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Request for Information on the National Digital Twins R&D Strategic Plan

Dr. Douglas L. Van Bossuyt, Associate Professor, Naval Postgraduate School
Dr. Bryan Mesmer, Associate Professor, the University of Alabama at Huntsville
Dr. Rob Cuzner, Professor, University of Wisconsin-Milwaukee
Dr. Zhen Zeng, Assistant Professor, University of Wisconsin-Milwaukee
Mr. Roger Cutitta, PhD Candidate, Naval Postgraduate School
Mr. Jason Bickford, Research Director, Naval Surface Warfare Center Port Hueneme Division
Dr. Kristen Fletcher, Faculty Associate of Research, Naval Postgraduate School
Ms. Marina Lesse, Faculty Associate of Research, Naval Postgraduate School
Dr. Rich Malak, Associate Professor, Texas A&M University
Dr. Don Brutzman, Associate Professor, Naval Postgraduate School
Dr. Daniel Selva, Associate Professor, Texas A&M University
Dr. Giovanna Oriti, Professor, Naval Postgraduate School
Dr. Ana Wooley, Assistant Professor, University of Alabama Huntsville
Dr. Wei (Wayne) Chen, Assistant Professor, Texas A&M University
Dr. Doug Allaire, Associate Professor, Texas A&M University
Dr. Astrid Layton, Assistant Professor, Texas A&M University
Mr. Tom Bozada, Research Scientist, CEERD-CERL US Army Corps of Engineers
Dr. Michael Keidar, Professor, George Washington University
Dr. Britta Hale, Associate Professor, Naval Postgraduate School
Dr. Ron Giachetti, Professor, Naval Postgraduate School
Dr. Howie Huang, Professor, George Washington University
Dr. Michael Watson, President Elect, International Council on Systems Engineering; SE&I Branch Manager, Space Division, Leidos
Dr. Cameron Turner, Associate Professor, Clemson University
Dr. Gregory Mocko, Associate Professor, Clemson University
Dr. Allison Ledford, Assistant Research Professor, Auburn University

To whom it may concern,

We are submitting a joint comment on the Networking and Information Technology Research and Development Request for Information on Digital Twins Research and Development Request for Information Document Citation: 89 FR 51554, Page 51554-51555 (2 pages), Document Number: 2024-13379. Below are the authors of this document:

Dr. Douglas L. Van Bossuyt, Associate Professor, Naval Postgraduate School
Dr. Bryan Mesmer, Associate Professor, the University of Alabama at Huntsville
Dr. Rob Cuzner, Professor, University of Wisconsin-Milwaukee
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Dr. Allison Ledford, Assistant Research Professor, Auburn University

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We come from a wide swath of the federal government, academia, and industry. We believe diverse viewpoints and stakeholders are necessary to develop the National Digital Twins R&D Strategic Plan and to see the Strategic Plan through to fruition. This comment outlines our vision for 13 core topics identified in the RFI, and how they can be integrated into a national strategy. The Strategic Plan can be realized only through significant and close collaboration, and we are positioned to undertake the endeavor through a future National Digital Twin Center.

<u>Artificial Intelligence (AI):</u>

Although the role of **Artificial Intelligence** (AI) in the context of Digital Twins (DTs) has been recognized[1], there has been limited focus on how DTs can generate sufficiently large **training datasets** to enhance AI training and testing. Specifically in military and mission scenarios, DT models can impact **mission scenarios** by accelerating the development process and reducing the time and cost required for AI training[2].

The past few years have seen the advancement of generative models (a part of the larger **artificial intelligence** domain) and their success in many domains. Although past work has shown that generative models can be leveraged in DTs to, for example, extract features from high-dimensional data[3] and predict future states[4], the integration of **generative models** to DTs is still understudied. The most important capability of generative models involves learning data distributions, which can be exploited to learn the (potentially high-dimensional) uncertainties of the physical twin's state based on sensor data (e.g., the geometric uncertainties of fabricated part[5] or uncertainties of the physical twin's future state given its current state). This will allow more robust control of the physical twin's outcomes. The challenges will be two-fold: 1) the lack of data to train a high-fidelity generative model and to update the model in real-time and 2) the model's generalization ability to unusual or extreme conditions.

One of the challenges of integrating different models into a **Digital Ecosystem** is real-time information retrieval from heterogeneous sources. **Artificial intelligence** agents (a.k.a. cognitive assistants) can assist the user to seamlessly and quickly retrieve information from different sources, which can be applied throughout the system's lifecycle, from design[6] to operations[7]. **Question Answering (QA) systems** allow for information retrieval from multiple data sources in natural language. However, traditional QA systems based on question intent classification, parameter extraction, and predefined queries and answer templates, lacks scalability and flexibility. **Large language models** (LLMs) have been recently used to significantly expand the capabilities of information retrieval and QA systems. LLM-based systems can now be integrated into AI agents to interpret natural language questions, retrieve the relevant information from an information space, and generate natural language answers, without the need for pre-specifying a set of known question types[8]. However, the use of LLMs has brought new challenges. First, LLM-based QA is slower than traditional QA systems, in part because of the latency of the request to the application programming interface (API). Second, organizations have expressed concerns about the **security** of their data; if any dialogues between users of the QA system and the tool go through the servers of the organization providing that API service, that undermines the confidential nature of the data, especially if the API service provider uses that data to train their models. Finally, for some applications there are challenges related to computing infrastructure requirements. Many of the more powerful LLMs are based on APIs that require an internet connection. Some models exist that can be hosted locally but they are less powerful. One can also train smaller language models for a particular task, but that may require access to significant computing infrastructure.

An interesting new approach that DT enables is based on **Artificial Intelligence** and machine learning harnessing the power of plasma chemistry as a programmable intelligent material with a new concept of a chemical-based algorithm[9]. The focus of some future research will be on integration of DTs with AIto allow development of predictive capabilities by DTs.

Business: Business Case Analysis:

Despite the advantages of DT and Industry 4.0, **small and medium manufacturers (SMMs)** face low **Industry 4.0** readiness[10] due to challenges in understanding how DTs optimize operations, enhance product development, and improve maintenance processes. This is compounded by a lack of **business case analysis** studies demonstrating return on investment, difficulties in identifying suitable applications, and issues with compatible software solutions. Furthermore, SMMs often lack clarity on where to begin, what steps are involved, and what resources are needed, which stalls progress and deters manufacturers from pursuing DT initiatives. A higher understanding of business cases for using Industry 4.0 solutions is essential to prepare SMMs for investing in such capabilities[11]. Because they are purpose-driven, a given DT must match the fidelity and scope of the model to the type of problem being solved. Excessive detail (fidelity), highbandwidth updates (frequency), and broad boundaries (scope) add unnecessary cost and complexity, delaying value realization. This challenge is compounded by a lack of common definitions of DTs, their components, and capabilities. The DT Consortium and other bodies have invested in creating common definitions and reference frameworks for DT use cases. These **standards** must now be widely utilized, revised based on real-world implementations, and enhanced with complimentary tools that accelerate DT adoption. Research should be done to help SMMs deciding upon system boundaries, curating minimum-viable datasets, and making efficient choices to focus system development on the problem statement. Manufacturing executives need tools to evaluate whether DT is a good fit for their problem, challenge, or business need, while system architects need guidance on scope, frequency, and fidelity to maximize business value. IT/OT professionals require estimates of the labor needed before a DT system produces outputs to allocate resources and set expectations effectively.

Traditional **simulation and DT models** share the same capability to replicate physical systems in virtual environments[12], but they are fundamentally different[13]. Simulation is in the core of DTs leading to confusion and the mislabeling of simulation models as DTs and vice versa[14]. Unlike simulations, DTs feature continuous bilateral communication, sensor-based monitoring of physical system changes, and real-time decision-making support. Research has found that a significant portion of literature claiming to present DT case studies fails to achieve true DT capabilities, instead presenting simulations as DTs[15]. Even among correctly built DTs, many underutilize their potential. This highlights a persistent gap between the conceptual understanding of DTs and their **practical application**. Research is needed to develop business decision-making tools, such as decision trees, to help determine when a DT is viable for a problem or if a simulation model will suffice. These tools would guide the selection of the appropriate technology based on the specific scope and requirements of each problem.

The **Department of Defense** (DOD) is transitioning the **acquisition community** for the development of new military systems to a digital engineering environment in which computer models and formal representations of the system are used to inform decisions throughout the entire life cycle of the system. One goal is to have a **digital thread** connecting all the disparate models of the system. Ideally, a DT would be a part of the **digital engineering** infrastructure. Specifically, research is needed in how conceptual and detailed design models can be used to generate some or all of a DT. Such an approach of integrating the development of the DT with the development of the system would greatly reduce costs of DT development and support **verification** that the DT represents the physical system. Also, each additional ship, plane, tank, etc. produced by a DOD program tends to incorporate many engineering changes and technology upgrades which make it significantly different from previous systems in its class. Research is necessary in processes and technologies to generate and manage serialized DTs corresponding to individual fielded systems.

<u>Data:</u>

Research has shown that within enterprises, over 90% of data exchanges are not governed and around 90% of data element exchanges lack digital connectivity[16,17]. Additionally, key vessels of data such as models and documents are often spread across dozens or hundreds of disparate storage locations for stand-alone efforts. Therefore, a primary hurdle that must be overcome for successful DT development and implementation is the adoption of **data management best practices** that enable the realization of the **digital thread**. When determining what data will be used to create the DT, it may be helpful to categorize the data as being related to four different phases of DT implementation: Representation, Replication, Reality, and Relational[18]. Prior to realization of the DT, it is advisable to deploy a methodology to identify disparate and ungoverned elements of data within the system of interest. Once the elements of data are identified, they can be systematically categorized as relating to the Representation, Replication, Reality, and Relational phases of the DT, and consequently, the **digital thread** will be enabled alongside the DT.

Ecosystem:

For **military and mission planning** to make significant advances, a **national Digital Twin R&D ecosystem** must be established both of military and defense systems, and of the industrial and commercial systems that support them. **Mission engineering**[19], planning, operations and maintenance, and many other activities will be enhanced with better DT development and implementation[20]. Already, some work has pointed towards the effectiveness of DTs in improving outcomes for route planning[21], maintenance, and etc. Further, having better access to data through DTs will allow for rapid fielding of new capabilities that can be achieved by integrating existing systems into systems of systems, and identification of capabilities gaps.

The complexity of adapting to existing and future **climate change** impacts and reducing emissions to try to mitigate future effects requires a diverse R&D ecosystem to facilitate the flow of ideas and expertise toward relevant research and technologies. **Artificial Intelligence** and DTs can add to the R&D ecosystem through identifying and quantifying the sources and amount of emissions along with advancing environmental monitoring and efficient data collection and analysis[22]. A DT of the **climate system** allows for better models that simultaneously produce interactive information for **climate adaptation**, emissions reductions and streamlining carbon capture processes[23].

DT **behavior** is a key element in understanding the **functionality** and **operability** of the physical system with the digital model. The modeling of system behavior involves the identification and use of system state variables in the construct and execution of the DT. **State Analysis Modeling** (SAM) is an emerging system state variable modeling approach that provides a digital representation of the system behavior in an interactive simulation[24]. SAM includes the software algorithm, hardware state machines, and mission/flight timelines representing the integrated system behavior in an accurate representation of the physical system. Operator/user input can be supported in the execution of this DT model providing interaction with the user input as well as software to fully encompass DT behavior of the system. This DT of the system behavior has been applied in a few examples and the development of the SAM DT representation is needed in multiple technical domains within the US industrial base. Identification of system state variables and construction of accurate hardware state machines is essential in the model achieving DT behavior representation. Operator/user interaction also requires investigation in providing both live and simulated human behavior interacting with the SAM. The development of this modeling concept provides a system simulation that encompasses a DT of the physical system behavior.

International:

Historically, military systems have struggled to balance security, standards, and proprietary equipment. As a result, military equipment often does not fully leverage **international integration standards**. The result of this coupled with different international languages, units of measure, and other factors can result in **interoperability** issues. The end result can drive increased costs and complexity of development, test and evaluation, training, and failure to maintain a shared operational picture and full transparency across international partners[25].

During system architecture, design, and initial synthesis, the development of early virtualization **DT frameworks** can provide a readily available testable solution for **verifying interoperability** throughout early phases of a system's lifecycle. This will significantly reduce the risk that once fielded, systems will face integration hurdles that become more costly later. Once a system approaches low-rate production and begins being used to test the many diverse use cases required by international partners, the DT can offer significant value to low-cost early test and evaluation to allow stakeholders the ability to defer many requirements to later test phases resulting in significantly more **risk reduction** data collection and reduced overall total ownership costs.

The utility DTs offer for **operations support** is widely described throughout this document, but from an **international partners** perspective there is significant need for **shared operational picture** and **maintaining transparency** across stakeholders. When considering the operational picture, different stakeholders may have different assets and resources available to create international solutions to local problems. DTs that monitor the use of assets in the field and provide contextual awareness of functionality to those partners will significantly speed up response times and improve efficiencies of those operations by eliminating the need to regularly communicate status and request supports. In effect, a DT – Physical Asset pair allows people on the periphery of direct operations to act autonomously in their support to the activity. From a **transparency** perspective, there is significant value in objective quality evidence of what assets are doing. The maintenance of DTs and distribution of their data sets can allow international stakeholders (both allied and others) to have **higher confidence** in activities and **validate assumptions**. The result is allies will know that they are being given accurate information, and adversaries can eliminate suspicion of nefarious activities.

Long Term:

Since its inception, DT has always been intended to exist in all four phases of the **product lifecycle**: create, build, operate and sustain, and dispose. However, there is a common misconception that DTs can only be created once a physical product exists. This belief is understandable, given that most discussions and applications of DTs occur when there's a tangible product to work with. However, a DT exists from the beginning of a product's development and, in fact, precedes the physical product and it is a false notion to claim otherwise. The essence of a true DT lies in its ability to represent something that is intended to exist physically. A DT starts as a foundational model early in development, capturing the product concept for further refinement. As the project progresses, the DT incorporates design specifications and performance data. During operation and sustainment, it serves as a tool for real-time monitoring and optimization of the ongoing performance of the product. When considering the journey of a DT throughout a product's lifecycle, it is essential to understand its evolution and adaptability. Research is needed to show how DTs **evolve** with the product throughout its **lifecycle**, highlighting their **adaptability** and utility f**rom conception to disposal**. Furthermore, the value of having a DT before the physical entity exists should be illustrated.

Regulatory:

The more complex a DT, the more information it requires or produces, and the longer a DT is in operation, the more potential regulatory and legal challenges may exist. Developers and users of DTs must be aware of a variety of such issues including **data ownership**, **causation** and **liability**. In particular, a **regulatory framework** must consider **cybersecurity**, protocols for **modelling risk**, **intellectual property**, allocation of risk and external requirements such as responsibility for data quality and effective function[26]. The risks posed by DTs differ depending on the nature of the DT; a **regulatory** regime will need to take such differences into account, while also facilitating the growth of sustainable DTs[27].

Responsible:

The US Navy's Smart Ship Systems Design (S3D) platform using Formal Object Classification for Understanding Ships (FOCUS) requires **compliant data** relative to a ship design such as properties and geometry for ship components, interconnects (i.e. shafts, piping and cables) and structures (i.e. hulls and bulkheads), behaviors, and simulation results with their Leading-Edge Architecture for Prototyping Ships (LEAPS) repository[28] is an example of a **responsible** approach to DTs. Nothing is released into LEAPS that is not FOCUS-compliant. FOCUS compliance includes **time stamps** and pointers to relevant **measured data** from which parameters are derived. Building on the FOCUS **compliance concep**t of including identifiers on ownership and **intellectual property/data ownership** to the already existing (or in process) **traceability** to data sources and Technical Readiness level of data is critical to having responsible, **ethical** DTs.

Standards:

The sudden proliferation of publications on DTs could be counterproductive to the advancement of the state of the art in any field of application for DTs due to the lack of **standardization**. The term "DT" is sometime used to replace the terms "modeling and simulation" and the objectives and functionalities of the published DTs are often unclear. The recently published DoDI 5000.97[29] clearly places DTs within the larger **digital engineering ecosystem**, providing the first, basic DOD standard on this topic. Future **standards** should focus on the **interoperability** of DTs, with clear definitions of inputs and outputs, connections, communication, data exchange, etc. Within a system, each subsystem or component could have a DT developed by different manufacturers. Clear and detailed standards will ensure that all DTs can be connected together to form a larger system. This concept is similar to what happens with power electronics-based power distribution systems, such as microgrid or transportation power systems, where power converters from different manufacturers work together to form the power system.

Sustainability:

The manufacturing industry consumes significant energy and raw materials globally. Often, locally inefficient decisions, such as using excess packing material, are made to simplify the overall distribution system. Logistics chains, material usage, and product design processes are optimized for business needs rather than **sustainability**, with little focus on end-of-life considerations, re-use, recycling, or circularity during the initial design and business model development stages. DTs can integrate cross-domain information to support more informed local decisions. For example, using less packing material for a product shipped locally versus across the country. Research should highlight how the holistic system view provided by DTs can reduce waste, increase efficiency, and support **circular economies**.

The development of DTs – and any **Artificial Intelligence** technology that is developed to address **climate change** – must consider the **life cycle emissions** of the DT. Without that, the tool that is expected to help model, monitor or reduce impacts is adding to emissions and exacerbating climate change in the process. It is critical that DT prioritizes energy demand reduction first and energy-efficiency second. Reducing energy demand over the life of the DT not only reduces future climate impacts but also models such opportunities for other technologies. Simultaneously, a DT can be used to model improvements in future technologies and extend the life cycle of products through predictive maintenance thus driving **sustainability**[30].

DTs can be designed with **energy efficiency** as a design objective; the virtual twin continuously collects and processes data from the physical twin and can provide feedback to the user about energy consumption and potential energy savings, thus influencing user habits. Further, the DT could take action to reduce energy consumption, for example during the time in which the physical twin is on standby.

Additional energy savings could be obtained with DT to reduce maintenance events, as previously stated, through prognostics and predictive maintenance, to replace scheduled maintenance. However, DTs inherently increase energy consumption, due to the parallel operation of control systems, particularly if **Artificial Intelligence** is implemented. **Guidelines and standards** for use of AI should be provided to avoid abuse, which could drive energy consumption with no obvious return on investment. In other words, not all DTs must have extraordinary processing capabilities to be able to run AI algorithms which are energy-hungry. Designing DTs with **sustainability** in mind is imperative from the start.

Trustworthy:

Security in the context of DTs applies to (1) modeling of the physical system components in the DT so as to elucidate **cybersecurity** issues, (2) security of the DT system infrastructure, and (3) security of the interaction between the DT and physical system and other external components including other DTs as a system of systems of DTs (SoSDT), covering information, updates, controls, and changes that are transmitted among these systems. The authenticity of data and reliability of the DT or SoSDT are thus contingent on networking security. Bitencourt et al.[31] have identified two primary perspectives of **trustworthiness** for the DT: 1) trust in the DT's information and that information has not been tampered with[32] and 2) trust from the user that the DT's information is correct to support decision-making[33].

Developing **secure and trustworthy** DTs presents some unique challenges and opportunities. As DTs grow in complexity, it is essential to ensure all the interactions across different components within the DT, as well as between the DT and the modeled physical systems, are **secure**. Furthermore, if the DT enables a real-time, accurate modeling of the relationships within the physical system, this can unveil hidden **vulnerabilities** and **attacks** that would otherwise go undetected. Therefore, it is imperative for the DT to capture and understand these important relationships for a better **situational awareness** of the complex, dynamic, and highly interconnected environments that the DT represents. A promising solution to meet these demands is the adoption of a knowledge graph approach, which offers a robust and efficient **security** strategy for DTs[34]. This approach employs graph data structures that are made up of nodes (entities) and edges (relationships) and can utilize a variety of techniques, from conventional graph algorithms to cutting-edge machine learning and **Artificial Intelligence** models, such as graph neural networks. In the event of a security incident, the graph methods can help analyze the dependency within the system, trace the steps of an attacker, and mitigate the risks and damages.

Developing a **secure and trustworthy** DTs system infrastructure could be substantially enhanced by adopting **threat modeling** approaches. Threat modeling is a critical component throughout a software product development process and plays an important role in ensuring software security. The analytical process of threat modeling examines the system's architecture and design to identify and mitigate security vulnerabilities[35]. The analysis of threat modeling not only helps in crafting robust security measures specifically designed for the system's needs but also ensures a security-focused mindset throughout the DT system design, leading to a more secure and resilient DT system infrastructure.

The implementation and operation of DT system infrastructure require seamless integration with multiple system components and coordination across various operational platforms. Such integration of diverse systems can introduce numerous vulnerabilities, posing significant challenges for timely mitigation in such an interconnected environment. Adopting **risk-based vulnerability management**[36] approaches can enhance the secure implementation and operation of DT system infrastructure by providing effective and efficient vulnerability management across the integrated DT system. Risk-based vulnerability management approaches patch vulnerabilities more efficiently than the traditional one-for-all approach, especially when remediation resources are limited and may provide a more comprehensive understanding of vulnerabilities and associated risks for DT system infrastructure in the interconnected environment.

Given the vulnerabilities of networked-focused **cybersecurity** and the benefits of data-centric security, focusing on application layer security requirements is essential in this regard. Namely, it may not be within scope to ensure full and adequate network protections suitable to DT and SoSDT needs, but it is possible to institute standards for **cryptographic controls** on application layer protocol protections that are uniquely suited to the needs of the DT and SoSDT environment. Promising approaches in this area include continuous key agreement protocols such as the Messaging Layer Security (MLS) protocol[37] that offers asynchronous application layer security support with end-to-end encryption[38].

Additionally, adequate control and management of key infrastructure for DT and SoSDT use is essential. Given historical issues, vulnerabilities, and exploit with standard certificate use in Internet of Things, work on development and widespread actualization of DTs should look at **Certificate Transparency** and **Key Transparency** as promising solution areas for long-term protections against DT system and component impersonation (both internally and externally). Such approaches support a **zero-trust** approach and can offer solutions for complex systems[39].

Verification, Validation, and Uncertainty Quantification (VVUQ):

As the use of DTs becomes more widespread across the product life-cycle there is a need for formal methods to support **Verification, Validation, Uncertainty Quantification** and **Calibration** and **Certification**. A recent systematic literature review on the verification and validation of DTs in manufacturing found a lack clear definition for the **verification and validation** of DTs[31]. Additionally, very few academic works claiming to create DTs reported that the DTs had been verified and validated[31]. Moreover, there is a need to track the changes and life-cycle of the DT through a digital ecosystem. DTs may be used in the early stage of design to support design decisions of future systems, often denoted as simulation-based design. Conversely, DTs may be used during deployment and usage to monitor the operation and health of the systems. This range of use cases provides a unique opportunity to develop a digital ecosystem of DT development and usage.

An example of DT usage throughout the life of a system is the design and development of an autonomous tracked vehicle. A simulation model of a tracked vehicle was developed to support early-stage **conceptual design exploration**. The models were developed based on existing models of wheeled vehicle and first principles. This digital asset was developed and subsequently used to make certain decisions about the design and related physical asset. A physical representation of the system was developed as a test rig that was closely mapped to the simulation model. The physical system was exercised through a series of planned experiments and data was synchronized across the digital and physical assets. Based on the DT, a deeper understanding of the physics, the use-case, and modeling assumptions was developed, and the simulation models was refined resulting in a **validated** DT. Subsequently, the designed system, as vetted in the test rig and the associated simulation model, were integrated to the full-scale vehicle and used for autonomous driving. The full-scale vehicle was then tested and synchronized with a full-scale DT. The example highlights several key challenges in DT development including the **lifespan** of the digital and physical asset, linking the DT to increasingly detailed design decisions, capturing the stream of data between the digital and the physical world.

There are challenges associated with DT **validation** and a conceptual framework is needed that addresses modeling realism, data uncertainty, system dynamics, use case alignment, and reporting of invalid models. Dahmen and colleagues[40] proposed a testbed for **validation and verification** of DTs through three components: 1) DT representations, 2) simulation approach, and 3) the virtual testbed. The testbed must be structured to capture a modular architecture of the physical system and the associated simulation models. Key areas of interest that represent significant research and educational challenges within DT include: 1) characterizing simulation model **fidelity**, 2) **coordinating and synchronizing** physical system data with predictive simulation models, 3) developing formal approaches for capturing **uncertainty quantification** and mathematical models of fidelity, 4) creating threads that capture the **traceability** of the virtual and physical assets, 5) guidance on level of model fidelity and the mapping to a lower fidelity physical asset, 6) creation of approaches for generalizing DT relationships and extending them to yet-realized systems, and 7) identify approaches for simulation model development, text and data **formalization**, and the thread between the digital and the physical representation, essentially creating a formal approach for capture the devolutionary development of DTs. DT must be **useful and trustworthy** to support the lifecycle of complex systems.

Workforce:

Digital twin **workforce** development has implications across several national interests including defense, energy, manufacturing, and infrastructure. There is an opportunity to enhance existing engineering programs at individual institutions through a national testbed and training resource set. Significant challenges associated with DT development often exist because of limited access to models and data across the lifecycle of the systems and the limited complexity of systems commonly found in traditional academic institutions. To address these challenges, a testbed is needed that consists of digital representations and data that capture both the simulation and physical space. These assets will be curated for complex systems that may include such systems as autonomous ground vehicles, wind turbines, electric vehicle powertrains, microgrids, manufacturing plants, and industrial HVAC systems. The curated DTs will enable **training and education** modules to be developed at scale and complexity of real systems while not impacting the operation of the physical systems. The **future workforce** prepared for DTs will span several domains, thus it is imperative to create opportunities for workforce development that targets deep expertise as well as **systems-thinking** and **integration** skills.

In addition to curated sets of data, the testbed must be highly dependent on working with software providers within the CAD, product life-cycle management (PLM), and **digital thread** space. Universities often lack the infrastructure to deploy complex software systems so mutually beneficial relationships with software solutions providers must be leveraged and established to enable the **future workforce** to access and use tools that are often accessible within industry and government. Such examples include the use of systems modeling approaches (i.e., SysML) and PLM tools to support digital assets associated with DTs[41]. There are numerous opportunities to establish a **shared resource** across institutions to scale learning and research opportunities across partner institutions and companies.

Additionally, integrating **cybersecurity training** into the DT workforce development program will equip system developers and operators with the necessary skills to manage cyber incidents related to network and data-centric security. This training includes hands-on cybersecurity laboratory exercises that replicate real-world attack and defense scenarios. By participating in such training, the DT workforce will enhance their proactive thinking about cyber risks and improve their ability to apply effective mitigation techniques during DT system operations, thereby bolstering their capacity to protect digital twin environments.
Training is a pervasive critical component in the fielding and sustainment of any system, and training pipeline establishment is costly. Leveraging or modifying DTs that are designed to emulate physical system behavior allows a low-cost, scalable, and geographically dispersed training system. If disconnected from physical assets then the operational concept is a virtual twin or a simulation environment for training, but if live streams from assets undergoing test and evaluation, demonstrations, or low-rate fielding will enable classroom environments to participate in dynamic live events, increasing the variability and depth offered over traditional training environments.

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