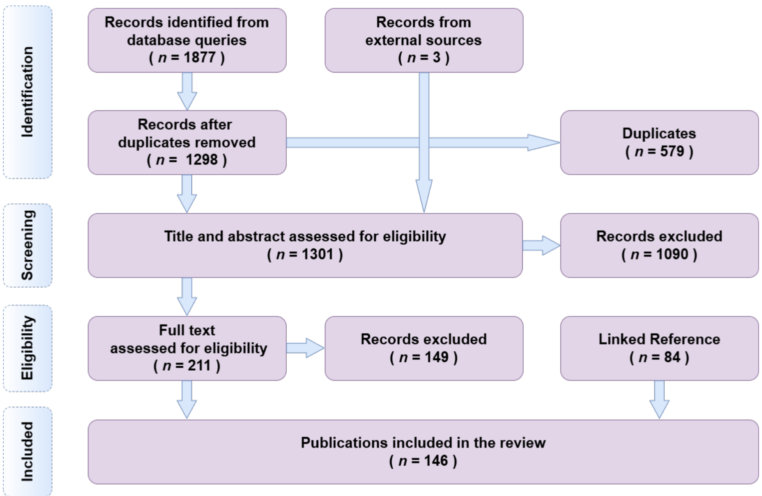

Figure 1. Literature Screening Workflow.

To begin, we identified our search strategy and initially filtered relevant publications. Considering that the integration of Unmanned Aerial Systems (UAS) with CPS first appeared in 2012 [29], this review set a time frame spanning 13 years to cover the field's development trajectory comprehensively. However, our research focus and search criteria were concentrated on DT in UAV and AAM, an emerging area of study where the most relevant literature has been published in recent years.

We selected keywords for both AAM and DT to retrieve relevant literature systematically. For AAM terms, we selected "Unmanned Aerial Vehicle", "UAV", "Unmanned Aircraft System", "Unmanned Aerial System", "UAS", "Urban Air Mobility", "UAM", "Advanced Air Mobility", "AAM", and "drone". These terms cover different aspects of unmanned aviation, general UAV terminology (UAV and drone), regulatory and system-level definitions (UAS and Unmanned Aerial System), and advanced operational paradigms for urban and regional air mobility (UAM and AAM).

For DT terms, we used "digital twins", "cyber twin", "virtual twin", "DT", "Cyber-Physical System", and "CPS". These keywords cover different conceptual and technical aspects of DT. Digital twin and DT are the most commonly used terms. The cyber twin and virtual twin emphasize different modeling perspectives, and the cyber–physical system (CPS) is the broader framework that integrates physical and digital components, which is the foundation of DT.

In our search strategy, we combined keywords within the same category with "OR", and AAM-related and DT-related terms with "AND". This ensures that the retrieved papers are study the integration of UAVs and DTs, which is the focus of this review.

To perform the publication query, we selected four databases: Scopus (1337 results), IEEE Xplore (408 results), and ScienceDirect (132 results), yielding a total of 1877 publications. Additionally, two relevant publications were manually added based on external references. The search was run multiple times, and the latest update was performed on 12 January 2025. After removing 579 duplicate records using publication titles and Digital Object Identifiers (DOIs), the remaining records were screened for eligibility. To be specific, our screening criteria were as follows:

- The paper title must include one or more search keywords.
- The paper must be published in a peer-reviewed journal or conference and not be a short survey, review, letter, or book chapter.
- The paper must primarily focus on drones as the main research subject rather than broader topics such as cities or the environment.

During this process, we identified 211 studies that met our criteria for further analysis in subsequent stages. Subsequently, we refined our research scope through theoretical screening, focusing on studies involving DT construction and applications in UAV. The specific screening criteria included the following :

- Studies discussing DT core architectures, frameworks, or key technologies that contribute to understanding DT development trends and technical challenges.
- Research on DT applications or optimizations, including DT's role in modeling, simulation, and state assessment.
- Research addressing DT or CPS consistency mechanisms, even if not explicitly mentioned in the title, keywords, or abstract. Such studies were included to comprehensively understand cyber–physical consistency's development trend across more mature fields like manufacturing.

Through further review in this stage, 149 papers were filtered out. Additionally, we identified 22 studies directly related to UAV-based DT construction. These core studies will be analyzed in detail in Section 4 to extract key insights from the field.

In the final stage, the data synthesis incorporated cross-citation analysis and identified 84 studies of significant reference value through cross-citation analysis of relevant papers. To bridge the research gap in UAV-based DT, we integrated representative literature that covers definitions, methodologies, and approaches for constructing and updating DT models from other fields to enhance the depth and comprehensiveness of our analysis.

We then grouped the studies into thematic clusters, including (1) DT framework architectures for UAVs, (2) multi-dimensional modeling approaches, and (3) cyber–physical consistency mechanisms and cross-domain insights from manufacturing and traditional aviation. This thematic organization allowed us to identify the current state-of-the-art in UAV-based DT development and highlight gaps in the current research landscape.

Visual Analysis

In the visualizations, we included flowcharts and summary tables to present information such as the publication year, the most frequent conferences and journals where relevant papers were published, and the geographical distribution of these publications by country. In subsequent sections, we also provided summary tables categorizing studies based on different modeling dimensions (see Section 4). These tools supported our analysis of temporal trends and the evolution of key modeling paradigms.

Over the past five years, the application of DT in this field has shown exponential growth, and it is expected to continue expanding. Figure 2 displays the number of papers published over the last five years and possible trends over the next three years.

Table 1 further lists the academic journals and conferences with the highest paper publication volumes in this field, with IEEE Internet Of Things Journal leading at 19%, indicating a strong research focus on IoT-driven DT implementations, connectivity, and real-time data integration. This is followed by AIAA IEEE Digital Avionics Systems Conference Proceedings, highlighting the importance of DT in avionics and aircraft system design. Additionally, journals and conferences in the field of transport and manufacturing also accounted for a portion, suggesting a strong intersection between DT applications and intelligent transportation, autonomous mobility, and vehicular communication systems. Moreover, this review examined 146 journals and conferences, indicating that DT research spans multiple disciplines and exhibits broad application prospects.

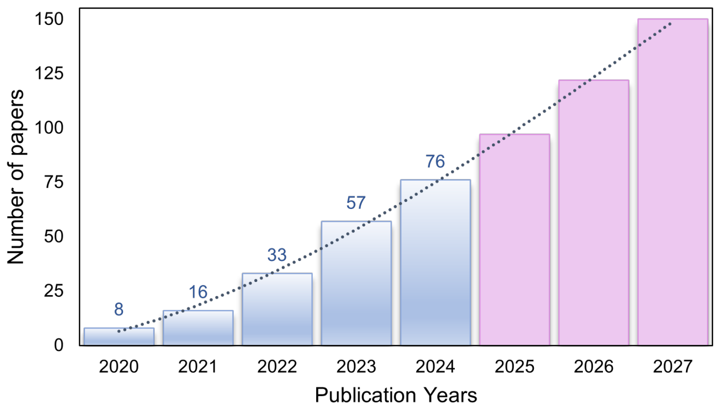

Figure 2. Number of publications over past 5 years (2020–2024).

Table 1. Journals and conferences with the highest number of publications in the field.

Journal/Conference	Article Count
IEEE Internet Of Things Journal	7
AIAA IEEE Digital Avionics Systems Conference Proceedings	5
IEEE Journal On Selected Areas In Communications	4
IEEE Transactions On Intelligent Transportation Systems	4
Journal of Physics Conference Series	4
Lecture Notes In Networks And Systems	4
IEEE Transactions On Consumer Electronics	3
IEEE Transactions On Vehicular Technology	3
IEEE Vehicular Technology Conference	3

Figure 3 shows the distribution of countries contributing to this field, with Chinese academic institutions leading in paper publications, accounting for 25%, followed by those from the United States, at 8%.

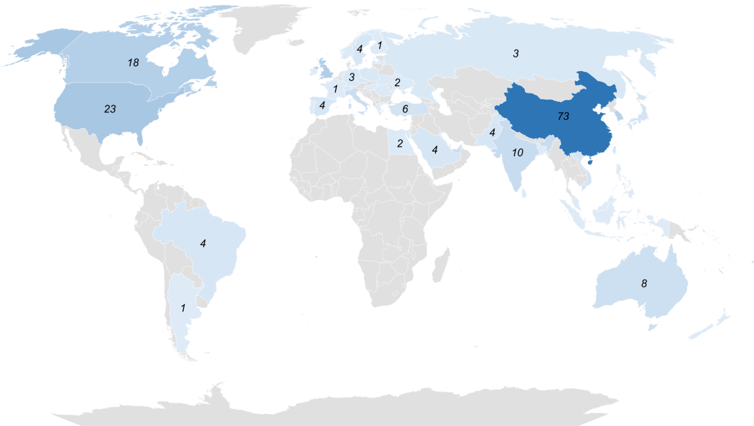

Figure 3. Publication count categorized by country.

The critical appraisal of individual sources of evidence was not conducted, as this review aimed to map the available literature rather than evaluate the methodological quality of studies.

3. Cyber–Physical Systems and Digital Twin for UAVs

3.1. Cyber–Physical Systems (CPS)

CPS are advanced embedded systems integrating sensing, computing, communication, and control to enable seamless interaction between physical and cyber worlds [25]. They are designed to collect real-time data from physical entities, process the information through computational models, and respond to optimize system performance. Therefore, they enable autonomous decision making and are key elements in many application domains, such as intelligent transportation, industrial automation, and aerospace systems. For multi-UAV operations, a CPS architectural framework with five layers is shown in Figure 4 [30], where the Component and Intelligence layers are the physical UAVs and the intelligent algorithms running on them, respectively. The Cyber layer models the digital entities, builds the connection for the CPS, and enables communication between multiple UAVs. The Configuration and Deployment layers are based on the ground control station, which enables real-time simulation and predictive decision making of multiple UAVs through DTs, achieving self-configuration, self-adaptation, and self-optimization.

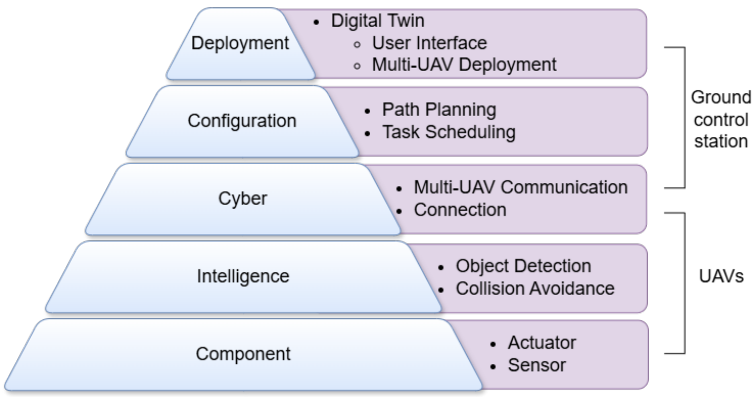

Figure 4. CPS architecture levels.

The essence of CPS lies in the tight coupling of its network and physical components. As shown in Figure 5, the sensor network continuously monitors the physical environment and generates data streams for computational analysis. Execution commands are then sent to modify the physical process, forming a closed-loop control mechanism. This bidirectional interaction requires high reliability and predictability, especially in safety-critical areas such as air traffic control [25], healthcare systems, and autonomous driving. Rapid advances in low-cost embedded systems, efficient sensors, and 5G have accelerated the adoption of CPS in many applications, from disaster response to security monitoring. The integration of UAVs further extends the capabilities of CPS because of their superior maneuverability, dynamic reconfigurability, and ability to operate in harsh or hard-to-access environments [31,32].

Figure 5. Cyber–physical systems sense and analyze the world to control systems.

Nevertheless, CPS for UAVs and AAM still faces many challenges. Firstly, the inability of the CPS to model future scenarios is a key bottleneck, indicating a lack of methods to generate monitoring rules and adapt constraints to system evolution. For example, in a UAV-based CPS, UAVs must comply with no-fly zones, speed limits, and battery management constraints [33–35], but the inability to simulate and predict these constraints before an actual flight results in the possibility of unintended deviations. A common example is the degradation of the battery management system of delivery UAVs: outdated voltage thresholds over multiple charging cycles can lead to a mismatch between the actual battery state and its numerical model [36,37]. Failure to anticipate this situation in advance and model it beforehand may result in mission failure due to unexpected battery depletion. Secondly, the requirement that the virtual product must correspond one-to-one with a real-world counterpart necessitates extensive physical testing [38]. In the case of UAVs, testing in a physical environment is resource-intensive, poses safety risks, and can potentially damage equipment. Additionally, this challenge makes it difficult to integrate new virtual users in the airspace for testing in AAM operations. Moreover, the scientific foundation of CPS that emphasizes fundamentals over implementation [39] creates an abstraction gap between the theoretical frameworks and the engineering practices.

The emergence of DT technology can effectively solve the above problems. In the subsequent subsections, we will discuss DT in detail.

3.2. Definition and Development of the Digital Twin

DT is a digital runtime system of cyber–physical assets or processes that rely on real-time data to simulate and predict the behavior of the physical system. As the key technology of CPS, DT provides a clear and feasible way to realize the functions of CPS. Though integrating simulation into CPS, DT allows for testing in cyberspace and reduces the cost and risk of implementation. It also provides the ability to predict the future, helping decision makers to make optimal decisions. In AAM, DTs are expected to enable not only real-time updates and bidirectional control between physical and virtual UAVs but also support real-time maneuvering through pre-flight simulations and in-flight trajectory predictions [35].

The term Digital Twin (DT) was first introduced by Grieves when he introduced PLM [40]. Although the initial concept was vague, the initial form of DT included physical and virtual products and their interconnections. Another early definition is due to the concept of dual-reality objects [41–43] in which a physical object also lives in the cyber world and is augmented with cyber-generated behavior. From its initial definition in the literature to today, the use of DT techniques has experienced rapid growth. However, there is still no universally accepted definition to explain its meaning and implications. There are many different interpretations of what a DT actually is and what it should be able to do. Therefore, in Table 2, we list the conceptual changes in DT as the technology has evolved and applications have expanded. Table 3 lists the unique concepts of DT in different domains.

Table 2. Definitions of DT.

References	Definition of DT
Grieves M. [40]	Digital twin consists of "(a) physical products in Real Space, (b) virtual products in Virtual Space, and (c) the connections of data and information that ties the virtual and real products."
Smith R.B. [41]	Dual-reality objects create a CPS.
Lifton J. et al. [42]	Dual-reality objects with augmented reality.
Rosen R. et al. [44]	Digital twin is seen as the next step in the development of simulation. It supports the simulation as a core functionality along the entire life cycle, e.g., supporting operation and service with direct linkage to operation data.
Stark R. et al. [45]	Digital representation of a unique asset that comprises its properties, condition, and behavior by means of models, information, and data.
Söderberg R. et al. [46]	Using a digital copy of the physical system to perform real-time optimization.
El S. [47]	Digital replications of living as well as non-living entities that enable data to be seamlessly transmitted between the physical and virtual worlds.
Qi Q. et al. [48]	Virtual models of physical objects are created in a digital way to simulate their behaviors in real-world environments.
Xu Y. et al. [49]	Simulates, records, and improves the production process from design to retirement, including the content of virtual space, physical space, and the interaction between them.
Kritzinger W. et al. [50]	Digital twin is a concept in which the data flow between an existing physical object and a digital object is fully integrated in both directions. The digital object might also act as controlling instance of the physical object. There might also be other objects, physical or digital, that induce changes of state in the digital object. A change in state of the physical object directly leads to a change in state of the digital object, and vice versa.
Kannan K. et al. [51]	Digital representation of the physical asset that can communicate, co-ordinate, and cooperate in the manufacturing process for improved productivity and efficiency through knowledge-sharing.
Autiosalo J. et al. [52]	Digital twin has a one-to-one correspondence to its real-world counterpart, enabling product-centric information management, and additionally, a digital twin is "a modular entity".
Lu Y. et al. [53]	A virtual representation of manufacturing elements, a living model that continuously updates and changes as the physical counterpart changes in an asynchronous manner.
Bickford J. et al. [54]	A model that helps stakeholders answer specific questions by providing a readily available, rapidly testable digital analog to the system of interest.
Silion D. et al. [55]	Digital Twin serving as a cloud-hosted digital replica of physical entities, ranging from machines and buildings to entire systems, and even the human body.

Table 3. Domain-specific definitions of DT [56].

References	Industry	Definitional Focus
Glaessgen E. et al. [19]	Aerospace	DT is an integrated multiphysics, multiscale, probabilistic simulation of an as built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin.
Grieves M. et al. [17]	Manufacturing	Virtual information structures replicating physical products at atomic to geometric scales.
Sacks R. et al. [20]	Construction	AI-driven data integration for design optimization and production management.
Bolton R.N. et al. [21]	Service Infrastructure	Lifespan virtual representations utilizing real-time data for system reasoning.
Croatti A. et al. [16]	Healthcare	Digital replicas enabling remote monitoring of medical assets without physical proximity.

By organizing and summarizing the DT definitions, we found that the definition for the air mobility domain is still missing. Based on our past work on collaborative robotics and UAS [57–61], we attempt the following definition:

Definition 1. *A* UAV-based DT *consists of a set of causally connected UAV runtime models, including a world model, that unify physical entities and their virtual counterparts through real-time data synchronization, multi-layered adaptation, and formalized behavioral representation.*

Runtime models are crucial in implementing Self-adaptive Systems (SAS), especially in uncertain environments [62]. That is, changes in the runtime model directly affect the running system, and vice versa. Commonly, SAS are conceptualized through the MAPE-K control loop [63,64].

A UAV-based DT is considered to maintain a world model in a runtime context, i.e., a runtime model that provides an appropriate and evolving representation of the operational AAM environment. This UAV runtime world model, or UAV world model, integrates various elements, such as physical structures, moving entities, and real-time data, to facilitate seamless coordination between operators, UAVs, and their environment. Also, it represents a digital replica of the physical environment, capturing both static elements (like UAV positions or local obstacles) and dynamic interactions (such as local airspace changes and movement patterns).

The components of a UAV-based DT specifically include runtime models, the mechanisms for synchronization between physical objects and virtual entities, the simulation execution and visualization environments [65], and prediction models. Consequently, the structure of a DT system closely resembles that of a CPS, as both consist of physical entities, digital models, and their connecting mechanisms [66]. However, DTs extend beyond CPS by incorporating a twin service layer, as Figure 6 illustrates. This twin service layer, besides providing a visualization interface and simulation environment, primarily manages real-time and historical data. In the context of UAV-based DT, such data may include UAV trajectory data, weather information, and sensor data. These capabilities enable DTs to perform predictive analysis, optimize operations, and enhance decision making. In a word, UAV-based DT DTs rely on integrating multiple technologies, among which modeling [67] and simulation play a central role, serving as the prerequisites for their successful application.

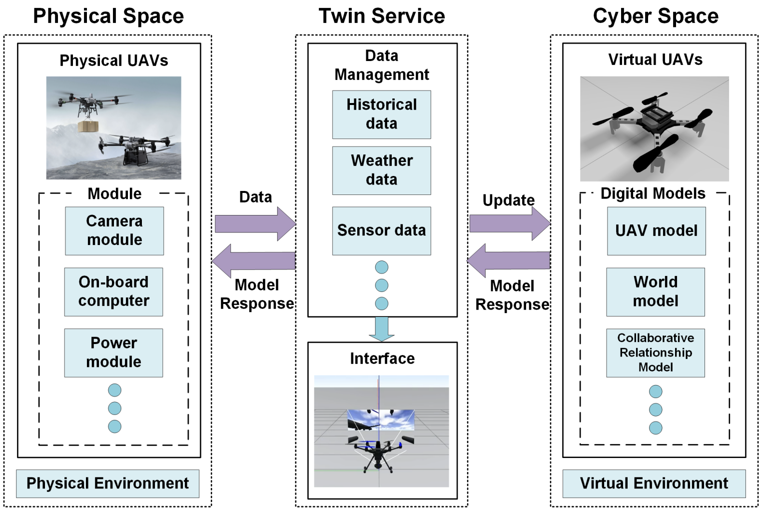

Figure 6. DT framework for UAVs.

The DT category can be divided into static and dynamic DT based on its characteristics. Static DT is created before manufacturing and relies mainly on design data and historical data; dynamic DT or Simulation-based Digital Twins (SDTs) integrate real-time sensor data to continuously update the system and support AI-driven analysis and decision making [18].

SDTs enable real-time simulations during UAV flight, enabling data estimation when physical sensors are unavailable or provide low-accuracy measurements. Traditional simulations cannot be completely accurate, and models can deviate from reality over time, resulting in inconsistencies. However, SDTs can continuously correct DT models to achieve cyber–physical consistency [68].

In addition, we need to distinguish the concept of "Digital Model", "Digital Shadow", and "Digital Twin". As shown in Figure 7, DT enables the interaction between the physical space and cyber space through bidirectional data flow. In contrast, the digital shadow only allows one-way data flow from the physical system to the virtual system, and the digital model is static and will not update based on real-time data [69].

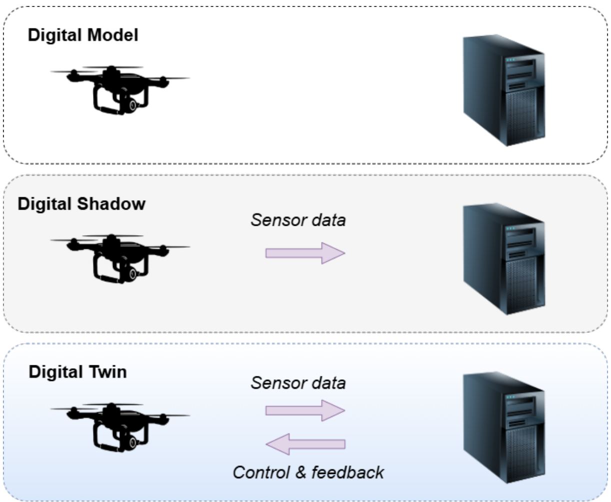

Figure 7. Differences between digital twin, digital shadow, and digital model.

To achieve a DT, a modeling method must be established to accurately represent the actual object process, attributes, and dynamics. Scholars have proposed different modeling frameworks to promote the development of DT. Grieves first proposed a three-dimensional DT model, including physical entities, virtual models, and their connections [40]. Tao et al. [70] added service and DT data dimensions on this basis and proposed a five-dimensional DT model. These models provide theoretical guidance for the construction of DT and production of DT, but they are still relatively abstract and lack specificity in specific implementation. In addition, Semeraro et al. [71] summarized the key issues that have been answered in DT research (Table 4).

Table 4. Key research questions and results in the DT study [71].

Research Questions	Results
"Where is appropriate to use a Digital Twin?" (Digital Twin Contexts and Use Cases)	1. Healthcare: Improving operational efficiency of healthcare operations. 2. Maritime and Shipping: Design customization. 3. Manufacturing: Product development and predictive manufacturing. 4. City Management: Modeling and simulation of smart cities. 5. Aerospace: Predictive analytics to foresee future aircraft.
"Who is doing Digital Twins?" (Digital Twin Platforms)	GE Predix; Siemens PLM; Microsoft Azure; IBM Watson; PTC Thing Worx; Aveva; Twin Thread; DNV-GL; Dassault 3D Ex-perience; Sight Machine; Oracle Cloud.
"When has a Digital Twin to be developed?" (Digital Twin Life Cycle)	1. In the design phase: The digital twin is used to help designers configure and validate the product development more accurately, interpreting the market demands and customer preferences. 2. In production phase: The digital twin shows great potential in real-time process control and optimization, as well as accurate prediction. 3. In service phase: The digital twin can monitor the health of a product and perform diagnosis and prognosis.
"How to design and implement a Digital Twin?" (Digital Twin Architecture and Components)	1. The physical layer involves various subsystems and sensory devices that collect data and working parameters. 2. The network layer connects the physical to the virtual, sharing of data and information. 3. The computing layer consists of virtual models emulating the corresponding physical entities.

3.3. Technical Challenges of the Digital Twin

3.3.1. Modeling Approaches

The benefits of implementing DT are obvious. Still, it also brings many challenges in modeling, networking, computation, and data analysis. Regarding DT modeling, although data-driven modeling and rule-based formal modeling [72] can be used separately, each has its limitations. Formal modeling is suitable for situations where the system dynamics and attributes are known and can establish transformation relationships for different states, but it requires rigorous model validation. Data-driven modeling [73] is suitable for systems with enough data, can be modeled quickly, and does not require system knowledge but cannot resolve causal relationships. Moreover, if the system structure or operating environment changes, the previously trained model will not work and needs to be retrained. Therefore, determining the theoretical foundations and modeling techniques that allow DT to accurately and reliably reflect the state of an object remains an open research question.

3.3.2. Cyber–Physical Consistency

Cyber–physical consistency (CPC) in DT, along with related challenges such as synchronization and consistency recovery, remains a fundamental research concern inherited from CPS.

The term *cyber–physical consistency* is defined as the state in which the virtual representation of a process (i.e., the assumed state of the physical world) matches the actual physical state measured by sensors during workflow execution in CPS or DT [74]. Formally, we define $S_{C,t} = \{c'_{1,t}, \ldots, c'_{n,t}\}$ as the set of virtual context factors at time t, where each factor $c'_t = (n', v'_t)$ comprises a unique identifier $n' \in N$ and an associated value $v'_t \in V_t$ valid at time t. Similarly, let $S_{P,t} = \{c_{1,t}, \ldots, c_{n,t}\}$ represent the physical context factors, where

$c_t = (n, v_t)$. Cyber–physical consistency holds at time t if and only if for every physical context factor $c_t \in S_{P,t}$, there exists a corresponding virtual context factor $c'_t \in S_{C,t}$ such that their identifiers and values are identical:

$$\mathrm{CPC}_t \Leftrightarrow \forall c_t : c_t \in S_{P,t}, \exists c'_t : c'_t \in S_{C,t} \text{ where } c_t \equiv c'_t \text{ with } c_t \equiv c'_t : (n = n') \wedge (v_t = v'_t) \quad (1)$$

To achieve cyber–physical consistency, the MAPE-K loop has been recognized as a proven solution [75]. It contains four phases: the monitor phase, analyze phase, plan phase, and execute phase, which are suitable for adaptive systems. To be specific, in the monitor phase, sensor data and process states are continuously collected to detect deviations between $S_{C,t}$ and $S_{P,t}$. The analyze phase evaluates these deviations against predefined assertions (e.g., threshold violations or timeouts) to identify inconsistencies. The plan and execute phases consist of finding and implementing compensatory measures in case of errors in order to continue the execution of the process as intended by the process modeler. The knowledge component of the MAPE-K loop represents the process knowledge, including the context of the CPS, system goals, and additional attributes, all of which are stored in and accessible through an external knowledge base. This closed-loop process enables dynamic restoration of consistency while accommodating domain-specific consistency levels (e.g., tolerating more sensor errors in flying versus strict industrial thresholds).

However, this consistency recovery method relies on predefined rules, and currently, MAPE-K can only deal with known problems and cannot cope with completely unknown scenarios. In addition, previous scenarios were limited to indoor scenarios, such as smart rooms, and were not extended to outdoor UAV flight scenarios.

Some literature has also addressed the cyber–physical consistency problem at the device level in manufacturing, e.g., Liu et al. [76] proposed a DT architecture based on Cyber–Physical Machine Tools (CPMTs), which leverages the MTConnect and OPC UA protocols to ensure data interoperability and real-time synchronization between physical devices and DTMTs. Similarly, Zhang et al. [77] and Liu et al. [78] studied the application of DT in production line optimization and synchronized the physical with the network by binding the PLC I/O points in the simulation model with the I/O addresses of the physical devices, etc. However, all of these studies are in the manufacturing industry, and there is still a lack of research on achieving cyber–physical consistency for DTs of air mobility. This means that in the field of AAM and UAM, DT is still in the initial exploratory phase. For instance, the European AURORA program is beginning to investigate the use of DT for the real-time monitoring and optimization of autonomous UAV operations in urban environments [8]. Because of the fact that DT in UAV and AAM are not being researched as much as the manufacturing and maintenance domains, future research should focus on bridging the gap between industrial DT modeling and UAV-based DT modeling to ensure cyber–physical consistency, real-time data fusion, and intelligent decision support.

4. Construction of UAV-Based Digital Twins

In the DT construction research for UAVs, academia and industry are exploring efficient methods to couple physical UAVs with runtime models to enable real-time monitoring, accurate prediction, and intelligent decision making. In recent years, various DT construction methods have been proposed to address the diverse operational requirements of UAVs in complex application scenarios. This section summarizes existing studies to systematically understand the current state of research and key technological advancements in UAV-based DT constructions, focusing on the DT framework, modeling approaches, core technologies, and key characteristics. Table 5 provides a detailed overview of these studies, forming the basis for subsequent analysis.

Table 5. Summary of literature on the construction of DT for UAVs.

Title	Methods	Key Technologies	Notable Features
DTUAV: A Novel Cloud-Based Digital Twin System for Unmanned Aerial Vehicles [79]	Geometric Modeling, physical modeling, control modeling, sensor simulation, real-time data fusion	cloud computing, VR, human–machine interaction	Bidirectional interaction between physical and virtual systems; VR-based task management; cloud platform + 5G for remote monitoring; trajectory error detection and optimization.
Simulation and Digital Twin Support for Managed Drone Applications [80]	Edge computing architecture, wireless network simulation	AeroLoop design for UAV simulation framework, Linux containers (LXDs), ns-3 and ZeroMQ	PaaS (Platform as a Service) architecture; Fog/edge computing design; containerized simulation; runtime deviation detection; wireless network simulation.
Digital Twin Modeling Method for Individual Combat Quadrotor UAV [23]	Geometric Modeling, Physical Modeling, Motion Models (PID), Rule Models	SolidWorks, Gazebo + ROS, six-degree-of-freedom rigid dynamics model, QGC	Task-level rule modeling; integration of geometric + physical + motion + rule models; QGC-based functional services.
UAV Visual Navigation System Based on Digital Twin [81]	Virtual Layer, Twin Data Layer, Data-Driven Behavioral Modeling	Unreal Engine 4, MySQL	Simulates navigation decisions in virtual environments; supports multi-modal data analysis.
Deep Reinforcement Learning for Flocking Motion of Multi-UAV Systems: Learn From a Digital Twin [82]	Physical Entity, Digital Model, Data-Driven Behavioral Modeling, Connectivity Layer	Deep reinforcement learning (BCDDPG, LSTM), high-fidelity digital twin, behavior coupling policies	Combines digital twins with reinforcement learning; proposes a DT-based deep reinforcement learning (DRL) training framework for UAV flocking motion in unknown stochastic environments.
A Digital Twin Platform for Multi-Rotor UAV; A Digital Twin Simulation Platform for Multi-rotor UAV [65,83]	Geometric Modeling, Physical Simulation, Sensor Simulation, Electronic Circuit Simulation, Multi-Scale Data Fusion	Unity, ROS, MATLAB, SimulIDE	Co-simulation across multiple platforms; six-degree-of-freedom dynamics modeling; portable code to interface with real systems; sensor simulation.
A Middleware for Digital Twin-Enabled Flying Network Simulations Using UBSim and UB-ANC [84]	Data-Driven Network Architecture, multi-fidelity simulators, coordination interfaces	UBSim, UB-ANC, SimSocket coordination interface, UAV network optimization, flight control	Combines UBSim and UB-ANC UAV simulators; uses SimSocket coordination interface for signal exchange; enables co-simulation.
Design and Implementation of a VTOL UAV and Its Digital Twin [85]	Physical UAV, Geometric Modeling, Physical Modeling, Unity, Communication Interfaces	Unity, Blender	Focuses on high-fidelity and reliable simulation of UAV aerodynamics, physical characteristics, and control.
Digital Twin System for Propulsion Design of UAVs [86]	Physical Modeling, Propulsion System Simulation, Trajectory Planning	Matlab, Unity, Sliantro Flight Simulator	Integrates CAD modeling, aerodynamic calculations, and high-precision terrain modeling; enhances visualization and simulation accuracy for propulsion system design.
Data-driven physics-based digital twins via a library of component-based reduced-order models [87]	Data-Driven Physical Modeling, computational models based on discrete partial differential equations (PDEs)	Reduced-Order Modeling(ROM), Bayesian Inference	Suitable for large-scale complex systems; real-time model library updates using sensor data; supports UAV structural health monitoring and dynamic mission planning.

Table 5. *Cont.*

Title	Methods	Key Technologies	Notable Features
Toward Predictive Digital Twins via Component-Based Reduced-Order Models and Interpretable Machine Learning [88]	Data-Driven Physical Modeling, component-based reduced-order models, interpretable machine learning	High-fidelity finite element simulation, optimal decision trees	Enhances scalability and adaptability of DTs; integrates interpretable ML for real-time updates based on sensor data; applied to UAV structural health monitoring and mission re-planning.
VTOL UAV Digital Twin for Take-Off, Hovering, and Landing in Different Wind Conditions [72]	Data-Driven Physical Modeling, wind effect rule modeling, simulation validation	Euler rigid body dynamics equations, aerodynamic calculations, Gazebo simulation	Mathematically models aerodynamic forces on VTOL UAVs under varying wind conditions; creates digital twin system for training takeoff, hovering, and landing.
Digital Twins in Unmanned Aerial Vehicles for Rapid Medical Resource Delivery in Epidemics [89]	Physical Entity, Information Prediction System, Rule Modeling	Deep learning (enhanced AlexNet), channel prediction, resource optimization	Proposes a UAV-based digital twin system for medical resource delivery; uses enhanced AlexNet for information prediction; does not explicitly discuss DT model construction.
Enhancing the Security of Unmanned Aerial Systems Using Digital-Twin Technology and Intrusion Detection [90]	Data-Driven Behavioral Modeling, real-time intrusion detection	Machine learning, deep learning, GPS spoofing detection, anomaly detection	Employs ML models to validate GPS spoofing detection; enhances UAV system security through real-time threat detection.
A Probabilistic Graphical Model Foundation for Enabling Predictive Digital Twins at Scale [91]	Data-Driven Behavioral Modeling, probabilistic graphical models, coupled dynamic systems	Bayesian statistics, dynamic systems, control theory, sensor data updates	Uses experimental data to calibrate UAV-based DTs; enables real-time dynamic updates.
Model-Based Approach for Building Trust in Autonomous Drones Through Digital Twins [92]	Model-Driven Behavioral Modeling, consistency verification	Petri nets, Finite State Machines (FSM), model-driven approaches	Uses Petri nets and FSMs to evaluate trust-building processes; FSM compares digital twin behaviors.
Digital Twin-Enabled Decision Support in Mission Engineering and Route Planning [93]	Model-Driven Behavioral Modeling, task engineering	SysML, multi-attribute utility theory (MAUT)	Combines mission engineering (ME) and Model-Based Systems Engineering (MBSE) to develop DTs; supports UAV mission path selection and optimization; analysis module based on MAUT identifies success criteria.
Toward Intelligent Cooperation of UAV Swarms: When Machine Learning Meets Digital Twin [94]	Physical Entity, Data-Driven Behavioral Modeling, Decision Models, Connectivity	Deep neural networks (DNNs), intelligent network reconstruction, real-time data acquisition	Combines deep learning for UAV swarm collaboration; employs reinforcement learning to optimize strategies; features bidirectional communication mechanisms.
Unmanned Aircraft System Airspace Structure and Safety Measures Based on Spatial Digital Twins [95]	Rule Modeling and Neural Network-Based State Transition	Convolutional neural network (CNN), wireless communication technology, energy-weighted clustering algorithm (EWCA)	Uses spatial digital twins to analyze packet loss rate, network performance, and safety interruption probability; proposes measures to control node count and cluster switching.

Table 5. *Cont.*

Title	Methods	Key Technologies	Notable Features
Position Estimation Method for Small Drones Based on the Fusion of Multisource, Multimodal Data and Digital Twins [96]	Geometric Modeling, Physical Modeling, Motion Modeling (PID), multi-modal data fusion	Extended Kalman filter (EKF), tight coupling optimization model, GPS fusion based on pose graph optimization	Fuse data from the real drone and its digital twin and feed the filtered position information back into the real drone's control system.
A Bigraphical Framework for Modeling and Simulation of UAV-based Inspection Scenarios [61]	Behavior Modeling, Model checking, Simulation	Bigraph, Bigraphical Reactive Systems(BRS), ROS, Gazebo	Formal modeling and simulation of multi-UAV systems using BRS; model checking-based planning for collision-free multi-agent path finding; executable semantics with behavior rules, supporting both verification and simulation.

Based on the literature summarized in Table 5, current research on UAV-based DTs spans multiple modeling perspectives, integrating geometric, physical, behavioral, and rule models to enhance fidelity and functionality. These studies highlight different approaches, ranging from multi-dimensional DT architectures to specialized frameworks focusing on behavioral modeling, network simulation, and cyber–physical consistency. Therefore, in the following subsections, we will thoroughly analyze the literature on the construction of multi-dimensional UAV-based DT frameworks and specific UAV-based DT runtime models, including geometric, physical, behavioral, and rule models, based on [70]. Additionally, we will review relevant literature on cyber–physical consistent modeling.

4.1. Multi-Dimensional Digital Twin Frameworks for UAVs

As DT frameworks for UAVs have evolved, diverse architectures have emerged, incorporating multiple simulation levels, real-time data fusion, and cloud-edge computing. Existing work has presented various UAV-based DT frameworks focusing on system-level integration, operational consistency, and real-time interaction between virtual and physical entities.

Some studies propose cloud-based architectures leveraging virtualization and high-performance computing for UAV operations. For example, DTUAV [79] presents a multi-layer DT system with cloud computing, VR-based task management, and real-time trajectory error detection through a remote monitoring platform. Similarly, other approaches, such as PaaS-based UAV simulation platforms [80], use containerization (e.g., LXDs) and wireless network emulation to enable edge computing for managed UAV applications.

Another direction in DT framework development is multi-platform collaborative simulation, enabling seamless interoperability between software environments like ROS, Unity, MATLAB, and SimulIDE [65,83]. These frameworks provide high-fidelity multi-scale data fusion and sensor simulation, ensuring portability and synchronization with real UAV systems. Middleware-based solutions like UBSim and UB-ANC [84] facilitate networked DT architectures that coordinate UAV flight control and communication via modular interfaces.

Emerging DT frameworks also integrate advanced computational methods like Bayesian inference and Reduced-Order Modeling (ROM) [87,88] to support real-time system adaptation. Predictive DTs use interpretable machine-learning techniques to scale models and dynamic task planning based on sensor-driven data updates. These advancements improve the reliability of UAV-based DT systems in complex and dynamic environments.

These DT frameworks collectively form a more robust UAV system supporting various AAM applications, like medical resource delivery [89], autonomous swarm operations [94], and safety-enhanced airspace management [95]. However, several challenges still exist. Many frameworks lack standardized integration protocols [65,83], which results in increased system complexity and dependencies [84] and thus introduces computational overhead and network latency [79,80]. Additionally, the cyber security of UAV-based DT remains a big issue because DT systems are based on cloud services, and UAVs communicate with ground control stations often and are prone to cyber attacks and threats [93]. Future work should address this by developing more adaptive, lightweight, and secure DT architectures. The next section will dig deeper into DT modeling.

4.2. UAV-Based Digital Twin Modeling

DT modeling is a core aspect of DT technology designed to accurately represent the behavior, state, and dynamic evolution of physical entities through multi-level and multi-dimensional runtime models. Current research predominantly focuses on geometric modeling, physical modeling, behavioral modeling, and rule modeling. The geometric model defines the UAV's shape and structural assembly. The physical model captures its aerodynamic properties, physical constraints, and operational limits. The behavioral model represents the UAV's dynamic responses to internal and external conditions. Lastly, the rule model leverages historical UAV data to encode implicit knowledge, enhancing the intelligence of the DT [70]. We summarize the existing studies according to the above modeling dimensions in Table 6.

Table 6. Summary of UAV-based DT construction literature based on modeling dimensions.

Modeling Dimension	Reference
Geometric Modeling	DTUAV: A Novel Cloud-Based Digital Twin System for Unmanned Aerial Vehicles [79] Digital Twin Modeling Method for Individual Combat Quadrotor UAV [23] A Digital Twin Platform for Multi-Rotor UAV; A Digital Twin Simulation Platform for Multi-rotor UAV [65,83] Design and Implementation of a VTOL UAV and Its Digital Twin [85] Position Estimation Method for Small Drones Based on the Fusion of Multisource, Multimodal Data and Digital Twins [96]
Physical Modeling	Physics-based modeling: DTUAV: A Novel Cloud-Based Digital Twin System for Unmanned Aerial Vehicles [79] Digital Twin Modeling Method for Individual Combat Quadrotor UAV [23] Design and Implementation of a VTOL UAV and Its Digital Twin [85] Digital Twin System for Propulsion Design of UAVs [86] Position Estimation Method for Small Drones Based on the Fusion of Multisource, Multimodal Data and Digital Twins [96]
	Data-driven modeling: Data-driven physics-based digital twins via a library of component-based reduced-order models [87] Toward Predictive Digital Twins via Component-Based Reduced-Order Models and Interpretable Machine Learning [88] VTOL UAV Digital Twin for Take-Off, Hovering, and Landing in Different Wind Conditions [72]
Behavioral Modeling	Model-driven modeling: Model-Based Approach for Building Trust in Autonomous Drones Through Digital Twins [92] Digital Twin-Enabled Decision Support in Mission Engineering and Route Planning [93] A Bigraphical Framework for Modeling and Simulation of UAV-based Inspection Scenarios [61]
	Data-driven modeling: UAV Visual Navigation System Based on Digital Twin [81] Deep Reinforcement Learning for Flocking Motion of Multi-UAV Systems: Learn From a Digital Twin [82] Enhancing the Security of Unmanned Aerial Systems Using Digital-Twin Technology and Intrusion Detection [90] A Probabilistic Graphical Model Foundation for Enabling Predictive Digital Twins at Scale [91] Toward Intelligent Cooperation of UAV Swarms: When Machine Learning Meets Digital Twin [94]
Rule Modeling	Digital Twin Modeling Method for Individual Combat Quadrotor UAV [23] VTOL UAV Digital Twin for Take-Off, Hovering, and Landing in Different Wind Conditions [72] Unmanned Aircraft System Airspace Structure and Safety Measures Based on Spatial Digital Twins [95]

Given the limited research on UAV-based DT modeling and cyber–physical consistent modeling, the following subsections will not only examine the studies summarized in Table 5 but also introduce well-established DT modeling methods from the manufacturing industry. By drawing on these established methodologies, we aim to provide a theoretical foundation for advancing UAV-based and AAM-based DT development.

4.2.1. Geometric Modeling

Geometric modeling provides a fundamental physical structure representation of the UAV in the DT, allowing simulations to be performed accurately. For example, with tools such as SolidWorks, Unity, and Blender, researchers have constructed 3D models of UAVs [23,65,83,85,96,97]. These modeling methods allow the UAV geometry to be accurately reproduced, thus supporting testing under different flight conditions. However, these methods mainly rely on static geometric information, making it difficult to effectively incorporate changes over time for adaptive tuning. In addition, the geometric models usually lack direct correlation with behavioral or rule modeling, limiting their application to UAV decision making [23,85].

4.2.2. Physical Modeling

Physical modeling is critical in simulating UAV dynamics, aerodynamics, and propulsion systems to support flight performance assessment and mission optimization. Researchers have employed aerodynamic modeling, six-degree-of-freedom rigid body dynamics, and wind influence modeling to enhance the realism and fidelity of UAV-based DTs in physical simulation platforms such as Gazebo [23,65,72,85,86]. The propulsion system has also been modeled, leveraging aerodynamic computations and terrain modeling to improve UAV flight performance [86]. To balance computational efficiency and accuracy, some studies have integrated high-fidelity finite element simulations with ROM, enabling real-time updates with optimized computational costs [87,88].

Despite these advances, traditional physics-based modeling approaches rely on precise mathematical formulas, leading to poor adaptability in uncertain environments. In contrast, data-driven physical-based modeling techniques enhance real-time adaptability [87,88]. We turn our perspective to the manufacturing industry, whose state-of-the-art experience may provide insights to address these challenges.

Multi-scale modeling techniques are now widely used in the manufacturing industry, enabling detailed representations at the macro, meso, and micro levels. For example, three-layer quality knowledge models effectively establish cross-scale correlations between geometric deformations and surface defects in metalworking, utilizing knowledge graphs to improve prediction accuracy [98]. Similarly, bionic design principles have led to the development of coupled geometric–behavioral process models that utilize multiphysics field interactions to achieve highly accurate simulations of rudder manufacturing [99]. These methodologies enhance the ability of DTs to describe complex physical systems by integrating multi-scale data, offering valuable references for developing UAV-based DTs in the context of AAM.

4.2.3. Behavioral Modeling

Behavioral modeling is essential to DTs, capturing the continuous behavior of UAVs, as well as the dynamics of the world. The accuracy of these models directly impacts the precision of motion and control in DT systems. Current research in DT behavioral modeling primarily follows two complementary approaches: model-driven and data-driven methodologies.

Model-driven approaches [100,101] use formal modeling techniques such as Petri nets, Behavioral Trees, and Bigraph to represent system behavior. Some studies have also used hybrid approaches to improve the accuracy of behavioral modeling [92,102,103]. For example, FSM combined with Petri nets was used to analyze behavioral consistency and evaluate the trust-building process of autonomous UAVs in a UAV-based DT system [92].

However, challenges remain in ensuring the logical completeness of behavior descriptions and improving model interoperability. While Petri Nets and FSMs have been widely used for formal UAV behavior modeling [92,93], their application scenarios are largely confined to deterministic behaviors governed by predefined rules, such as fixed flight mode transitions. These models struggle to adapt to unexpected disturbances, such as dynamic airspace conflicts, which require real-time behavioral adjustments [95]. Given that high-fidelity behavioral modeling is essential for UAV-based DTs, these models must achieve real-time accuracy and precisely represent the UAV's actual state. The recent emergence of Behavior Tree [103] and Bigraph [61] research in UAVs may be a new solution for UAV-based DT behavioral modeling. Table 7 compares their advantages and disadvantages, formal validation, and other aspects.

Table 7. Comparison of Petri Net, Behavior Tree, and Bigraph in modeling.

Dimension	Petri Net [92,102]	Behavior Tree [103]	Bigraph [61]
Modeling Capability	Suitable for modeling concurrency, synchronization, and resource conflicts	Suitable for task execution flow and behavior decision logic	Capable of expressing both structural (spatial) and behavioral dynamics simultaneously
Formal Verification	Supports reachability, liveness, and deadlock checking via model checking	Verified by behavior logic validation and simulation	Supports BRS reaction rules to validate consistency of structure and state transitions
Advantages	Mature formalism, rich tool support (e.g., CPN Tools)	Intuitive, hierarchical, easy to integrate with planning systems	Unifies structure and behavior, supports multi-agent context-aware modeling with reaction semantics
Disadvantages	Difficult to model complex hierarchy or spatial embedding	Limited support for structural modeling; hard to verify global consistency	Less mature toolchain; complex formalism; harder to implement in practice
Typical Applications	UAV task coordination, scheduling, and communication protocols	High-level autonomous mission planning (e.g., surveillance, strike missions)	UAV swarm behavior modeling and spatial state tracking in DTs
Performance Metrics	State space size, concurrency degree, execution latency	Behavior coverage, task success rate, path length	Structural behavior consistency, accuracy of transitions, traceability of reaction execution
Use Cases	Modeling low-level control logic, resource allocation	Reactive mission execution in dynamic environments	Modeling cyber–physical consistency and dynamic state–structure correlation in UAV DTs

In contrast, data-driven behavior modeling uses massive sensor data, machine learning, and probabilistic models to enhance the autonomous decision-making capabilities of UAVs [95]. For example, probabilistic graphical models calibrate UAV sensor data and facilitate real-time updates of UAV-based DTs [91]. In addition, some studies have combined deep learning with anomaly-detection techniques to develop data-driven network intrusion detection systems to improve the safety of UAVs [90]. There are also studies based on DNN and reinforcement learning strategies to optimize the coordination of intelligent UAV groups, develop two-way communication mechanisms to ensure real-time task updates, etc. [94]. Through these methods, behavior modeling enables UAVs to dynamically adjust their behavior and achieve autonomous planning in complex environments, enhancing the adaptability of UAVs to perform complex tasks.

Despite the advantages of data-driven methods, they also face challenges. Although existing studies have demonstrated improved adaptability of complex systems (such as structural health monitoring), computational efficiency is still limited by the accuracy of ROMs of high-dimensional PDEs [87,88]. In addition, some studies have explored DT on deep reinforcement learning (DRL-based DT) for the behavioral coordination of UAV swarms [82,94]. However, these methods rely heavily on high-fidelity simulation environments, resulting in high computational costs during training. More importantly, data-driven black-box models lack interpretability, which is a big disadvantage in AAM applications.

4.2.4. Rule Modeling

Rule models facilitate the extraction of implicit knowledge and the identification of evolutionary trends and patterns in UAV operations. These models are usually based on a data-driven approach to predict future states through neural networks and deep learning techniques. The authors of one study built a wind impact prediction model for VTOL based on Eulerian rigid-body dynamics equations to evaluate its flight stability under different wind speeds and directions and verified the model through Gazebo simulations [72]. Research has also been conducted to combine the CNN algorithm and UAV autonomous network to construct a UAV-based DT system using wireless communication technology, simulating and predicting its safety performance to assist in designing a more optimized UAV-based DT system [95]. At the application level, the authors of one study have proposed a UAV-based DT epidemic information prediction model based on an improved AlexNet neural network, which can predict possible future states and optimize the allocation of resources through the real-time image data collected by the UAV [89].

Although these methods have shown some progress, research in this area remains limited, and their application to AAM is still unexplored. For instance, establishing a rule model to analyze and predict UAV operation conflicts in the airspace and the corresponding safety measures has yet to be investigated.

4.3. Cyber–Pysical Consistent Modeling

Cyber–physical consistency is a fundamental requirement in DT modeling for complex systems [104]. It involves synchronizing the logical mission state of a UAV in cyberspace with its physical behavior in the real world and ensuring that the virtual model remains dynamically adaptive throughout the system's lifecycle to accurately reflect the physical counterpart [105]. Addressing this challenge requires advances in multiple dimensions, including model structure optimization, parameter updates, state synchronization, and error compensation. However, few research studies focus on cyber–physical consistent modeling for UAVs. To bridge this gap, this section will draw upon established methods from the manufacturing domain to inform UAV-based DT development.

Ensuring the model's accuracy during the initial modeling phase is critical. However, changes in conditions, either external or physical, can often lead to "model drift", an area not yet addressed for UAVs. In manufacturing, structural optimization techniques have been used to maintain model consistency, and relational rule detection methods have shown effectiveness in improving decision trees for manufacturing cells [105]. Genetic algorithm-based residual signal generators have also shown promise in mitigating cyber–physical discrepancies and thus enhancing cyber–physical alignment [106]. Since UAV geometric models are also prone to drift, these manufacturing industry methods can provide valuable insights to improve DT modeling for AAM applications.

For parameter optimization, machine learning and optimization techniques are mostly used in the manufacturing industry to adapt DT. Adaptive parameter-updating mechanisms via artificial neural networks (ANNs) incorporating time-sensitive factors have been proposed to mitigate the impact of short-term data fluctuations on model fidelity [107]. Particle swarm optimization (PSO) and reinforcement learning have also been used [108,109], but they are computationally expensive, especially in high-frequency data update scenarios. Moreover, most of the studies focus on single-device optimization; the consistency of the DT relationship model in a multi-UAV collaborative environment lacks theoretical support.

Real-time feedback and perception mechanisms are crucial for cyber–physical consistency, especially in dynamic applications such as robotic deployment and multi-UAV control. However, real-time updates of DT runtime models must address two main challenges: cross-disciplinary model coupling and data transmission delays. Event-driven synchronization techniques have been developed to adaptively adjust the transmission rate and improve synchronization efficiency [110]. However, their effectiveness remains constrained by the real-time performance of network infrastructures, especially in high-latency environments. In addition, subsystem topology anchor-matching techniques can automatically detect system changes [111], but their reliance on a centralized architecture increases management complexity.

To reduce synchronization delay, a study has proposed computational and communication resource optimization methods to reduce the average synchronization delay through a joint optimization strategy [112]. Hashash et al. [113] also reduced synchronization latency by minimizing asynchronous time as a bi-objective optimization problem using an edge-continuous learning approach and the Elastic Weight Consolidation (EWC) technique. However, as data grow exponentially, model update latency remains a bottleneck in real-time DT performance. This is critical for AAM systems, as low-latency updates are crucial for UAV safety.

Error-compensation mechanisms complement state synchronization, enabling active error prevention. Studies have been performed to address cyber–physical spatial mapping errors by introducing reinforcement learning-driven frameworks [114] and Generative Adversarial Networks (GANs) [115]. Moreover, trust-weighted aggregation in federated learning scenarios has also been proposed to reduce global model bias [116]. Maintaining DT runtime model consistency is further complicated by data errors and system uncertainties and requires robust uncertainty quantification techniques. Probabilistic machine learning approaches like sparse Bayesian regression allow model updates while incorporating physics-based basis functions, providing interpretable mathematical expressions [117].

In summary, existing research focuses on data-driven method integration with geometrical or physical models and uncertainty quantification. These can be used to maintain the cyber–physical consistency of UAV-based DTs. However, challenges remain in the cross-domain generalization and real-time processing of high-dimensionality data.

5. Applications of Digital Twins for UAVs

While DTs are well-established in traditional aviation manufacturing and maintenance, their application in UAS and AAM remains an emerging research area. In the following subsections, we specifically discuss DT-based applications.

5.1. Foundational Applications in Traditional Aviation

In the traditional civil aviation industry, DT is mainly used for predictive maintenance of aircraft components to detect faults as early as possible and improve operational reliability [118]. For example, the US Air Force has implemented an aircraft DT framework to optimize structural management and is currently evaluating its feasibility within the Royal Canadian Air Force [119]. Beyond structural management, DT-based models have been developed for aircraft fault diagnosis, including hydraulic system monitoring, which enables early anomaly detection across diverse operational scenarios [120]. Additionally, advanced DT-based techniques, such as guided wave response analysis and dynamic Bayesian networks, have been employed to predict wing fatigue crack propagation, thereby improving aircraft safety [121]. Other DT applications in aircraft subsystems include turbofan engine diagnostics [122], tire wear prediction during landing [123], and ground steering system optimization [124]. This dynamic, condition-based maintenance scheduling helps avoid unplanned mid-flight failures and downtime. This concept is being applied to eVTOL fleets, resulting in higher safety margins and more reliable service [125]. Additionally, the DT records historical data, allowing investigators to analyze incidents and improve safety.

Beyond maintenance and diagnostics, DTs contribute significantly to manufacturing precision and traceability. Real-time displacement detection and digital thread-based frameworks facilitate seamless integration across the production lifecycle [126]. Furthermore, integrating DTs with blockchain technology ensures secure and efficient data management, addressing challenges related to data integrity and interoperability [4]. Additionally, DT-driven intelligent algorithms have advanced reconfigurable fixture solutions for precision trimming in aircraft assembly processes [127].

5.2. Applications for Enhancing Safety Risk Assessment

DTs enhance the safety of UAVs by identifying and mitigating risks before incidents. They serve as virtual testbeds for safety strategies, predicting component failures and rehearsing emergency scenarios, and ensuring compliance with strict regulations.

DTs offer a significant advantage in risk assessment and scenario simulation [128]. They allow for "what-if" simulations of hazardous scenarios in a no-risk environment, allowing regulators and operators to model critical events like power failures or drone communication loss [56,129]. The UK's SMARTER project [130] built a cloud-based 4D DT of integrated airspace to test such scenarios. By modeling emergency landings or contingency flight paths, planners can identify safe outcome strategies before an actual emergency. DTs also support regulatory compliance by allowing authorities to test whether proposed operations meet safety standards [128]. This allows AAM providers to fine-tune their operations to align with urban aviation regulations before launching the service.

DTs also provide a safe environment for rehearsing emergency responses and training pilots and first responders. Simulations can be staged in virtual city twins to evaluate response times and procedures. Studies [131,132] have proposed using DT simulators for AAM to train pilots and test human-factor issues for certification. This immersive simulation, often combined with VR tech, helps crews practice emergency protocols in a realistic digital environment, leading to better preparedness in real life. Cities can also integrate their emergency services into the AAM twin to assess their response to various air incident scenarios. This study can simulate thousands of flight hours under diverse conditions, demonstrating airworthiness and ensuring operator operations adhere to rules. This approach provides evidence and confidence to regulators by virtually "test-flying" the system in all conditions. DTs in safety act as a proving ground, identifying risks, preventing failures, and ensuring compliance, which is crucial for public trust and regulatory approval [133].

5.3. Applications for Intelligent Mission Planning and Control

DT enables efficient mission planning and control of UAVs. In intelligent mission planning, DTs can be integrated with intelligent algorithms, such as DRL, to facilitate autonomous decision making and optimal task allocation. By conducting simulation-based training in cyberspace, UAVs can refine their strategies before deployment in real-world scenarios [82,93]. In multi-UAV systems, DTs function as decision-making hubs, fusing real-time perception data to optimize path planning and dynamically adjusting UAV action strategies based on mission requirements.

Beyond mission planning, DTs have also been explored for intelligent control applications. For example, VR-based DT control systems have demonstrated stable and efficient manipulation of multiple UAVs in virtual environments [134,135]. Additionally, DTs are leveraged for runtime trust evaluation, ensuring the safety and reliability of autonomous UAVs, such as delivery UAVs and autonomous inspection UAVs, when operating in complex and dynamic environments [92,136].

To further enhance the adaptability of UAVs, researchers have already proposed an adaptive DT testing platform, which enables UAVs to adjust their decision making during the execution of a mission dynamically and improves the stability of their mission execution in dynamic environments [137]. In addition, DT has been combined with the attentional mechanism in imitation learning to improve decision-making accuracy in complex operating environments [138].

5.4. Applications for UAV Swarms

The integration of DT with UAV swarms has been explored in various fields, such as intelligent control, collaborative decision making, perception, and communication optimization.

A major research direction is the use of DT for swarm intelligent control, where the data generated in DT are used for model training and the optimization of multi-intelligence DRL algorithms. Simulating different operational scenarios in DT enhances the safety, adaptability, and decision-making capabilities of UAV swarms [139]. In addition, studies have used machine learning-based decision-making models to track and analyze UAV swarm behavior for efficient group collaboration [94].

Regarding task execution, a study proposed a hierarchical DT-enhanced collaborative sensing architecture. In this architecture, multiple UAVs equipped with small base stations act as edge servers that can manage different airspaces with multiple terminal UAVs, thus improving sensing accuracy and situational awareness [140]. Research has also implemented a DT-based UAV swarm system for optimizing wildfire monitoring missions, demonstrating the effectiveness of DT in large-scale environmental monitoring and disaster management [3].

In addition, DT helps to improve UAV swarm communication and computational efficiency. Joint-learning edge-computing architectures based on DT have been proposed to mitigate data privacy risks and communication overhead [141]. Some studies have explored the integration of DT with hardware acceleration and investigated the feasibility of FPGA-accelerated DT simulations in striking a balance between high-precision modeling and computational efficiency [142].

5.5. Applications for Monitoring Tasks

The integration of UAV and DT technologies is widely applied in monitoring tasks, including structural inspection, asset management [12], etc. This approach has the advantage of addressing the limitations of traditional manual inspection methods, which are time-consuming, laborious, and prone to subjective bias.

In solar park monitoring, a formal modeling approach for multi-UAV inspection tasks is presented by [61] by using BRS, enabling dynamic representation of UAV behaviors and environmental contexts. This study integrates Planning-by-Model-Checking to ensure collision-free path planning, ensuring consistency between verification and execution.

In cultural heritage preservation, the combination of UAV photogrammetry and DT-based structural monitoring enables high-precision crack detection [143,144]. Similarly, in post-earthquake building assessment, DT frameworks combining finite element analysis (FEA) and computer vision techniques help to quickly and comprehensively assess high-rise structures. These frameworks also optimize UAV patrol routes, improving the efficiency and completeness of damage assessment [145].

For roof inspections, the problem of occlusion is prone to occur in traditional methods. Some researchers have developed a high-resolution orthophoto generation technique based on UAV photogrammetry and DT data for this [146]. In addition, in bridge infrastructure assessment, inspection data collected by UAVs are used to dynamically update bridge DT models, which plays a key role in seismic performance assessment [147].

Integrating UAVs and DTs has also driven advancements in precision agriculture, particularly in orchard and vineyard management. By leveraging UAV-collected data, AI-driven analytics, and 5G communication technology, DTs provide real-time crop monitoring, yield prediction, and data-driven optimization of agricultural operations. These innovations contribute to sustainable resource management and improved agricultural productivity [148,149].

Regarding other perception research, the authors of [140] proposed a hierarchical DT-enhanced cooperative perception framework to improve real-time cooperative sensing in multi-agent systems with intelligent model acquisition, model migration algorithms, and dynamic priority allocation mechanisms. In 3D spatial perception, PTZ camera-based spatial grid mapping with target tracking algorithms and TinyML edge computing have been shown to enable UAVs to perform spatial grid mapping, dynamic target tracking, and vision correction and hence DT adaptability in changing environment [150].

5.6. Applications for Cyber Security

Cyber security in UAV networks is a critical research area for DT applications in AAM. By integrating computational intelligence and deep learning models, DTs can detect cyber attacks targeting UAS and develop defense mechanisms to enhance system robustness [90,151]. Research has also explored the application of DTs in autonomous UAV networks, employing CNNs and similar techniques to improve UAV swarm security in complex airspace structures [95]. Additionally, DTs can assess UAVs' sensitivity to network threats to optimize security protection strategies [90].

Overall, the application of DTs in AAM is evolving from single-task optimization to broader system-level integration [152]. Meanwhile, existing studies have demonstrated the feasibility of DTs in intelligent planning and decision making, swarm, monitoring, emergency response, and cyber security. A further direction could be enhancing the real-time performance, robustness, and compatibility of DT runtime models with low-power computing platforms to meet practical application demands, improve UAV system intelligence and adaptability, and advance DT adoption in AAM.

6. Challenges and Future Directions

6.1. Challenges

Based on our comprehensive review, we observe that the majority of existing research primarily focuses on UAV-based DT, with only limited attention given to the AAM-based DT. To this end, we propose an extended definition that encapsulates the full scope of an AAM-based DT system:

Definition 2. *An* AAM-based DT *is composed of two tightly integrated layers: a fine-grain layer that includes individual UAV-based DTs, and a coarse-grain layer that shares infrastructure models, forming a system-of-systems DT.*

Compared to a UAV-based DT that is focused on the local, individual-level representation of a single UAV's state, behavior, and environment, an AAM-based DT shifts the scope to a global, system-wide view. It brings together these individual DTs into a cohesive framework that captures not only interactions between UAVs but also system-level dynamics such as airspace occupancy, vertiport usage, individual flight missions and trajectories, and communication topologies across the UTM network. This global view allows the system to capture emergent behaviors and support cross-entity coordination and mission-level optimization that would not be possible with isolated UAV-based DTs alone.

Although UAV-based DTs have made progress, a multi-dimensional DT framework that integrates all AAM-relevant entities across physical, cyber, and social dimensions is missing. Moreover, maintaining temporal and behavioral consistency between fine-grain UAV-based DTs and coarse-grain AAM-based DT is technically challenging. Updates at the UAV level (e.g., a sudden route change) must be reflected immediately in the global system context (e.g., airspace conflict detection), and vice versa.

DT runtime models must mimic real-world interactions to ensure the high fidelity of models in dynamic and complex environments. In general, DT runtime models can be classified into four types: geometric, physical, behavioral, and rule model. The challenges of geometric modeling are balancing the accuracy and cost of modeling and tracking the full lifecycle of evolution. For physical modeling, the challenge is to achieve highly accurate aerodynamic models, which are computationally expensive and difficult to update in real time. The challenge of rule modeling is that models are not adaptable to complex tasks in existing studies, and there are limited data to handle dynamic changing environments. In behavioral modeling, data-driven approaches are highly dependent on training data and computationally expensive, while model-driven approaches are structured but often inflexible. Traditional UAV behavioral model-driven approaches such as Petri nets and FSM [92,93] have limitations in highly dynamic environments and multi-UAV collaborative tasks.

Moreover, there are fewer studies on modeling behavioral interactions among multiple UAVs or on the AAM-based DT level, especially in collaborative mission execution and airspace conflict detection and resolution. Addressing these challenges is crucial to advancing and deploying AAM-based DT research in real-world applications.

Cyber–physical consistency is a fundamental challenge in DT research. Inconsistencies occur due to factors such as inaccurate modeling, delays in sensor data fusion, and network packet loss [90]. However, research on cyber–physical consistency for UAVs is scarce. While there is progress in manufacturing, the formal correction of DT behavior is largely unexplored, especially in cross-domain generalization, real-time processing of high-dimensional data, and multiphysics coupling. Moreover, optimization mechanisms for multiphysics coupling need to be validated.

Regarding runtime monitoring and intelligent decision making, the DT must continuously monitor the UAV's flight trajectory, issue obstacle-avoidance commands, and perform battery management [33–35]. However, existing monitoring frameworks lack automated constraint validation mechanisms and cannot adjust monitoring logic dynamically. Although the Model Driven Engineering (MDE) paradigm [100,101] helps bridge the gap by generating code from system models, there is still an implementation gap in mapping monitoring requirements to physical configurations. In addition, the existing DT-based decision formalisms need to handle dynamically changing environments, such as airspace conflicts and weather changes.

Security and privacy are also major issues. Cloud-based DT architectures are vulnerable to data leakage and cyber attacks. In addition, synchronized attacks on virtual and physical entities can lead to data tampering, compromising UAV decision making accuracy. Despite these risks, current DT research lacks robust security mechanisms to mitigate such threats effectively.

Finally, the scalability and efficient deployment of DT in multi-UAV collaborative missions remain challenges. As the number of UAVs increases, the computational complexity of DT grows exponentially, making it difficult to guarantee real-time performance in a high-density airspace. However, resource optimization in existing studies remains under-explored, e.g., Unity-ROS co-simulation [65,83] makes it difficult to maintain real-time execution under such conditions. In addition, the implementation of DT systems needs to span multiple platforms, and inconsistencies in inter-platform communication and modeling protocols hinder system integration and cross-platform applications (e.g., inconsistent geometric modeling standards between Unreal Engine and Blender [81,85]), leading to inefficient deployments.

6.2. Future Research Directions

6.2.1. Advanced UAV-Based DT Modeling

Future DT frameworks should advance geometric, physical, behavioral, and rule modeling approaches to improve runtime model accuracy and adaptability. In geometric modeling, research should focus on automating model generation to reduce manual intervention and improve efficiency. Machine learning-based feature extraction and shape recognition can improve model fidelity at low computational cost. In physical modeling, reinforcement learning can improve real-time adaptability, so DTs can adapt to real-world uncertainties and improve simulation accuracy dynamically. In rule modeling, integrating interpretable machine learning (e.g., Optimal Trees) with multi-objective optimization can improve model generalization and decision transparency [88,93], so DTs can maintain logical consistency while adapting to complex UAV operations. In behavioral modeling, future research should focus on more coordinated and distributed approaches by leveraging advanced formal modeling techniques such as Bigraphs [61]. Runtime world models and UAV models can be effectively designed using bigraphical models [57,59–61], as Bigraphs integrate two complementary views: an object view, which represents entities in the environment (e.g., UAVs), and a role view, which captures their interactions.

Also, establishing a swarm-level safety-performance joint evaluation system by extending SysML task engineering models and defining multi-objective optimization functions for multi-UAV behavior constraints can help balance critical trade-offs like communication energy consumption, collision-avoidance thresholds, and task completion rates. Furthermore, advancing a "behavior-rule-first, data-driven-supplementary" gray-box modeling paradigm, for instance, by embedding formal verification techniques into DRL frameworks [82] as prior constraints, can improve model interpretability while being adaptable to dynamic environments.

6.2.2. Cyber–Physical Consistency Synchronization and Dynamic Correction

Maintaining accurate synchronization between DTs and their physical entities is a challenge. Future research should focus on model synchronization, fusion, and error-compensation mechanisms to improve cyber–physical consistency.

At the data-driven model level, probabilistic graphical models [91] can be used to quantify the difference between simulated and real flight data, while Bayesian networks can facilitate dynamic corrections.

From a model-driven perspective, exploring formal methods-based modeling approaches to check consistency is a good way to deal with this issue. Additionally, real-time structuring of DTs can be achieved through graphical-rewriting techniques, ensuring that the behavioral model remains consistent with changing environmental conditions. In our past work, we explored the use of BRS, a rewriting-based approach, to achieve cyber–physical consistency. BRS-based models offer a unified representation that simplifies the

MAPE-K architecture: monitoring is facilitated through bigraph matching, analysis and planning are conducted by evaluating temporal properties, and execution is managed through bigraph rewriting.

6.2.3. Advanced Computational Frameworks and Security

As DT applications for UAVs expand and evolve to AAM, future research should focus on cloud-edge collaborative computing architectures to optimize resource allocation, enhance scalability, and ensure real-time performance. A distributed DT computing framework could improve task adaptability, alleviate the computational burden on centralized systems, and support dynamic mission requirements.

Task-aware offloading strategies should be explored at the computational level to dynamically distribute DT computing tasks between cloud and edge nodes, minimizing latency and optimizing resource utilization. At the network level, real-time synchronization mechanisms leveraging 5G/6G technologies could enhance DT stability in rapidly changing operational environments. Furthermore, optimizing DT task-migration mechanisms would enable flexible computational resource allocation across different contexts, thereby improving overall energy efficiency in DT computing.

Network security is also a major issue in AAM, so end-to-end protection mechanisms are required to protect DT. Future work should focus on blockchain-based distributed access control, encrypted data synchronization, and advanced network security. Combining these security frameworks with real-time anomaly detection and automated threat response systems is required to ensure safe and secure DT operations in high-security scenarios.

6.2.4. Advanced Decision-Making for UAV Collectives

Model-driven approaches to decision making are often structured and inflexible, with limited effectiveness in highly dynamic environments. These methods rely on predefined state transitions and lack the adaptability to handle unforeseen situations. As a result, individual UAVs may not possess the intelligence to account for new airspace users or unexpected obstacles.

In contrast, DRL-based group intelligence mechanisms [82] have shown promise in addressing dynamic task allocation, obstacle avoidance, and energy management in UAV collectives. By leveraging adaptive learning strategies, DRL can improve coordination efficiency and responsiveness in complex environments.

To enhance adaptability while avoiding the risks of black-box models in safety-critical applications, DTs can integrate formal methods with DRL [139] to support more reliable and interpretable decision making in dynamic mission scenarios.

6.2.5. Standardized and Interoperable AAM-Based DT Framework

To have an AAM-based DT, future research should aim to develop a unified and modular DT architecture that supports seamless interoperability across multiple layers and components in the AAM ecosystem. This includes not only the various types of UAVs—fixed-wing, rotary-wing, and hybrid with different flight dynamics and control mechanisms—but also shared infrastructure elements like vertiports, airspace zones, communication networks, and UTM systems. And the framework should include environmental and social dimensions like weather, regulatory constraints, and mission-level context.

A first step in this direction is to establish cross-platform modeling standards, including formal DT languages and APIs. This will allow seamless integration and synchronization and communication among DT components developed by different vendors or research communities.

In addition, future AAM-DT frameworks must support runtime interoperability to allow for the real-time exchange of state, behavior, and mission-level information between UAV-based DTs and coarse-grain AAM-based DT.

7. Conclusions

The rise of AAM has opened new opportunities for deploying multi-UAV systems in dynamic urban environments. As the demand for UAV applications in logistics, emergency response, and urban inspection continues to grow, developing high-fidelity, real-time synchronized DTs is becoming essential to ensuring UAV operational safety and efficiency. However, significant research gaps remain—particularly in constructing scalable and consistent AAM-based DTs.

This paper provides a comprehensive overview of the enabling technologies and current research in UAV and AAM-based DTs. We draw insights from both the UAV world and established CPS/DT practices in the manufacturing domain and examine modeling approaches across multiple dimensions—geometric, physical, behavioral, and rule-based modeling—and runtime synchronization and application layer integration. We show the evolution of DT capabilities in UAV systems and distill the key trends for future research and development.

Our findings indicate that significant challenges remain in the construction of DT submodels, ensuring the correctness and consistency of runtime models, achieving security and efficiency in DT frameworks, enabling intelligent decision making, and establishing coarse-grain layer standardized and interoperable AAM-based DT frameworks. Although existing layered architectures provide basic DT functionalities, they present notable limitations when applied to multi-UAV systems and heterogeneous environments—key scenarios in AAM applications.

The limitations of this review include the restriction to peer-reviewed, English-language publications, which may have excluded relevant gray literature and non-English studies. In addition, the topic is still evolving rapidly, and some studies may not be included. Furthermore, this paper focuses on the technical aspects of UAV-based DTs and does not go into depth on other characteristics of AAM, such as urban airspace and regulatory restrictions. These aspects are identified as directions for future work.

As a core enabling technology that bridges the physical and cyber worlds, the development of DTs will influence the maturity and deployment of AAM systems. However, realizing this vision requires close collaboration between academia and industry in areas such as runtime model construction, consistency enforcement, and cross-domain knowledge transfer. Addressing these challenges will be essential to overcoming the "last-mile" barriers to real-world implementation.

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Abbreviations

The following abbreviations are used in this manuscript:

ANNs	Artificial Neural Networks.
AAM	Advanced Air Mobility.
BRS	Bigraphical Reactive Systems.
CNN	Convolutional Neural Network.
CPC	Cyber–physical consistency.
CPMTs	Cyber–Physical Machine Tools.
CPS	Cyber–Physical System.
DT	Digital twin.
DNNs	Deep neural networks.
DRL	Deep Reinforcement Learning.
EKF	Extended Kalman Filter.
EWCA	Energy-Weighted Clustering Algorithm.
EWC	Elastic Weight Consolidation.
FEA	Finite Element Analysis.
FSMs	Finite State Machines.
GAN	Generative Adversarial Network.
IoTs	Internet of Things.
LXDs	Linux Containers.
MAUT	Multi-Attribute Utility Theory.
MBSE	Model-Based Systems Engineering.
MDE	Model Driven Engineering.
ME	Mission Engineering.
PaaS	Platform as a Service.
PDEs	Partial Differential Equations.
PRISMA-ScR	Preferred Reporting Items for Systematic reviews and Meta-Analyses extension. for Scoping Reviews.
PSO	Particle Swarm Optimization.
ROM	Reduced-Order Modeling.
SAS	Self-Adaptive Systems.
SDTs	Simulation-Based Digital Twins.
UAM	Urban Air Mobility.
UAS	Unmanned Aerial Systems.
UAVs	Unmanned Aerial Vehicles.
UTM	Unmanned Aircraft System Traffic Management.
VTOL	Vertical Take-Off and Landing.

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