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

Commenting Organizations:

Idaho National Laboratory

National Renewable Energy Laboratory

Pacific Northwest National Laboratory

Fermi National Accelerator Laboratory

Argonne National Laboratory

Princeton Plasma Physics Laboratory

Response to NITRD RFI on Digital Twins Research and Development

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1. Artificial Intelligence (AI):

1.1. Integration of Digital Twins (DT) with AI

Integrating machine learning (ML) models with DTs has a profound gestalt enhancement, and more research is needed to realize these benefits for diverse national assets (facilities, laboratories, and their key systems). For example, a DT's utility can be greatly augmented by adding a fast-executing, lower-fidelity "data-only" prediction capability that is computationally cheaper than using higher-fidelity, slower-executing physics-based simulations. For example, in real-time control applications on complex, nonlinear problems such as controlling traffic lights in a city to reduce the emissions created from traffic, reinforcement learning based on pre-trained ML models could be deployed to map the state of the system to the control action to be taken, which may be quicker, yet perhaps less accurate than, say, deploying a high-fidelity simulation. These lower-fidelity models may be purely data-driven and trained from data gathered by the physical device, or trained using simulation data produced by higher-fidelity physics models.

DTs can also leverage AI surrogates built using a mixture of many lower-fidelity simulations complemented with higher-fidelity simulations. Advancements in AI models such as diffusion models enable comparing higher-dimensional data (e.g. video) between the digital and physical assets. Investment in the development of these capabilities to integrate simulations of different fidelities and AI architectures for physical-world realistic comparisons will greatly enhance the generalizability of DTs.

Integrating ML models with DTs can also enable real-time anomaly detection. ML algorithms can be trained to identify irregularities in data that deviate from the norm. Unlike traditional anomaly detection methods that compare the incoming data to a predefined threshold value, AI anomaly detection relies on complex models that can adapt to changing underlying conditions and can accommodate situations where many different variables impact the anomaly being detected. Despite its benefits, several challenges in integrating anomaly detection methods with DTs remain. Investment is needed to ensure that methods for data-driven anomaly detection that are integrated with DTs are secure, safe and assured. In addition, there is a need to better understand how DTs can be used in combination with risk analysis methods for identifying anomalies that can't be easily anticipated.

When integrated with DTs, ML technology can also be used in applications where systems performance needs to be optimized. In high-complexity assets such as particle accelerators, high-throughput scientific computing, and the civil infrastructure of large facilities, we find all of these

DT-plus-AI applications, as well as a need for using DTs in the context of control and forecasting when maintenance is required. In applications such as cryogenic facilities where the effects of control actions take long and variable times to observation, the predictive function of a DT may be used by the controller to take precise action without over- or under-correcting. For all of these applications, investment is needed for both research and implementation.

1.2. Generative AI for DT Modeling & Simulation

Investment is needed in the application of generative AI to augment data from physical systems. In many applications there is a lack of data, and this is a hindrance to optimal decision making. In some applications, collecting data is highly resource intensive, and collecting a sufficient amount of data for calibrating models that underlie DTs is hardly possible. In other applications, one may wish to deploy DTs for a wide variety of scenarios, with particular interest in scenarios that have not been observed in the past, but that could have huge implications for resiliency and planning. For such cases, generative AI capabilities are highly relevant. If generative AI can create data to reliably fill in data-sparse regimes, whether rare or simply prohibitively costly, we will be able to better calibrate models and understand behaviors of the system in unexpected and rare settings, increasing resilience and safety. Yet this work remains to be researched.

1.3. AI Trustworthiness

The use of AI in DTs can enable safety because different (AI-generated) scenarios or underlying data driven models allow to explore a wide range of possibilities. However, with AI models mostly being black boxes that lack explainability, there is a danger that blindly relying on AI within DTs may not be safe. Especially when exploring scenarios that have never been seen before (but that are plausible), the amount of trust put into AI should be limited as AI models are known to not extrapolate well. To this end, when leveraging AI models in DTs, uncertainty quantification methods must be integrated that will accurately reflect how trustworthy a DT based on AI is.

In addition, explainable AI methods and techniques offer insights into the decision-making process of AI, creating transparency and understanding around a particular decision or prediction. Explainable AI plays a key role in enhancing accuracy and reliability of AI models. By providing developers insights into the decision-making process of their models, these tools allow them to identify and rectify flaws within the model. Although AI models themselves are computationally cheap, explainable AI tools are computationally expensive, challenging real time implementations.

2. Data:

2.1. Data Collection

DT reusability depends heavily on data collection practices. Data collection frameworks used today vary between domain applications, and even within domains, due to a lack of guidance on best practices. There is a need for governance on communication protocols, that bring DTs closer to real-time and to industrial standards, that can be reusable across DT applications. Often data is collected through domain specific enterprise level data management software and vary from system to system. The enterprise software consumes proprietary data and codes that are not shared with external parties. It would be beneficial to develop a template for non-disclosure agreements that third parties can sign up to access the data and code for the larger good of the domain.

2.2. Data Curation and Provenance

Data and metadata standards and curation methods differ from domain to domain and are needed to bridge the gap between raw observed data with machine readable scientific knowledge. Although some of the data curation can be automated, often a domain expert may be required to tag and standardize the data and metadata. Once data and metadata are standardized, data may also need to be converted to common formats especially with time series data. Time should be standardized across all raw and observational data and any transformation to a common grid should use standard protocols to propagate errors and uncertainties. Standardization and curation should follow protocols to ensure that the data is Findable, Accessible, Interoperable and Reusable (FAIR). Quality Assurance/Quality Control documentation is required as one type of metadata when datasets are curated, disseminated and published. Published datasets should use persistent (i.e., digital object identifiers [DOIs]) when data are shared. The provenance of the data is important to capture in the standardized metadata to help enable reproducibility. A broad notion of data should be taken, where the data includes the DT models themselves, such as the hyper-parameters and weights for machine learning models.

2.3. Data Sharing and Usage

There is a need for investment in data sharing solutions that ensure an integrated data usage across domains and across system lifecycle phases. Data collected during system design (i.e. requirements, system assets, system functions, spatial footprint) is produced by different stakeholders within different domains and may go from micro-scale to system level scale. Traditional documents centered design data management can lead to silent errors, cost overruns and schedule delays. There is a need for the implementation of model-based systems engineering practices that provide an authoritative source of truth and enable data transfer across domains and scales. Models generated using model-based system engineering can then serve as early maturity DTs, and be used to validate the system, accelerate operator training, and produce data required for AI algorithms training and testing.

Data sharing across system lifecycle phases is equally as important as data sharing within design teams. Early maturity DTs described above can evolve into DTs that enable autonomous operation at their highest maturity level. The advancement of digital thread technology is essential for taking model-based systems engineering models out of isolation and providing an interface with external digital definitions created later in the system development process.

Data collected during system operation is produced by different domains and also need tools that enable integration and transfer of this data across models and spatial and temporal scales that support system operation (e.g., optimization models, high-fidelity physics models, reduced order models, anomaly detection models, etc.)

Some domains sensitive to national security may require that the data are not shared among users outside their project. As an example, hydropower facilities prefer to keep their operational data secure and accessible only to their operational teams. Data Management and dashboards need to be set up with the right access controls to ensure that the data is securely shared only among project members.

2.4. Shared Public Datasets and Repositories

Data is essential for training of AI algorithms and tunning control methods. While data is abundant, its format, availability and provenance are highly inconsistent. Investment in structured public datasets and repositories can enable the advancement of AI and control technology within a domain. In addition, these datasets and repositories enable cross-cutting DT development. Leveraging commonly adopted and standardized API's to access data and metadata from publicly managed data repositories will advance the use of AI to train and validate DT for complex systems.

Having access to the underlying data and provenance helps to enable reproducibility and derive common benchmarks that can drive long-term research and development activities.

2.5. Real-Time Data Integration

DTs are widely used for optimizing operations and controlling complex systems, e.g., DFW airport terminal. To do this effectively, DTs need access to real time data, and use it in continuous recalibration and adaptation of models to adjust to system dynamics and enable decision making. This requires investment in data infrastructure and data processing tools that can integrate heterogeneous data and use it to optimize models on the fly. High performance computers and data centers as well as edge-computing will be essential for collection and further processing of data not only in real-time but also over longer timescales for recalibration of the DT. Particularly important for distributed sensor environments. Depending on the application, questions may arise as to how data changes over time, if older data could be discarded, which data are important for a certain task and uncertainty/noise associated with real time data. Historical data can also be used to predict or prescribe maintenance of complex systems. For aging complex systems such as hydropower facilities, historical maintenance data need to be digitized and may require the need to use machine learning and image processing to sort, filter, and tag data. High throughput and high volume (near-) real time data integration is critical for safety and response type applications.

3. Ecosystem:

DTs are being developed and deployed in a wide variety of scientific applications. These include materials synthesis and discovery; real time traffic control to reduce congestion in cities and reduce associated emissions; in virtual biofuels engineering; future climate modeling; offshore wind farm design and control; buildings modeling and control; modernizing electricity infrastructure and attaining 100% renewable electricity goals (e.g. LA100, PR100, LT100); buildings modeling and control; and grid resiliency.

While some of these applications appear similar in nature, there are no standards that would allow for interoperability of models, including a lack of agreed-upon communication protocols, data naming conventions, data QA/QC and other processing steps, or DT updating rules. While the smart buildings sector is increasingly using a common language to allow various sensors to talk to each other, such advances are missing in other scientific domains where DTs are developed for bespoke control actions. This leads to a lack of scalability and reusability. Moreover, even within a specific science domain, there is a variety of tools that can be leveraged leading to a potentially confusing landscape of which tool to use when and how the tool's input requirements fit with the data collection mechanisms.

3.1. Cross-cutting Collaborations

To address the challenges of interoperability, sensor communication and availability, and cascading effects of interruptions, investment in a holistic systems approach is needed. Such approaches can only be realized through tight cross-cutting collaborations that involve domain scientists from all areas, e.g. every entity that may be affected by disturbances and failures (directly and indirectly), as well as computational and data scientists who will be able to devise optimal control strategies and visualization capabilities that enable informed decisions by providing a holistic picture of the physical process under investigation.

3.2. Twin-of-Twins Demonstrations

Along with the need for investment in cross-cutting collaborations there is a need for investment in cross-cutting DT demonstrations and testbeds. Multiple DT demonstrations have been performed to this day within domain boundaries. These DT applications are built to meet their physical counterpart's needs and objectives. However, in order to overcome challenges associated with interoperability, sensor communication, and cascading effects of interruptions, the next generation of DT demonstrations will need to allow for communication between domain specific twins, that not only meet their individual system's needs and objectives, but also collaborate to meet global needs and objectives. For example, the DT of a nuclear reactor may assist operational process in maintaining high performance and enforcing security, while also communicating with the DTs of hydrogen, solar, wind and biomass systems, that coexist with the reactor in an integrated energy grid, to assist the entire system in meeting the grid's demand. For such demonstrations to take place, interdisciplinary testbeds with DTs will need to be built and be operating.

4. International:
Certain systems that may benefit from the application of DT technology cross national boundaries (e.g., air traffic control systems, supply chain systems). To overcome the challenges of interoperability and cascading effects of disturbances or interruptions at a global scale, DT demonstrations that cross national boundaries are needed. These demonstrations will require investments that support international collaborations and the establishment of international DT standards.

5. Long Term:
Long term research and development questions revolve around the updating and/or maintenance of DTs and their adaptation to changing systems or environments, e.g. add-ons of new data collecting sensors, integration of new tools, new processes, changing risk profiles, etc. The heterogeneity and multi-scale nature of the tools, models, and data that come together in a DT can be vast and require documentation to enable updates, integration, and long-term support. There needs to be a built-in flexibility in the design-build-operate cycle that allows changes and modifications, with the goal to not limit operability to the specific conditions present when the DT was first created. If funding were available to develop standards and best practices for these long-term concerns in the DT field, considerable expense could be saved.

In applications such as buildings control, traffic control, wind farm operation, user facility operation, or materials synthesis, a continuous feedback loop between the DT and the physical counterpart is used, where data informs the models in the DT. These models are currently used to inform operations or experimental control, and newly acquired data from the physical system is utilized as input to the DT for model recalibration and updating. Enabling predictive nature of digital twins, going beyond reflecting what happened in the past and what is happening now would be a natural next step. Therefore, determining what is "right" data to be collected to infer information critical for model calibration, and adaptation, and minimizing overheads arising from data transfer is essential to allow for optimal and predictive real-time controls. Moreover, the data infrastructure must be in place, e.g., in laboratory settings, the transfer of data from diagnostics instruments to the DT must be enabled, which may require infrastructure investments.

Experimental facilities have very long lifetimes and the DTs need to evolve with the technology. The existence and performance of the underlying software needs to be ensured over the lifetime of the experiment. Hence, investments in software sustainability and long-term reproducibility are necessary for DT technology to penetrate into the experimental facilities.

To ensure the benefits of DTs in the long term, it is critical to invest in developing and promulgating best practices for support, documentation, and human-in-the-loop operation, mitigating the risk to knowledge retention which otherwise threatens a DT with loss of functionality or performance.

6. Regulatory:

DTs have a role to play in regulation, if the investment is made to realize it. The compulsory licensing and regulatory process in several industries can be slow, expensive and convoluted. For instance, the currently mandated process to obtain a construction permit and operating license for a nuclear reactor can take up to decades and incur costs that escalate to hundreds of millions of dollars. From design, to construction, to operations and eventual decommissioning, the nuclear reactor goes through rigorous scrutiny from the regulator who is charged with ensuring adequate protection of public health and safety. DT technology can potentially accelerate these processes as the DT allows the regulator to virtually test scenarios, evaluate potential impacts, and verify compliance with regulations while avoiding the time-consuming burden of document review, information retrieval, and reasoning through safety and security compliance. In addition, DTs can continuously monitor operations and conditions. This real-time data can be used by regulators to ensure ongoing compliance with licensing requirements. There is a need for investment in the integration of DT technology with licensing and regulatory processes.

7. Responsible:

7.1. Ethical Use of DTs

Investment in DT safety, security, and assurance solutions is critical for ensuring the ethical use of DTs, especially in high-risk use cases. Ensuring robust security measures protects sensitive data and upholds ethical standards for privacy protection. Ensuring safety of DTs involves rigorous testing and validation to prevent malfunctions or harmful outcomes, protecting users from potential risks with the deployment of DTs. Assurance processes ensure information generated by DTs is trustworthy and will not lead to harmful decisions.

7.2. Data Privacy

Often there are two categories of data used to derive DTs, public data captured and made accessible, and private data that is not shared. The private data may be proprietary or have other restrictions on its usage. To maintain data privacy, an investment in privacy preserving and federated learning methods may be appropriate. In these methods, the public data can be used to generate a DT and the private data can be used by those with appropriate access to refine the DT for their particular situation. By passing model parameters back to the public repository, the public DT may be improved without compromising the private data, but checks should be devised to ensure that private information cannot be extracted inadvertently from such a public repository. In practice, maintaining data privacy will require investment in "red teaming" exercises that simulate an attack on the DT to identify vulnerabilities and weaknesses.

8. Standards:

8.1. Standardization of DTs across Asset Lifecycle

There is a need for investments that support standardization of DT technology across the system lifecycle to ensure consistency in how DTs are developed, deployed, and utilized. This consistency will facilitate seamless transition and integration of data and models used for design, manufacturing, operation, and maintenance to new applications, and to improving existing DT applications.

8.2. Standardization of DTs across Domains

Standardization of DT technology by individual domains ensures consistency in how DTs are developed, deployed, and utilized within that domain. However, many industries increasingly rely on interconnected systems that work together to achieve common objectives in addition to their individual objectives. In order to do so, DTs of specific domains need to work together seamlessly through data sharing and coordination. There is a need for investment in federated common data interchange formats at the domain boundary to facilitate easier integration and analysis of data from diverse sources, enhancing decision-making processes.

8.3. Shared Public Domain Ontologies

Ontologies provide a common vocabulary and framework for defining concepts and relationships within a specific domain. By investing in efforts that make specific domain ontologies available to other domains to access, different organizations in multidisciplinary systems can ensure consistency in terminology and data representation, promoting interoperability and data integration.

9. Sustainability:

9.1. DTs Computational Requirements

DTs rely heavily on computational resources (e.g., high performance computing, data centers, etc.). There is a need for investment in solutions that help to minimize computational requirements of DTs, and reduce the strain on these computational resources, which will lead to decreased energy use and reduced carbon foot-print of DT operations, and expanded adoption in applications which can benefit from the DT approach.

9.2. DT Lifecycle Continuum

DTs are evolutionary by nature, and their scope changes as their physical counterpart evolves through the different phases of its lifecycle. A DT built during a system's design phase can be used for extensive simulation and testing before physical prototypes are built, reducing the need for material resources and minimizing waste. As the DT evolves, "digital threads" allow for the seamless flow of data across all phases of a system's lifecycle. This data continuum can ensure consistency and accuracy, helping organizations avoid silent errors that lead to redesigns and additional resource consumption and waste. There is a need for investment in solutions that foster this DT lifecycle continuum, such as digital threads and semi-autonomous design.

9.3. Cross-cutting software ecosystem

There is a need for investment in the development of a cross-cutting software ecosystem. Having a cross-cutting software ecosystem for multi-disciplinary DT applications could avoid the duplication of data and models across organizations and minimizes the computational resources needed to maintain a DT operational. As mentioned previously, minimizing computational resources lead to lower energy consumption by the DT, making the technology more sustainable and its adoption more feasible.

9.4. Reusable, Repeatable and Transferable DTs

Similarly, there is a need to ensure that new iterations of DTs are reusable, repeatable and transferable, leading to twins that can be deployed multiple times within similar domain scenarios, can be replicated across different domain scenarios, and can be adapted for different domains, respectively. This also minimizes computational resources and lowers energy consumption, making DTs more sustainable. Work is needed in order to realize these benefits.

10. Trustworthy:

10.1. System Engineering Practices for DT Design

DT design often involves multiple disciplines, such as mechanical engineering, electrical engineering, software development, and data science. Systems engineering practices facilitate the integration of diverse knowledge into a cohesive and effective design, while providing means for risk identification, assessment, and mitigation throughout the design process. There is a need for federated integration of this holistic approach to DT design, not yet widespread in the national labs. Systems engineering can help align the scope for the DT, and anticipate potential challenges and uncertainties associated with its components, ensuring reliability. Another important characteristic of DTs is their evolutionary nature, with maturity levels being reached at different stages of its lifecycle. Systems engineering practice considers the entire lifecycle of the twin, ensuring that the twin is designed with scalability, sustainability and long-term usability in mind.

10.2. Integration of DT Design and Cyber Security Processes

DTs often handle sensitive data related to physical systems, operations or even personal information in sectors like healthcare. Investments in the integration of cybersecurity considerations into the DT design process ensures that this data is protected from unauthorized access, breaches and cyberattack. In addition, cybersecurity measures implemented at the design phase can help prevent malicious actors from disrupting the DT processes during system operation (e.g, unauthorized control of critical systems). Cybersecurity safeguards can also help maintain the integrity of the data within DTs. This includes ensuring the data is accurate and has not been tampered with, which is essential for making informed decisions based on DT outputs. Here, a coherent program of investigation in the very near term can save much hassle and redesign in the future.

10.3. Risk Analysis and DTs

DTs can simulate different scenarios to determine the likelihood and impact of various risks. This can help organizations prepare response strategies tailored to specific risk events and enhance resilience. This is particularly important in multi-domain environments, where DTs can be used for cross-disciplinary risk analysis by integrating data and insights from different domains, and enhance resilience to cascading failure scenarios. However, it is equally important to include DTs as a potential vulnerability when performing risk analysis. As mentioned previously, DTs are vulnerable to cybersecurity threats, and are as much part of the system as the other physical components. Therefore, it is extremely important to understand, detect and mitigate the risks associated with its implementation, including potential malicious use and ingestion.

10.4. DTs Interdependence Analysis

DTs often model complex systems with interconnected components and processes. Investment in DT interdependencies analysis is needed to help stakeholders gain a comprehensive understanding of how different elements interact and influence each other within the DT. It can also help identify critical components and relationships that are essential for the accuracy and reliability of the information generated by the twin.

10.5. Assurance

Investment in assurance methods is critical to ensure that DTs are reliable, safe, and perform as expected. This involves rigorous validation and verification processes to check the accuracy and fidelity of the DT models. Techniques such as formal verification, simulation-based testing, and hardware-in-the-loop (HIL) testing are used to validate DTs against real-world scenarios. Assurance methods also include continuous monitoring and diagnostics to detect and address any discrepancies between the DT and the physical system. Ensuring high levels of assurance is vital for applications in critical sectors such as healthcare, aerospace, and energy, where failures can have significant consequences.

11. Verification, Validation, and Uncertainty Quantification (VVUQ):

11.1. DT Key Performance Indicators (KPI)

There is a need for identification of DT KPIs across different applications. KPIs provide a quantifiable way to monitor the performance of DTs over time against some predefined objectives such as improving efficiency, reducing down time, or enhancing product quality. KPIs can highlight areas where the DT may be underperforming and enable targeted improvements to DT models, processes or data inputs. This is crucial for maintaining the reliability of information and control actions generated by the twin.

11.2. Integration VVUQ Practices and DT Deployment

Uncertainties are inherent in any physical system, and accurately modeling these uncertainties is crucial for the effectiveness of DTs. Well-modeled uncertainties allow the DT to capture the variability and unpredictability of the real world, providing more reliable simulations and predictions. This is particularly important in use cases such as predictive maintenance, where understanding the range of possible outcomes can inform better decision-making. Techniques such as probabilistic modeling, Bayesian inference, and Monte Carlo simulations are commonly used to account for uncertainties. There is a need to integrate VVUQ methods with DT development and deployment. By incorporating these methods, DTs can provide more robust and resilient solutions across various applications.

11.3. Propagation of VVUQ across domains

There is a need for investment in the propagation of VVUQ methods across disciplines. Different disciplines often have unique methods for VVUQ. Propagating these processes across domains ensures that DTs developed by multidisciplinary teams can be consistently applied and trusted across various applications.

11.4. UQ for DT

Uncertainty quantification is needed for reliably deploying DTs, especially when high risk decisions are at stake. DTs may be used to understand scale-up processes, for example, and reduce the risk associated with decisions. Thus, uncertainties in the DT must be properly quantified. This includes the quantification of both aleatoric and epistemic uncertainties and their propagation through the DT, ideally delineating what part of the total uncertainty should be ascribed to the data (aleatoric) and the model (epistemic) including underlying simulations, modeling choices, or ML models used within the DT. Depending on the computational expense associated with DTs, different UQ approaches must be considered, including multi-fidelity, Monte Carlo, Bayesian, and ensemble methods. The outcome of the DT should therefore be quantities that can be used in visualization approaches that indicate to the decision maker or control process how much trust to have in the DT, and which parts of the DT to attribute the uncertainties to.

11.5. DT for UQ

Conversely DTs have the potential to be used to enable uncertainty quantification of the physical processes they represent, if research into this is funded. For instance, to understand the variability associated with stochastic processes, it is in practice often impossible to create a large ensemble of these processes. Here, a DT can enable and significantly accelerate the needed UQ by repeatedly executing it for the same state, assuming it represents the underlying physical processes accurately.

In the same vein, DTs can be used to execute multiple what-if scenarios that would otherwise not be possible to study by experimenting with the real physical processes.

12. Workforce:

12.1. Cross-Disciplinary STEM Education

While there is benefit in teaching individual disciplines in separate pillars to hone in on the intricate details and enable students to fully understand the fundamentals, more cross-disciplinary classes must be taught to elucidate the tight connection between diverse disciplines. These classes would enable students to better understand the complexity of systems and systems of systems, allowing them to make connections as to how topics learned in one class can be leveraged to solve problems in a different discipline. Such classes would also enable students to learn how to engage with non-experts from other backgrounds, and thus improve their interdisciplinary communication skills as well as broaden their horizons with respect to the usefulness of their area of specialty. DTs in particular are approximations of complex systems and require the collaboration of experts in various fields to be successful and capture all aspects of the physical process under investigation.

12.2. DT Addition to STEM Curriculums

DTs are increasingly used in various industries. Integrating DT education into STEM curriculums can thus better prepare students for future careers, and equip them with the necessary skills to succeed in an increasingly digital world. As DT technology becomes more widely used, regulatory standards and compliance requirements are likely to arise. There is a need to reform STEM curriculums to include DT education and ensure students adhere to industry standards and best practices.

12.3. DT for Workforce Training

DTs provide a powerful tool for workforce training by creating realistic and interactive simulations of physical systems. These simulations can be used to train employees in a risk-free environment, allowing them to practice and develop their skills without the consequences of making mistakes in the real world. This is particularly valuable in industries where errors can be costly or dangerous. By using DTs, organizations can enhance the training process, improve safety, and increase the overall competence of their workforce. Additionally, DTs can be used to develop and test new training programs, ensuring they are effective before implementation. There is a need for integrating DTs into workforce training processes.

12.4. Democratization of DT

There is a need for investment in the democratization of DT technology. Making DT technology accessible to a wider audience ensures that more organizations, regardless of size and resources, and more individuals, regardless of their circumstances, can benefit from its capabilities and career-enhancing capabilities. This promotes inclusivity and fosters a broader range of innovation and collaborative efforts.

12.5. Education on Operating with DTs

As DT adoption increases across industries, it is likely that system operation will require some level of interaction between operators and DT technology. There is a need for education on operating with DTs. DT education for operators can ensure their interaction with the technology is efficient and allows them to leverage the full capabilities of DTs to monitor, analyze and optimize processes. At the same time, the organizational leadership must be educated about DTs, so that they realize the challenges and the great potential of putting DT technology to work.