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Digital Twins and Artificial Collective Intelligence: Synergies for the Future

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Digital twins (DTs) and artificial collective intelligence (ACI) are transformative technologies that, when combined, hold significant potential for managing complex systems across diverse domains, such as smart cities, health care, and manufacturing. DTs encompass both physical objects and their virtual counterparts, enabling real-time monitoring, control, and predictive modeling, while ACI enhances decision-making by leveraging the collective knowledge from multiple models. This article explores the synergies between DT and ACI, focusing on their integration into federated DTs (FDTs), which are networks of autonomous, collaborative DTs. By leveraging collaboration, FDTs optimize processes, improve scalability, and adapt to dynamic environments. We analyze the properties of DTs and ACI and identify opportunities for innovation and challenges in areas, such as scalability, adaptability, and fault tolerance. This integration paves the way for smarter systems capable of addressing the complexities of modern technological and societal challenges.

Digital twins (DTs) are greatly attracting attention from both research and industrial communities due to their great potential for the development of systems as challenging as smart cities, e-health, aerospace vehicles, or energy management. The concept was originally coined by Grieves and Vickers in 2003,[1] who identified three main elements: 1) a real space, 2) a virtual space, and 3) a link between both spaces for the bidirectional flow of data to offer the convergence of the real and virtual world. This model simply identifies these elements without describing how they should interact nor indicating which technologies should be used to achieve it.

The Internet of Things (IoT)[2] is presented as a powerful enabling technology for DTs, as it enables the connection of numerous devices (sensors and actuators) that make possible the convergence of the real space and the virtual space.[3] IoT devices collect large amounts of data in real time, but these data scarcely hold value without proper processing and analysis. DTs offer a step forward by facilitating that data monitored by IoT devices are processed, analyzed, and fused to offer information for further processing to make better analysis and decisions. *Artificial Intelligence* (AI), another technology revolutionizing the current landscape, plays a crucial role in processing and exploiting the information gathered by IoT devices to control behavior, predict failures, etc. Together, the IoT and AI are crucial for unlocking the full potential of DTs.

Most of the research developed to date has focused on developing DTs as "monolithic applications," which are highly cohesive systems designed to support very specific business use cases. Some examples of use of DTs are predictive maintenance for specific equipment in industrial settings,[4] optimization

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production of manufacturing lines,[5] control of heating, ventilation and air conditioning (HVAC) systems in smart buildings,[6] and personalized patient monitoring and treatment optimization in health care.[7]

There is an urgent need for breaking these monoliths and instead developing a composition of DTs enabling collective insights and enhanced capabilities. This new concept, recently coined *federated DTs* (*FDTs*),[8] consists of autonomous DTs (ADTs) that support independently their business use cases while collaborating and sharing knowledge to improve predictions, optimize processes, and effectively adapt to dynamic environments. Indeed, achieving such a behavior is still an open research question: How can the development of DTs transition to the development of ADTs capable to work as FDTs?

In parallel, AI has intersected with *collective intelligence* (CI) in a catalytic way, enhancing data processing and decision-making capabilities across various fields. CI refers to the phenomenon in which a group of individuals collaborate to solve problems, make decisions, or create knowledge, achieving better results than a single individual.[9] This intersection of AI and CI is called *artificial collective intelligence* (*ACI*).[10] ACI leverages the collective knowledge and capabilities of multiple AI models to enhance decision-making, problem-solving, and innovation.

The integration of *FDTs* with *ACI* will represent a significant leap forward in terms of scalability, adaptability, and management of complex and multifaceted systems. ACI enhances the functionality of FDTs by facilitating the exchange of knowledge across multiple ADTs. For example, in a smart city application, FDTs of different urban subsystems, such as traffic, energy, and waste management would collaborate through ACI to jointly optimize resources across the entire city. ACI enables continuous learning by transforming each DT in an ADT able to improve its own model through learning from others. This provides adaptation to dynamic circumstances, like fluctuating traffic patterns or unexpected shifts in energy demand. This collaborative approach improves accuracy, while providing a holistic view of the system, leading to better decision-making and more efficient management of urban environments.

The integration of these concepts, FDT and ACI, provides a transformative approach for managing complex problems in a broad range of domains. This groundbreaking integration inspires our work; hence, we explore the synergies between properties of DT and ACI and how their combination can enhance each other in innovative and impactful ways. We also detail the challenges and opportunities for their future development.

This article is organized as follows: In the "DTs: Properties" and "ACI"' sections, both concepts and their main properties are defined. Then, the "Vision: Synergies and Future Challenges" section presents the synergies between DTs and ACI, as well as some challenges and future research lines. Finally, the last section presents the conclusions of this work.

DTs: PROPERTIES

Since the initial conception of DTs, these have evolved from solely modeling physical objects in the virtual world to simulating their dynamics, monitoring their state, and controlling or predicting their behavior. These abilities greatly depend on the type of DT being developed, as they can be classified into three different categories,[11] as Figure 1 illustrates. These categories are defined based on the type of interaction between the physical object (PO) and the logical object (LO) in the virtual space:

- *Digital model:* The data between the PO and the LO are exchanged manually, so the state of the PO and the LO are not directly synchronized.
- *Digital shadow*: The data from the PO flows to the LO automatically, but the reverse is manual. Thus, the state of the PO is updated in its LO, but not vice versa.

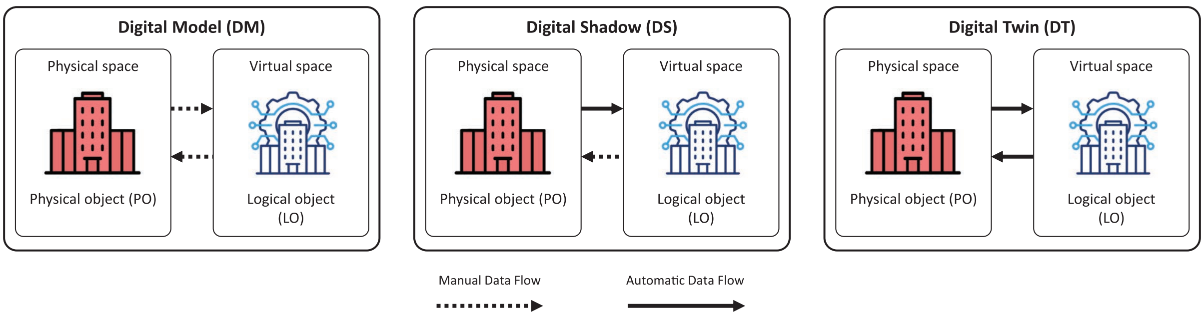

FIGURE 1. Digital model (DM), digital shadow (DS), and land DT (adapted from Kritinger et al.[11]).

› *DT:* There is an automatic bidirectional flow of data between the PO and LO. Therefore, any change in either the LO or the PO directly affects its counterpart.

Minerva et al.[3] feature the properties that should be satisfied for being considered a DT. These DT properties are classified into two groups: essential properties and add value properties. The first set of properties, *essential properties*, ensures that the DT accurately represents the PO and behaves similarly to it within a specific context. This set consists of three properties.

› *DT1: Representativeness and contextualization:* The LO supports only those attributes of the PO relevant to its context of use.
› *DT2: Reflection:* The LO must univocally represent measurable aspects of the PO. Each measurement of the PO must correspond unambiguously to a set of values in the LO, ensuring that the PO's status is perfectly described within its context.
› *DT3: Entanglement:* A continuous flow of information between the PO and LO is required so that they are synchronized in real time or close to real time.

The second set of properties are those that *add value* to the DT. The properties to be satisfied by the DT depend on the specific business use case to be supported by the DT. In the following, those properties more relevant to ACI are described.

› *DT4: Replication:* This is the creation of multiple replicas (LOs) of a PO in different environments to satisfy specific demands. A key challenge is that all of the replicas (LOs) must be consistent with the PO.
› *DT5: Memorization:* The LO must store both current and historical data relevant to the DT business use case. These data convey information about the past behavior of the PO and the context where it belongs. This property it is key for supporting two properties: persistency (DT6) and predictability (DT10).
› *DT6: Persistency:* The LO must be persistent and resilient over time. If the PO malfunctions, then the LO must re-establish and synchronize with the PO to an acceptable and meaningful state. Additionally, the LO must mitigate those issues caused by the lack of serviceability of the PO.
› *DT7: Composability:* This is the ability to combine multiple LOs into one more complex DT able to monitor and control both the composite DT and the individual DTs. This property is the foundation for the development of FDTs.
› *DT8: Accountability/manageability:* This is the ability of the LO to offer self-healing facilities to recover from failures autonomously.
› *DT9: Augmentation:* The LO should allow the addition of new attributes and functionalities to increment and enhance the capabilities of the PO.
› *DT10: Predictability:* The LO must predict or make decisions by exploiting large datasets describing the past of the PO (DT5: memorization). Furthermore, DTs should simulate their own behavior and their interactions with others over time under specific conditions.

Predictability, along with the other DT properties, reveals the most outstanding capability of DTs: control, simulate, and act on systems as complex as smart cities, factories, or logistic networks.

ACI

In addition to human, animal, and AI, Malone and Woolley[9] state that another important kind of intelligence exists: the *CI* of groups of individuals. CI refers to the phenomenon where a group of individuals collaborate to solve problems, make decisions, or create knowledge, often leading to outcomes that surpass those achievable by individuals alone.[12] In its simplest form, CI can be observed in everyday life, from families to companies or scientific communities, where the aggregated contributions of many exceeds the capabilities of any single individual.[9]

Historically, the concept has roots in various fields, including sociology or evolutionary biology, where examples, such as the foraging patterns of ants or the coordinated movements of bird flocks, showcase how the group can outperform the individual in nature.[13] In sociology, a classic example of CI can be found in Francis Galton's experiment at a rural fair, where he observed that the collective estimation of a group regarding the weight of an ox was surprisingly accurate, despite individual variations.[12] This kind of CI is called *natural CI*.[10]

More recently, technological advances have enabled the rise of *digital CI*, which is characterized by the integration of the Internet and computers with human collaborative efforts, creating a hybrid intelligence that leverages both human cognitive capabilities and machine efficiency. This concept aligns with social computing, which emphasizes human-centric interactions facilitated by technology, and human-based computing, where human input is an integral part of computational processes.[14] Platforms, such as Wikipedia or open source projects, rely on the Internet's ability to scale rapidly, enabling the participation of diverse and global human contributors.[9] These platforms exemplify how digital CI can harness the collective knowledge of users worldwide, thus expanding the traditional boundaries of CI.

Additionally, in recent years the concept of ACI has emerged too. According to Casadei,[10] ACI refers to the CI exhibited by human-made machines. In other words, ACI represents the phenomenon where multiple models work together, much like human groups or natural systems, to produce outcomes that outperform individual ones. Thus, instead of a single model acting independently, a group of them collaborates, often through parallel processing or distributed decision-making, to solve complex problems.

According to Peter Flach,[15] combinations of models are generally known as *model ensembles*. For instance, *ensemble learning* is a widely used technique, where multiple models work together to make more accurate predictions than any single model could. Techniques, such as *bagging*, *boosting*, and *stacking*, combine the outputs of different models to reduce error and improve generalization. An example is the use of *Random Forests*, which aggregate the decisions of multiple decision trees to improve prediction accuracy. Similarly, *swarm intelligence* models, inspired by natural systems like ant foraging or bird flocking, utilize multiple models that follow simple rules to solve complex optimization tasks.

ACI represents a transformative step in the evolution of AI. While traditional AI systems operate individually, ACI leverages the power of multiple models working together, often in real time, to solve complex problems.[16] Thus, in ACI, different models, such as machine learning (ML) algorithms, neural networks, or evolutionary algorithms, are combined to share insights and optimize decision-making. This mirrors the way biological or social systems, such as ant colonies or human crowds, pool individual expertise to achieve a collective goal. In ACI, these algorithms interact through a shared environment, exchanging information or contributing their own solutions to parts of a larger problem.

In order to analyze the potential synergies of ACI and DTs, we describe in the following the main properties of ACI[9,10,16]:

- *ACI1: Communication:* This is the process by which models exchange information, enabling the collective generation of ideas and solutions. An effective real-time communication is essential to align group efforts and improve decision-making.
- *ACI2: Collaboration:* This is the capacity of different models to work together, pooling resources and skills to achieve shared goals. Collaboration is based on interdependence, where the contributions of each participant enhance the collective outcome of the group.
- *ACI3: Coordination:* This is the management and alignment of group members' activities to ensure effective collective actions. It guarantees synchronization of efforts, avoiding unnecessary redundancies and optimizing overall performance.
- *ACI4: Cognitive diversity:* This is the variety of models used to solve problems and make decisions within a group. ACI systems benefit from a diverse group of contributors, which enriches the pool of knowledge and perspectives. Diversity can lead to more innovative solutions and reduce the likelihood of groupthink.
- *ACI5: Distributed problem solving:* This is the ACI system's ability to distribute tasks among models enhances its problem-solving capabilities. This decentralization fosters a wider range of ideas and solutions.
- *ACI6: Decentralization:* ACI systems empower individuals to act autonomously, facilitating individualism while promoting varied contributions, enriching decision-making processes.
- *ACI7: Aggregation of knowledge:* This is the capacity of ACI systems to effectively incorporate mechanisms to aggregate information and insights from various sources. This can involve algorithms that synthesize input data to form a coherent understanding or solution.
- *ACI8: Adaptability:* ACI systems evolve by learning from past interactions, refining algorithms, and enhancing performance based on accumulated knowledge.
- *ACI9: Scalability:* This is the capability of ACI systems to scale effectively, accommodating increasing numbers of contributors without a proportional increase in complexity or degradation of performance.

VISION: SYNERGIES AND FUTURE CHALLENGES

This section explores the synergies between the properties of DTs and the properties of ACI, highlighting how their integration enhances the efficiency of an FDT, where the group of ADTs is able to achieve better results than a single DT. As we delve deeper into these synergies, we also address the challenges that arise from this fusion, including scalability, real-time response, decision-making, evolution, fault tolerance, and ethical implications. By understanding these synergies and challenges, we envision the future of these technologies and highlight their potential to transform sectors, such as smart cities, e-health care, or smart manufacturing.

Synergies Between DTs and ACI Properties

This section analyses the synergies between DTs and ACI by considering the properties of both approaches. Figure 2 summarizes the identified synergies and their relations to DT and ACI properties that are analyzed in the following.

S1: Composability of an ADT to Achieve FDTs

An ADT operates independently, equipped with its own intelligent models, decision-making capabilities, and local data storage. To achieve autonomy, each ADT must have three ACI properties: *communication* (ACI1), *collaboration* (ACI2), and *coordination* (ACI3) (see Figure 3). These properties enable ADTs to function autonomously while maintaining the ability to exchange information, collaborate on tasks, and coordinate actions when necessary, ensuring effective operation within their use case.

As was stated earlier, the *composability* (DT7) property refers to the ability to develop a composition of multiple DTs. However, ADTs allow it to go one step further. Now, ADTs can be integrated into an FDT that enables each ADT to function both autonomously and as part of a unified system (see Figure 3). In this federated structure, ADTs work together to achieve complex goals that would be unattainable independently.

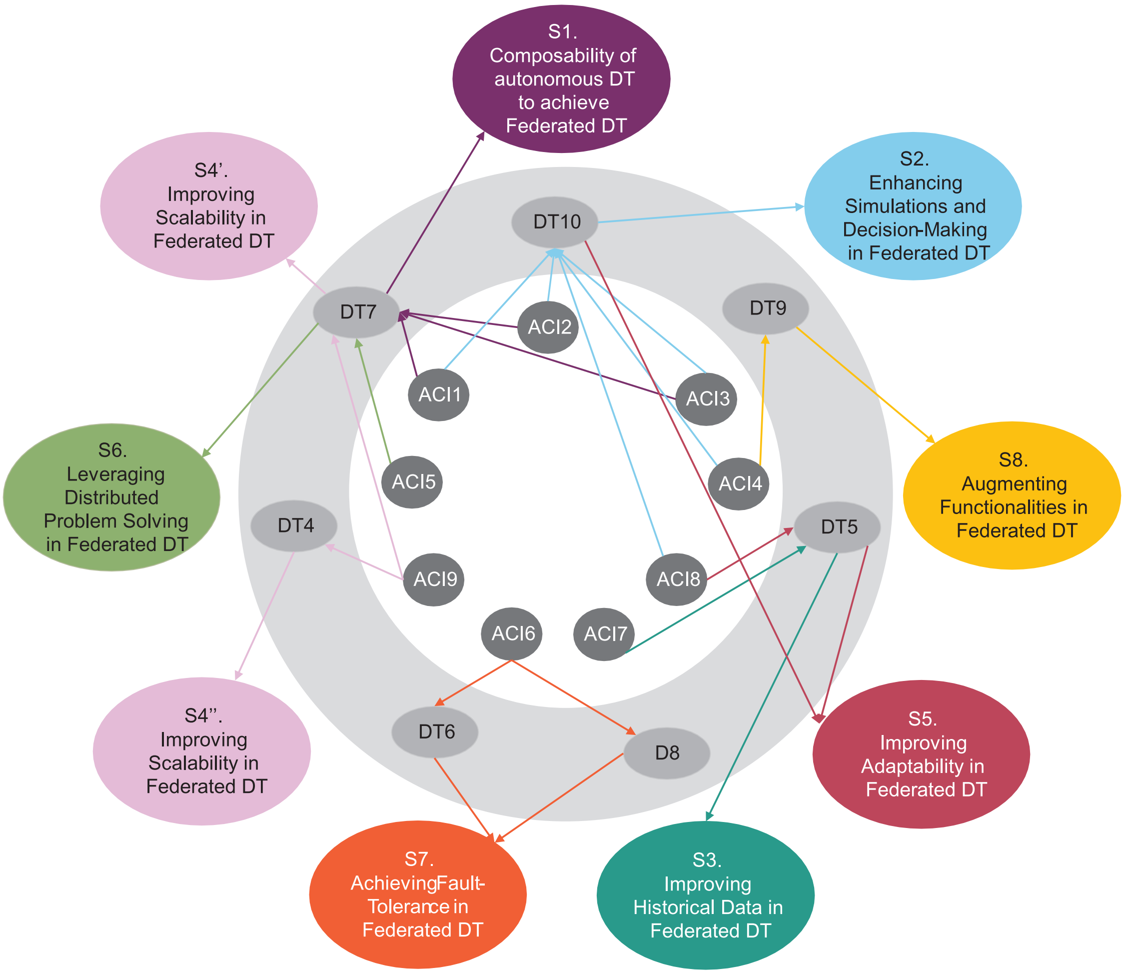

FIGURE 2. Summary of the synergies identified and their relations to DT and ACI properties.

For example, in the domain of smart cities, each urban infrastructure component—such as transport, energy, and security—can be each represented as an ADT. These ADTs can communicate, collaborate, and coordinate with each other, forming an FDT that optimizes the functioning of the entire city infrastructure.

S2: Enhancing Simulations and Decision-Making in FDTs

The *predictability* (DT10) property, when combined with *cognitive diversity* (ACI4), enables the FDT to improve predictions from two perspectives: 1) by combining multiple ADTs with different models, enabling more robust and precise predictions; and, 2) by leveraging different types of ADTs to obtain a global view of a larger system. Next, we detail both perspective in more detail.

On the one hand, in an FDT, *cognitive diversity* (ACI4) allows each ADT to use a different model, simulating the behavior of the PO under different conditions. ADTs collaborate to determine the future behavior of the PO, improving the accuracy and reliability of the simulations of the FDT. For example, in smart grid management, several ADTs could collaborate to simulate the future behavior of the power grid under different scenarios.

On the other hand, *cognitive diversity* (ACI4) enables each ADT to pursue its own business use case, while contributing to the FDT's goal. That is, each ADT leverages an intelligent model to make predictions with its specific information, which can be fused to better serve the common goal of the FDT. For example, in precision agriculture, an FDT could integrate analysis of factors, such as climate, fertilizer use, and soil conditions to improve decision-making.

S3: Improving Historical Data in FDTs

The *memorization* (DT5) property enables DTs to store relevant data from the present and past, providing a rich and detailed record of the PO. This capability can be improved with the *aggregate knowledge* (ACI7) property. Individual databases from multiple DTs are integrated into an FDT database. This shared repository leverages the historical data of each DT to enrich the overall dataset. In an FDT, historical data from different DTs contribute to improve the prediction accuracy of each ADT, enabling dynamic and autonomous responses to changing events.

For example, in a smart building, an FDT can be composed of different ADTs corresponding to the building's HVAC systems, occupancy patterns, and energy consumption. Historical data from each of these DTs can be aggregated to optimize

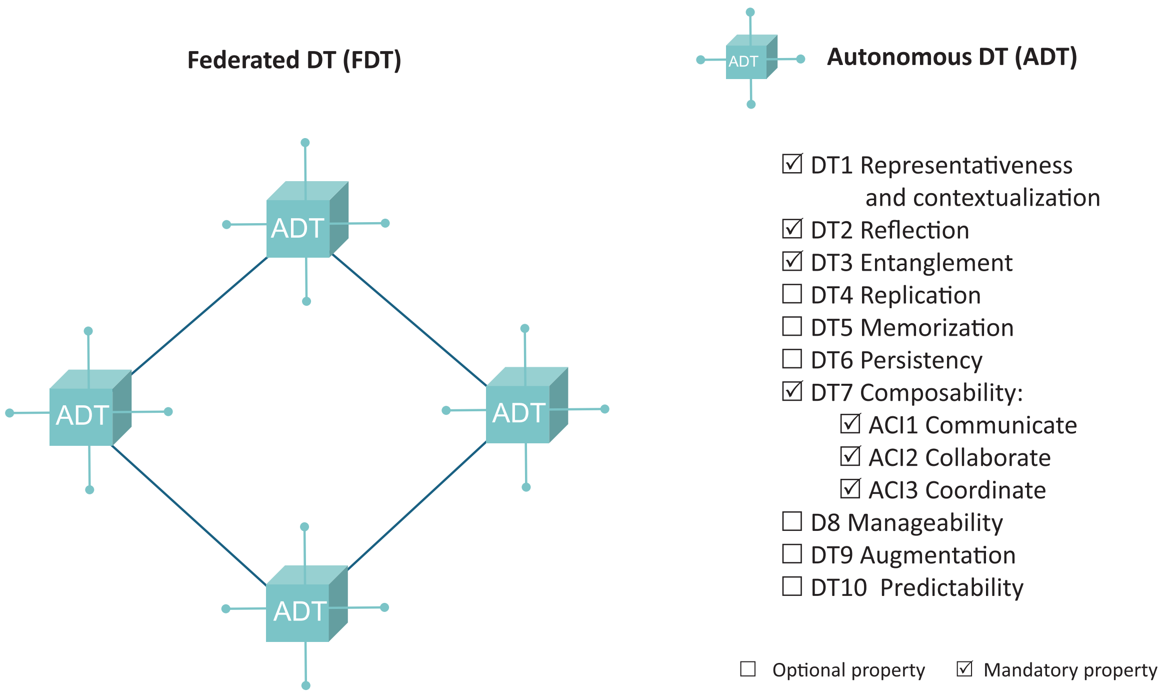

FIGURE 3. FDTs: ACI transforms DTs into ADTs.

energy consumption, predict maintenance needs, and improve comfort levels for occupants. By analyzing past performance data across these interconnected systems, each ADT can predict when an area of the building might require heating or cooling or detect anomalies in energy usage.

S4: Improving Scalability in FDTs

In an FDT, the architecture must be designed to scale, supporting the addition of more ADTs as the system grows. This is especially important in applications where new ADTs need to be continuously integrated as the FDT evolves. A scalable architecture enables the FDT to autonomously adapt to changing demands and optimize its behavior without human intervention. The *scalability* (ACI9) property can be achieved through the *composability* (DT7) property (see synergy S4′ in Figure 2) and also through the *replication* (DT4) property (see synergy S4″ in Figure 2).

First, composability ensures the modular addition of new ADTs without disrupting the FDT. Each newly added ADT can be seamlessly integrated into the FDT, enriching the overall system with new data and capabilities. For example, when a new building is constructed in the city, its corresponding ADT can be added to the FDT, contributing its data to improve the overall system overview and decision-making processes.

Second, replication involves duplicating certain DTs to cope with increased demand. By replicating an ADT, the FDT maintains its responsiveness and can handle higher data-processing loads without degrading its performance. For example, if an ADT managing traffic flow becomes a bottleneck due to increasing data volumes or complexity, multiple replicas of that ADT can be deployed in different nodes of the FDT.

S5: Improving Adaptability in FDTs

An FDT improves its *adaptability* (ACI8) through the properties *memorization* (DT5) and *predictability* (DT10). By leveraging the memorization, the FDT stores and recalls key past interactions and data, enabling the ADTs to recognize patterns and trends over time. This allows each ADT to adjust its models and responses based on all historical data, enhancing its ability to adapt to new conditions. Also, predictability enables each ADT to forecast potential outcomes by analyzing accumulated knowledge, anticipating future needs and behaviors. By combining these properties, the FDT can be more effective in responding to dynamic environments.

For example, in intelligent traffic management, an FDT can adjust traffic routes according to the real-time information received from ADTs managing individual traffic zones. As traffic patterns evolve throughout the day, an ADT can predict congestion points and reroute traffic accordingly, while also using historical patterns to optimize future decision-making. This adaptability ensures more efficient traffic flow and a better responsiveness to real-time events.

S6: Leveraging Distributed Problem Solving in FDTs

In an FDT, the *distributed problem-solving* (ACI5) property allows each ADT to focus on managing and solving specific parts of the FDT's challenges. This delegation of tasks enables the FDT to tackle complex problems by distributing responsibilities among its ADTs. The *composability* (DT7) property supports the distributed problem-solving, allowing each ADT to handle specific parts of the overall problem. This modular approach enables the system to be composed of smaller, specialized components that can independently solve subproblems.

For example, in a smart city FDT, different ADTs can manage separate aspects, such as traffic, energy distribution, and waste management. Each ADT focuses on optimizing its specific domain, while contributing to the overall efficiency of the city management.

S7: Achieving Fault-Tolerance in FDTs

The *decentralization* (ACI6) property supports the properties *persistency* (DT6) and *accountability/manageability* (DT8) within an FDT. In an open and decentralized environment, different ADTs operate independently, without relying on centralized control. If one of the ADTs fails, others can take over its responsibilities, ensuring the persistence of the system. This decentralized architecture of the FDT creates a resilient environment where at least one ADT is always available to maintain operations and provide self-healing capabilities to recover the PO when it fails.

For example, in health care, an FDT includes different ADTs for patient monitoring and equipment management. If a patient-monitoring DT fails, other ADTs, such as the equipment management DT, can temporarily take over the role of monitoring the patient's vital signs, so that care is not compromised. This decentralized structure ensures that even in the event of a failure, the system can continue to function with minimal disruption. In addition, other ADTs can assist to restore the patient monitoring DT by identifying the cause of the failure and initiating self-healing actions. This decentralized structure minimizes downtime, maintains system integrity, and preserves the quality of patient care.

S8: Augmenting Functionalities in FDTs

The *augmentation* (DT9) property is enhanced by the *cognitive diversity* (ACI4) property. In an FDT, multiple ADTs contribute specialized functionalities, which enrich the overall capabilities of the FDT.

For example, in smart manufacturing, an FDT can optimize factory operations by integrating ADTs specialized in production lines, inventory management, and energy efficiency. Each ADT brings diverse intelligent models designed to address different aspects of factory performance. Additionally, new functionalities, such as advanced analytics for predictive maintenance, can be added by incorporating new ADTs with different intelligent models, further enhancing the FDT capabilities.

Use Cases for ADT and FDT

The synergies between DT and ACI offer great potential in a wide diversity of application domains where the management of complex systems and data-driven decision-making are required. Some of them are:

- *Smart manufacturing:* In this domain, an FDT can be composed of ADTs representing various machines, production lines, and supply chains. The *composability* (DT7) property enables seamless integration of ADTs, ensuring that the different parts of the manufacturing system are managed and optimized in a collaborative way (S1). Additionally, the *distributed problem-solving* (ACI5) property allows each ADT within the FDT to specialize in optimizing specific production processes to achieve more efficient manufacturing (S6). Moreover, *scalability* (ACI9) is crucial, as new machines or production lines can be added to the FDT as the factory grows (S4).
- *Autonomous vehicles:* FDTs can be applied in autonomous vehicles to improve their *predictability* (DT10) (S2). *Collaboration* (ACI2) and *coordination* (ACI3) between vehicle ADTs, road infrastructure ADTs, and environmental conditions ADTs improves the predictability of the FDT, enabling more accurate forecasts of vehicle behavior in different scenarios. Additionally, the *persistency* (DT) property ensures the resilience of the FDT (S7). For instance, if the ADT managing the vehicle's navigation system fails, other ADTs can take over to maintain the autonomous vehicle operation. In addition, the *adaptability* (ACI8) of the FDT allows the autonomous vehicle to quickly adjust to changes in traffic patterns or weather conditions, improving vehicle efficiency and safety (S5).
- *Smart cities:* FDTs can enhance urban infrastructure by integrating various components, such as traffic systems and urban buildings. The *composability* (DT7) of these ADTs ensures effective *communication* (ACI1) and *coordination* (ACI3), optimizing the overall functionality of the city (S1). Also, the integration of historical data [*memorization* (DT5)] from each ADT in the FDT facilitates the *aggregation knowledge* (ACI7) from multiple data sources, which can be leveraged to improve urban planning (S3). *Scalability* (ACI9) is also essential for growing cities, where new buildings must be easily integrated into the FDT as the city evolves (S4).
- *Building smart management:* In this domain, FDTs represent various subsystems of a building, such as HVAC systems, lighting, and occupancy patterns. The *composability* (DT7) property enables the integration of these ADTs, ensuring that the different systems work in unison to optimize energy consumption, maintenance, and occupant comfort (S1). In addition, the integration of historical data [*memorization* (DT5)] provides valuable information for predictive maintenance [*predictability* (DT10)], helping to identify potential problems before they arise (S2, S3).
- *Smart grids:* FDTs of power generation sources, transformers, and distribution networks improve the efficiency and reliability of power systems. The *predictability* (DT10) property improves simulations by allowing ADTs to collaborate and predict future grid behavior under varying conditions (S2). Additionally, the integration of historical data [*memorization* (DT5)] from different ADTs allows for more accurate forecasts of demand and power generation, optimizing load balancing and maintenance schedules (S3). In addition, *distributed problem-solving* (ACI5) and *replication* (DT4) properties enable the specialization of ADTs in specific areas of the network, ensuring efficient system operation even under high demand (S6).
- *Health care:* In this domain, FDTs of patients, medical devices, and health-care infrastructures contribute to improved diagnosis and personalized treatment. *Collaboration* between ADTs improves simulation and decision making

[*predictability* (DT10)], enabling more accurate predictions of patient outcomes and treatment efficacy (S2). Also, the *persistency* (DT6) property ensures that if a failure occurs in one ADT (e.g. patient monitoring), other ADTs can temporarily take over critical functions, ensuring a continuum of care (S7). Finally, the *augmentation* (DT9) property also enables the integration of new diagnostic technologies into the FDT, extending its functionalities to support new health-care needs (S8).

- *Aerospace and aviation:* In the aerospace industry, FDTs of aircraft, airports, and air traffic systems are essential to optimize operations and ensure safety. The *predictability* (DT10) property enables more accurate forecasting of aircraft behavior and air traffic flow, which is crucial for scheduling and safety measures (S2). Additionally, the *scalability* (ACI9) of FDTs ensures that new aircraft can be introduced and integrated smoothly and without disruption (S4). Further, the *adaptability* (ACI8) of the FDT is also important, as it allows the system to respond dynamically to changes in air traffic and weather conditions, maintaining safe and efficient flight operations (S5).
- *Precision agriculture:* FDTs in agriculture integrate ADTs representing weather conditions, soil quality, crops, and farm equipment. These ADTs collaborate to enhance *predictability* (DT10) by optimizing irrigation, fertilization, and cropping schedules (S2). Additionally, the *memorization* (DT5) from various agricultural processes can be aggregated to improve yield predictions and resource management (S3). In addition, *distributed problem-solving* (ACI5) (S6) enables specialized management of different aspects of agriculture, such as pest control, soil quality, and water use, leading to more efficient farming practices.

CHALLENGES AND FUTURE RESEARCH DIRECTIONS

Analyzing the synergies between DT and ACI properties reveals different challenges and research lines that illustrate both the potential and success of combining the two approaches. Key issues involve composability, scalability, adaptability, fault tolerance, evolution, ethical implications, and data privacy. Below, we detail each challenge.

- *Scalability:* Ensuring scalability is a critical challenge in integrating DTs and ACI, especially in complex FDT involving numerous interconnected ADTs. As an FDT grows, the computational demands and coordination requirements increase, posing significant scalability issues. Scalability is crucial for environments like smart cities, where many ADTs must interact in real time, requiring efficient strategies to manage the complexity without a proportional increase in resource consumption. Future research should focus on developing *scalable architectures* to support FDTs, enabling the seamless integration of new ADTs without sacrificing performance. Exploring distributed and modular approaches will be key to achieving composability at scale.
- *Adaptability:* Many applications, such as intelligent traffic coordination or health-care monitoring, require real-time data exchange and adaptability to changing conditions. Ensuring that FDTs can respond accurately and in a timely manner under fluctuating conditions is a key challenge. Future research should focus on developing adaptive FDTs capable of adjusting to dynamic environments, while maintaining their overall performance.
- *Fault tolerance and resilience:* A fault-tolerance FDT requires mechanisms to maintain functionality even in the event of failures. Ensuring that multiple ADTs remain available and equipped with self-healing capabilities is essential for system recovery when a failure occurs. To achieve fault tolerance, it is crucial to effectively manage the ADTs and ensure that, in case of failure, others can seamlessly maintain the overall functionality of the FDT. Decentralization can be a key enabler of resilience but is not the sole factor in achieving fault tolerance. Additionally, each ADT must be equipped with self-healing mechanisms to automatically detect and fix issues as they arise. Future research should focus on exploring methods to enhance the self-healing and persistence of FDTs, ensuring long-term reliability and robustness in dynamic environments.
- *Decentralization:* A decentralized architecture of the FDT favors the composition of ADTs, ensuring that each one can contribute specialized knowledge and data. Decentralization plays a key role for enabling scalability in FDTs. ADTs are managed independently and can operate in parallel, resulting in a more dynamic and robust system architecture. Future research should focus on improving methods for autonomous composition of DTs, ensuring seamless interaction between different models and systems, while

maintaining the performance, scalability, and fault tolerance of the FDT.

- *Managing cognitive diversity:* The integration of multiple ADTs, each with its own model, enhances decision-making but also introduces complexity. Managing the cognitive diversity of models, ensuring effective communication, and avoiding conflicts are challenges that require advanced mechanisms for conflict resolution and knowledge aggregation. This is particularly relevant for systems like smart manufacturing, where multiple ADTs need to cooperate efficiently. Future research should focus on leveraging ACI's distributed problem-solving abilities to enhance the real-time decision-making capabilities of FDTs. Additionally, methods for effectively harness the cognitive diversity of different ADTs should be explored. By enhancing coordination and conflict-resolution mechanisms, FDTs can benefit from diverse perspectives while minimizing the drawbacks of conflicting approaches.
- *Evolution:* The evolution of both its constituents and the coalition should be considered from the very beginning. Any system is expected to evolve over time to remain useful for new and unexpected conditions, situations, events, or requirements. This implies that systems should learn from their environment and evolve their behavior by adapting their evolution rules and even discovering new evolution rules. Evolving is especially challenging in the context of ADTs, considering that they exploit heterogenous AI models that collaborate, cooperate, and coordinate to achieve the goals of both the FDT and the ADTs, enhancing their overall effectiveness and. Different future challenges should be addressed for facilitating such evolution: 1) Identify and evaluate those AI models amenable to be evolved through time; 2) manage cooperative and collaborative models efficiently as components of a coordinated FDT; 3) prevent the emergence of undesirable behaviors within the coalition of ADTs over time; and 4) evaluate the evolution of models establishing up-to-date metrics and frameworks. Addressing these four challenges will be crucial to support evolving autonomous and FDTs.
- *Data privacy and ethical implications:* Data privacy is particularly important in sectors such as health care, where sensitive information is processed. Developing FDTs requires sharing data among multiple ADTs, which raises concerns about data security and privacy preservation. Additionally, ethical issues, especially concerning human DTs (HDTs), involve determining the limits of autonomy and the boundaries of decision-making capabilities to prevent misuse or unintended consequences. Two critical aspects must be addressed. 1) *Privacy-preserving mechanisms for data sharing:* Robust privacy-preserving methods must be developed for handling sensitive data in FDTs. Techniques, such as encryption should be adapted to ensure data security while maintaining system efficiency. 2) *Ethical frameworks for HDTs:* establishing ethical guidelines for HDTs is crucial, especially regarding decision-making, autonomy, and privacy. Research should explore frameworks that define ethical boundaries, ensure user consent, and prevent harmful outcomes from unintended HDT behaviors.

CONCLUSION

This article explores the synergies between properties of DTs and ACI, analyzing how their combination can create powerful solutions to real-world challenges, while identifying key areas that require further research to fully harness their potential.

DTs and ACI are transformative technologies that, by leveraging their fundamental properties, can complement each other to unlock new capabilities in a wide range of applications, from smart cities to health care and manufacturing. The potential of FDTs go beyond the current state of the art, with significant challenges to be addressed in the next future, particularly regarding scalability, adaptability, composability, fault tolerance and self-management, ethical considerations and privacy preservation.

Nevertheless, the vision of fully integrated DT and ACI technologies is groundbreaking, promising smarter and more efficient solutions that can transform the way we manage and interact with complex systems, ultimately contributing to a smarter and more responsive future.

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