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FIRE: A Human-Centered Framework for Digital Twin Design

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ABSTRACT

The integration of human perspectives into digital twin (DT) design for sociotechnical systems (STS) is essential for addressing the complex relationship between social and technical elements. Despite advances in DT technology, its application to STS demands a human-centered approach that considers usability, user experience, and contextual factors. This work introduces ***FIRE*** (Framework for representing Intrinsic, Reflexive, and Extrinsic dimensions of a digital twin), a framework designed to guide the development of human-centered DTs. ***FIRE*** assesses DTs across three dimensions: Intrinsic (system autonomy), Extrinsic (contextual integration), and Reflexive (self-awareness and adaptability). As a design guide, ***FIRE*** ensures that human and social perspectives are integrated during the design. As a descriptive tool, ***FIRE*** provides valuable insights into existing DTs from the literature.

1 | Introduction

The rapid advancement of digital twin (DT) technology has enabled significant progress in various industries, from manufacturing to healthcare and smart cities [1]. However, applying DTs to sociotechnical systems (STS)—which involve complex interactions between social and technical elements—creates numerous challenges. Despite the increasing importance of human and social factors in such systems, current DT design often overlooks these dimensions, focusing on technological aspects. This gap can reduce the effectiveness, usability, and long-term sustainability of DTs in real-world settings.

This research focuses on integrating human and social factors into the development of DTs of STS. Traditional approaches often emphasize technological aspects while neglecting the crucial role of human-centered design, which is essential for ensuring that DTs of STS effectively address the social and contextual dynamics impacting system performance.

To bridge this gap, this paper begins by reviewing the existing body of knowledge on STS (Section 2.1) and DTs Section 2.3), tracing the evolution of STS and highlighting its key characteristics, which emphasize the interdependence of social and technical elements. It explores how DTs have been applied to manage complex systems like STS and investigates human interactions with DTs, reinforcing the importance of human-centered design principles in DT development (Section 2.4). The core of the paper is the introduction of the ***FIRE*** framework, which serves as a tool for designing and evaluating DTs in sociotechnical contexts. This framework is explained through its three dimensions: the Intrinsic dimension, which focuses on the autonomy of DTs (Section 3.2), the Extrinsic dimension, which addresses their integration within broader operational environments (Section 3.3), and the Reflexive dimension, which introduces the concept of introspection and self-awareness in DTs (Section 3.4). ***FIRE*** not only aids in analyzing and evaluating DT of STS development but also ensures that social and human elements are consistently considered throughout the design process. It acts as a sense-making model and a reminder that these factors are vital for creating DTs of STS that are effective, adaptive, and sustainable. Finally, the paper explores the practical applications of ***FIRE***, first demonstrating its use as a guiding tool for developing new DTs with varying levels of autonomy and integration (Section 4.1), and then applying it as a descriptive tool to analyze existing DT implementations across different fields, offering insights into current practices and areas for improvement (Section 4.2).

2 | Related Work

The STS paradigm is often a synonym for complexity when considering modeling, designing, or operating such a system. The DT can be considered as the perfect tool to assist in these tasks, but the development of this kind of tool is also complex. In particular, the interactions of human agents with DTs are central to these complex design activities. In this section, the evolution of the STS concept, the role of DTs in representing these complex systems, and the integration of humans within DTs are explored through a literature review. The objective is to develop a clearer understanding of the specificity and requirements that must be considered when integrating these concepts in the design of the DT of an STS.

2.1 | Sociotechnical System

The concept of an STS, originally introduced by the Tavistock Institute in the 1950s [2], aims at defining the relationships between people (social systems) and technology (technical systems) within an organizational or societal context. The primary definitions and understandings of STS have evolved gradually, reflecting a shift in focus from manufacturing contexts to broader organizational and societal applications. The first conceptualizations of STS emerged in response to the need for integrating the social and technical aspects of systems, particularly in manufacturing settings. The term was used to describe situations where the needs of technology and local communities had to be reconciled. This approach contrasted with Taylorism's reductionist methods, promoting the consideration of social and technical systems as distinct yet interdependent entities [3]. This interdisciplinary approach highlights the importance of considering both the social and technical elements of a system in an integrated manner, rather than in isolation.

These concepts were then generalized to articulate sociotechnical principles aimed at guiding the design of new systems, particularly those requiring the integration of new technologies and/or new management methods. Thus, these principles, formulated by Cherns [4] and expanded upon by Clegg [5], emphasize an integrated perspective, suggesting that effective design requires attention to systemic, content, and process aspects of systems. Such principles are intended to inform the work of managers, users, designers, technologists, and social scientists alike, making them foundational for developing and discussing detailed design practices.

More recent works define STS as a singular, holistic system [3] rather than distinct social and technical systems. This perspective emphasizes the integration of human and technological elements, with human components contributing strategic and analytical dimensions to the system's technological aspects [6]. In this approach, social systems are not seen as subordinate to technical systems but as guiding the overall system. The sustainability dimension [7] is further integrated by considering environmental impact, ethics, and social factors central to system performance. This approach requires analyzing systems as sets of engineered artifacts that are socially embedded and economically linked and highlights the need for sustainable and inclusive innovation within the design and operation of these systems.

A thorough understanding of STS necessitates acknowledging its characteristics, which emphasize the relationships between social and technical components within organizational and technological frameworks [6]. These systems operate on the principle of interdependence, recognizing that social systems, encompassing individuals, culture, and organizational structures, are linked with technical systems, comprising machinery, technology, and processes, for effective operation [3]. Thus, optimizing both social and technical elements is recommended to achieve optimal performance, emphasizing the importance of joint optimization rather than favoring one aspect over the other [5].

Moreover, it is imperative, when designing for STS, to be adaptable and flexible, enabling them to respond effectively to dynamic environments and ensuring their long-term relevance [5]. Integrating principles of human-centered design is essential, as it enhances well-being and cultivates supportive work environments [8]. Active engagement of stakeholders is needed for promoting ownership and incorporating diverse perspectives in system management [9, 10]. Additionally, as mentioned earlier, awareness of environmental and societal impacts is key to achieving sustainability and long-term viability [7]. Collectively, these findings highlight the significance of integrating human perspectives into the design process of supporting tools for STS.

2.2 | Digital Twin of Sociotechnical System

As previously mentioned, the STS concept has applications across a broad range of domains. The notion of complexity, applied to such systems, is characterized by significant variability in their constituent elements, difficulty in decomposition and defining interactions among elements, and decentralized decision-making, rendering their behavior unpredictable and uncertain [11, 12]. Therefore, developing a tool to depict and manage such systems demands a widespread approach, which can be particularly difficult to attain. This challenge arises primarily from the diverse array of activities conducted within or facilitated by STS, as well as the numerous parameters that must be considered.

The DT is widely acknowledged as a powerful tool for managing complex systems [13]. Initially conceptualized by NASA as "*a probabilistic, multi-physics, multi-scale integrated simulation of a vehicle or system as it has been built, using the best available structural models, updated sensors to reflect the life of its corresponding flying twin*" [14], the definition of DT has since evolved into a more encompassing description. It can now be understood as "*a dynamic representation of a physical system using interconnected data, models, and processes to enable access to knowledge of past,* *present, and future states for managing actions on this system*" [15]. This broader definition is significant as it avoids restricting the role of DT solely to system simulation. It highlights its utility in facilitating human situation awareness, as highlighted by the authors.

Jones et al. [16] further elaborate on the DT concept by identifying 13 key characteristics, including physical and virtual twins, their environments, connections, and processes. This characterization, combined with the components identified by Camara Dit Pinto et al. [15], serves as a valuable framework for positioning and clarifying the requirements in DT design.

Moreover, Kritzinger et al. [17] have identified various levels of data integration necessary for achieving a dynamic and real-time DT. They emphasize the importance of automating data flows between digital and physical twins to ensure flawless operation and effectiveness. In addition, D'Amico et al. [18] have introduced the concept of the "*Cognitive Digital Twin*", which represents an evolution of the traditional DT paradigm by integrating cognitive capabilities such as learning, reasoning, and semantic understanding, enabled by artificial intelligence (AI) and machine learning. The primary objective is to augment DT functionalities with advanced data analysis, predictive behavior, and adaptation with minimal human intervention. However, this shift toward automated decision-making faces significant limitations due to technical constraints, particularly computational limitations, and the acceptance by human stakeholders within the DT ecosystem. This last element is critical in STS context where, as stated above, human perspectives need to be considered.

The literature on DTs in the context of STS reveals a growing interest in integrated approaches that consider both social and technical dimensions. The notion of "*Sociotechnical Digital Twin*" have been defined in [19] as "*a system-of-systems that can include a learning component which is characterized by a relationship between a real world system and its partial virtual representation, whose fidelity, rate of manual synchronization, and choice of enabling technologies are tailored to theory exploration and explanation and will include a mix of modeling approaches including agent based simulation*." From this definition, the author explores the evolution of DTs from manufacturing to sociotechnical domains to identify challenges [19]. The main concerns highlighted by this study were related to social feasibility (acceptance, rights, and needs of Humans, privacy, security, transparency, trust…) and technical feasibility (mainly concerning multidisciplinary requirements and complexity of the STS). Moreover, it emphasizes the need to avoid "black box" approaches when designing these "*Sociotechnical Digital Twins*".

Other perspectives focus on the importance of characterizing the sociotechnical context and intended transformation for the success of digital transformation efforts. Thus, in (Cardoso et al. [20]), the authors propose an enterprise-level STS approach centered on DTs and model-based methods to accelerate the STS redesign cycle. A framework [21] is used to assist an organization in formulating a strategic methodology to integrate DTs effectively. They argue that incorporating a DT into the design and implementation of STS offers an enhanced opportunity to realize organizational advantages, such as achieving business performance objectives and enhancing product life-cycle management. Moreover, they suggest that this approach also extends to broader societal benefits, including advancements in social and environmental sustainability attributable to DT technology.

The integration of DT within a sociotechnical framework is also a pertinent tool to assist organizations in their digital transformation. By employing DTs of their organization as a strategic tool, enterprises can better visualize and understand the complex phenomena between their technological infrastructure and organizational dynamics, thus enabling more effective and efficient transformations [22].

2.3 | Human Interactions With Digital Twin

Studying complex systems and DTs reveals the important and diverse role that human agents play. At the core of these interactions lies the ability of human agents to integrate with DTs, thereby enhancing real-time monitoring, evaluation, and decision-making processes regardless of proximity. For instance, in healthcare, this integration facilitates the management of severe traumas, offering nearly real-time evaluations that significantly augment the responsiveness and effectiveness of medical interventions [23]. Moreover, this proposal by Croatti et al. [23], like several other DT propositions [24–26], demonstrates the value of multi-agent system (MAS) approaches for modeling and simulating human agents, technological agents, and their interactions within a single methodological framework.

The utilization of DTs in production systems highlights another aspect of human interaction within complex systems. Human agents leverage DTs to enhance system flexibility, adaptability, and resilience. By providing standardized descriptions of relevant information, MAS-based DTs can be key tools for considering individual agents, improving production efficiency, and reducing disruptions [26]. Similarly, in precise farming, human agents engage with cyber-physical systems through the use of DTs of plants. This engagement necessitates complex decision-making based on incomplete knowledge concerning plant growth factors and environmental conditions, highlighting the adaptability and managerial awareness of human agents in navigating these complexities [24].

Moreover, the concept of Human Digital Twins (HDTs) draws attention to the necessity for consistent human-agent interaction within intelligent environments. HDTs are engineered to manage this interaction by learning from and adapting to human interaction patterns, ensuring effective collaboration between humans and agents [27].

Building on this perspective, recent contributions have proposed structured approaches to guide the design of HDTs. The authors of [28] describe a general architecture composed of three core components: the real-world human, the digital model, and a data exchange system. Their work emphasizes the importance of modeling multiple human dimensions—such as physical, cognitive, and behavioral traits—and integrating feedback loops to support adaptation. In parallel, [29] introduces ETHICA, a five-phase design methodology that includes requirement analysis, architecture design, model development, system integration, and deployment. ETHICA places particular emphasis on user

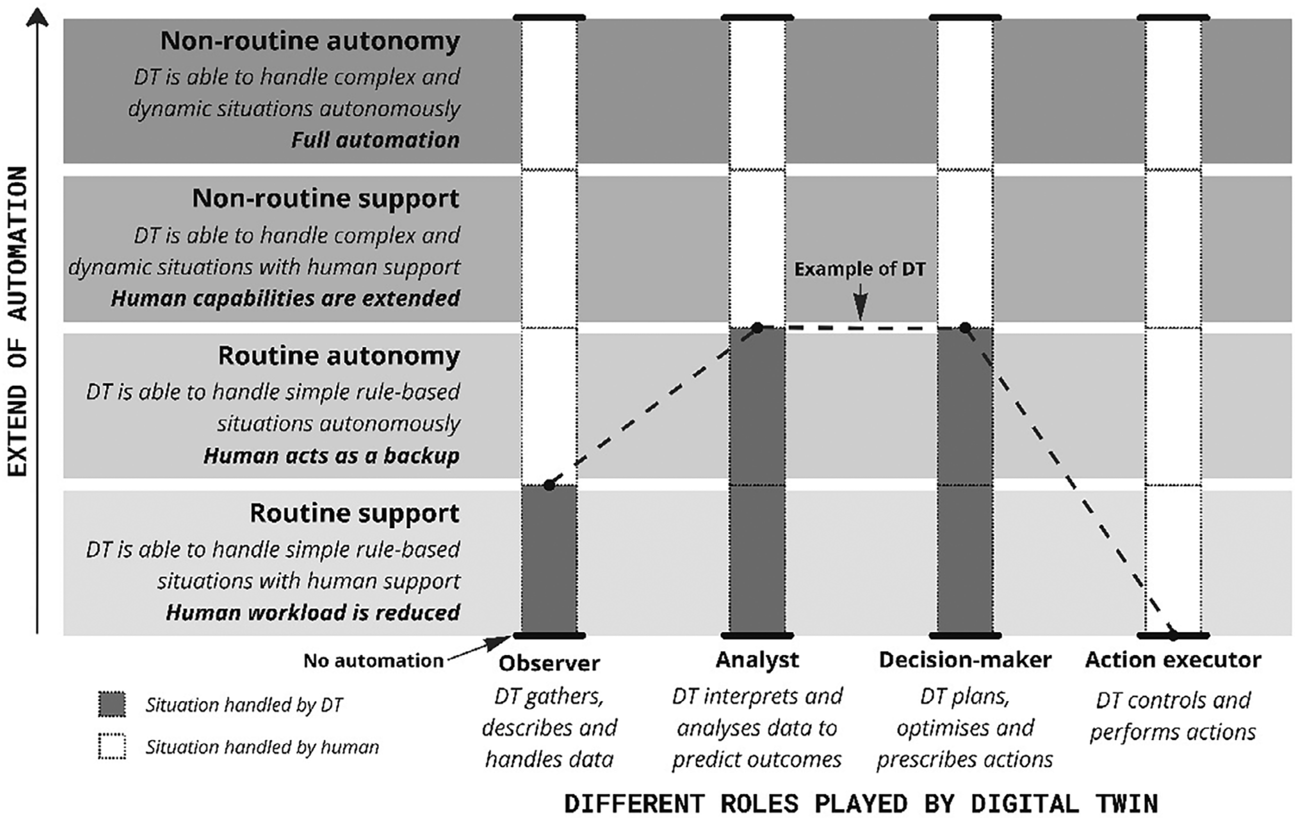

FIGURE 1 | LoDT framework inspired by [30].

involvement, ethical considerations, and iterative development. Together, these approaches highlight the need to combine technical modeling with human-centered and ethical design principles when developing HDTs.

This focus on structured design processes is complemented by work that addresses the strategic integration of DTs into broader organizational systems. In their work, Agrawal et al. [30] address the integration of DT technology and humans within work systems. They propose a conceptual framework named Levels of Digital Twin (LoDT), categorizing the roles DTs can play and the extent to which these roles can be automated. This framework aims to help practitioners systematically plan DT deployments, communicate goals and deliverables, and establish a strategic vision for DT implementation.

The framework (Figure 1) identifies four broad roles that DTs can assume within a work system:

- **Observer**: DTs gather, process, and present data from the physical environment, comparable to sensing and perceiving the status and dynamics of elements in the environment.
- **Analyst**: DTs synthesize and interpret data, considering specific goals, understanding what is desirable or necessary based on the collected data.
- **Decision Maker**: DTs evaluate options and make decisions based on analyzed information, planning actions to maximize desired outcomes.
- **Action Executor**: DTs execute actions based on decisions made, interacting with the physical environment to achieve specific goals.

The extent of automation for each role is divided into five levels, ranging from completely manual (no automation) to fully automated:

- **Manual**: All tasks are performed by humans without DT support.
- **Routine Support**: DTs assist humans in performing routine tasks based on explicitly programmed rules, while humans retain full control.
- **Routine Autonomy**: DTs autonomously complete routine tasks without human supervision.
- **Non-routine Support**: DTs assist humans in handling non-routine tasks, requiring DTs to learn and adapt to dynamic environments.
- **Non-routine Autonomy (Full Automation)**: DTs independently perform tasks in non-routine situations, adapting and improving performance over time based on learning and past experiences.

This structured approach to understanding and planning the integration of DTs and humans in work systems addresses the implementation of DTs in practice. It highlights the need for a clear understanding of the roles that can be played by DTs and the extent of their automation to avoid misallocations of resources, unrealistic expectations, and strategic misalignments.

2.4 | Synthesis

Designing a DT for an STS requires an approach that integrates humans, organizational structures, and technical systems. This integration ensures a thorough representation of the complex interaction between social and technical components within the system. To achieve this, techniques from human-centered design are necessary, emphasizing the prioritization of human needs, behaviors, and experiences in the design process.

Moreover, considering and modeling the context [31] in which the STS operates is essential for developing an accurate and effective DT. This contextual understanding enables the DT to capture the subtleties of the environment, stakeholders, and interactions that influence the behavior and performance of STS.

Additionally, employing multi-agent modeling and simulation techniques is valuable for creating dynamic and realistic representations of STS. By modeling the diverse agents and their interactions within the system, DTs can simulate various scenarios and predict potential outcomes, assisting in decision-making and system optimization.

The examination of human roles within complex systems and their representation within DTs reveals a dynamic interaction between human decision-making, behavioral adaptation, and technological integration. This interaction significantly contributes to the development of resilient and adaptable systems. Through this scientific literature, it becomes evident that human agents play a central role in the dynamics and evolution of complex systems, necessitating a holistic and integrated approach to their study and representation within DTs. Integrating human elements into the modeling processes of DTs not only enhances the precision and effectiveness of these systems but also presents opportunities for innovative strategies to navigate and manage the inherent complexities of DT of STS.

3 | The FIRE Framework

The purpose of this research is to propose a sense-making framework for designers of DT for STS. The need for a human-centered and even social-centered approach in developing such a tool has been demonstrated in previous sections. The methodology used to design this framework is based on the principles of systems engineering, particularly Human-System Integration [32]. This vision is based on the concept of System-of-Systems (SoS), which views a system as an agent, whether human or machine, and an agent (or agency) can itself be composed of agents (subsystems) that perform functions necessary for the proper functioning of the system. This recursive view, based on the work of Minsky [33] and the multi-agent approaches that followed [34], is ideal for the multidisciplinary design of complex systems like STS [35]. Thus, an STS (yellow rectangle in Figure 2) can be seen as a collection of agents (human or machine, physical or digital) grouped into agencies. The DT (green rectangle in Figure 2) of such a system is itself an SoS, including agents that represent all or part of the STS. Finally, the information flows between the physical and digital twins are also represented in Figure 2, whether they are automatic (solid red arrows) or manual (dashed red arrows), using the levels of data integration proposed in [17].

This representation was proposed by the authors of [25]. In this work, the authors highlight that such a DT allows for the addition of internal information flows within the DT, that are either non-existent or invisible (green lines in Figure 2), to improve the STS. Finally, this representation is complemented by the digital model of the physical process carried out by the STS to illustrate the ability to drive the STS thanks to DT capabilities.

If the STS embeds a DT as part of its components, for example, consider a manufacturing plant (the STS) where a robotic arm is already implemented as a DT, with its own internal models for movement, task planning, etc. Now, imagine creating a DT for the entire plant. This plant-level DT would need to integrate the robotic arm's DT data to optimize workflow, predict maintenance needs, and understand how the arm interacts with other systems and human worker. When an element within the STS is already a DT, it introduces a "model within a model" situation. The DT of the full STS must represent the DT of the robot or be the same element (Figure 3). In general DT of STS must be reflexive, in the sense that they have the capability to observe themselves. In the rest of the article, DT will refer to the DT of an STS.

The following section introduces a framework for understanding and describing DT of an STS. The proposed framework provides a structured approach to evaluate DTs by focusing on three dimensions: intrinsic, extrinsic, reflexive. This approach aims to offer a clearer understanding of how DTs are designed and how they function within complex systems.

3.1 | General View

This section elaborates on a "sense-making" framework of the conceptualization and description of DTs of STS. Unlike conventional approaches that might focus solely on the technological or social facets of these systems, this framework emphasizes a nuanced understanding of how these DT are envisioned, described and documented, especially during the design phase. To systematically categorize these systems descriptions, a naming convention that integrates three dimensions is proposed.

The aim is to propose a framework for characterizing the complexity of DT, focusing particularly on the human and social dimensions considered within these systems. This framework serves as a "sense-making model," enabling a high-level understanding the sociotechnical complexities inherent in a system and the descriptions employed during its design to understand its evolution. The proposed framework comprises three dimensions: intrinsic (autonomy), extrinsic (integration), and reflexive (introspection) and is named ***FIRE*** (Framework for representing Intrinsic, Reflexive, and Extrinsic dimensions of DT). These dimensions (Figure 4) are:

- The **Intrinsic dimension** relates to the system's autonomy. This dimension is interesting because it questions whether

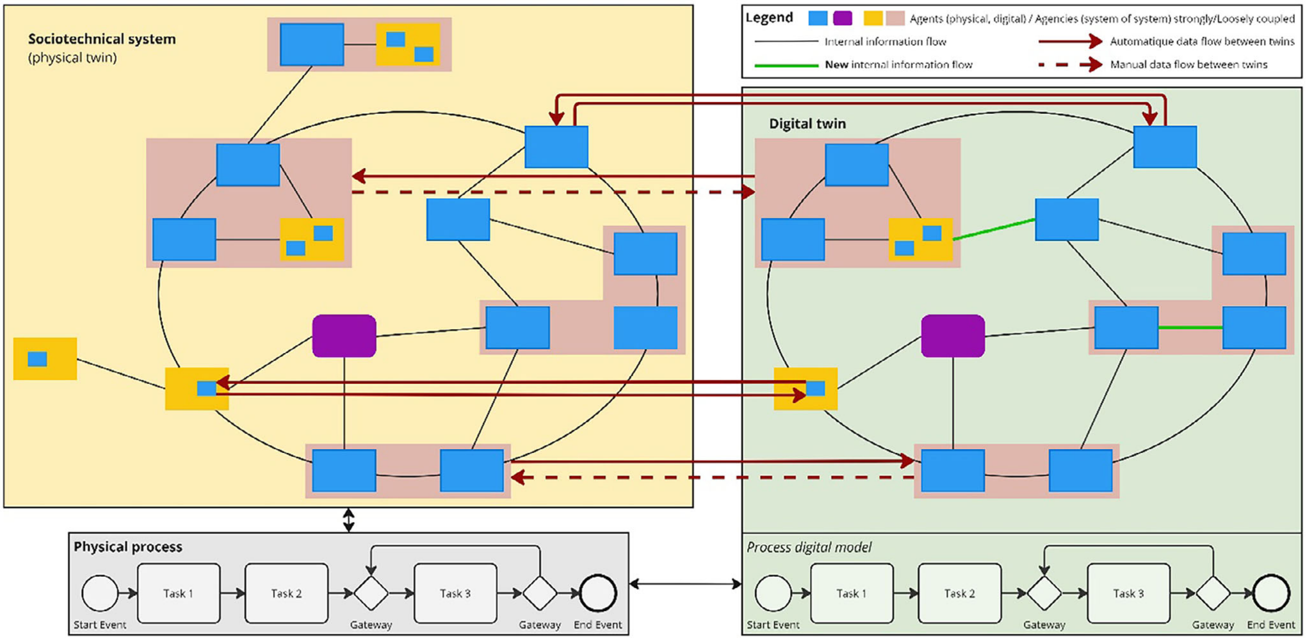

FIGURE 2 | System-of-Systems representation of an STS and its DT, extended from [25].

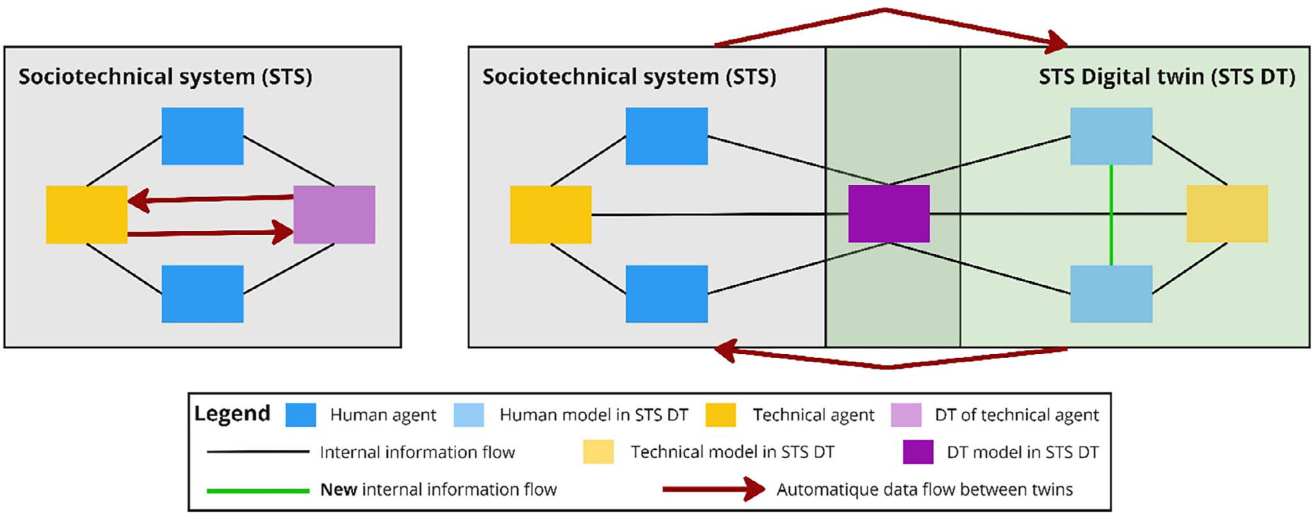

FIGURE 3 | Illustration of the “model within the model” concept.

the system is an autonomous agent within a society or only a component. In the design of complex systems, this dimension examines if the system is as complex as a human or just a cog in the machine.

- The **Extrinsic dimension** highlights the extent to which the technical system is designed to integrate into a social system. It ranges from purely technical systems to human-machine interfaces (HMI) to STS.
- The **Reflexive dimension** measures how much the system contains models of itself and the complexity of these models.

By systematically analyzing these dimensions, the aim is to provide an understanding of the complexity inherent in DTs.

3.2 | Intrinsic Dimension

The first aspect this framework aims to represent is the complexity of the System of Interest from a functional standpoint, with a focus on autonomy. Autonomy is important for understanding the level of integration between an STS and its human counterparts. A system without autonomy typically functions as a tool for human operators, while a fully autonomous system requires a deeper understanding of its integration within a social context. The significance of autonomy lies in its impact on the system's interaction with human users and its ability to operate independently. As STS (and their DTs) evolve from basic functions to fully autonomous entities capable of error handling and decision-making, the complexity of their autonomy increases. This evolution involves not only an increase in functions but

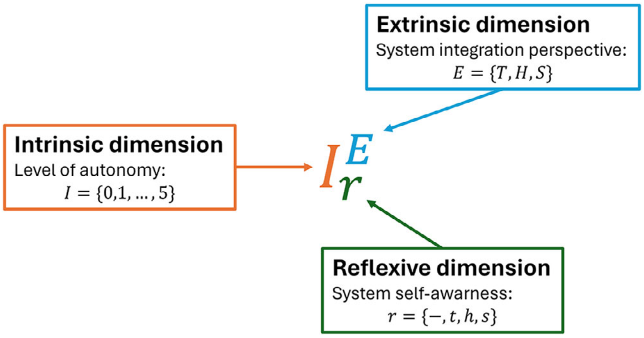

FIGURE 4 | Dimensions of the proposed framework.

also a transformation in how these systems interact with their environment and users.

Autonomy is a key factor in assessing the functional complexity of DTs, highlighting the relationship between technological sophistication and social integration. Initially, such a system may be designed to perform a straightforward function with minimal complexity, characterized by clear inputs and outputs. However, as the need for more advanced functionalities grows, these systems evolve to include multiple, interdependent functions, significantly increasing their complexity. These interdependencies require precise coordination and integration, ensuring that the performance of one function really influences others, often involving complex algorithms and control mechanisms.

As systems progress towards autonomy, they acquire capabilities for error detection, decision-making, and recovery from unforeseen circumstances without human intervention. This evolution involves both a quantitative increase in functions and a qualitative transformation in how these systems interact with their environment and users, manage uncertainties, and maintain operations under varying conditions. Achieving full autonomy represents the highest level of intrinsic functional complexity, where systems must navigate and adapt to various operational scenarios, maintain safety and efficiency, and autonomously rectify errors, while ensuring integration of multiple functions.

This progression highlights the relationship between technological sophistication and functional complexity, presenting a challenge for designers to balance innovation with reliability, adaptability, and user-centric considerations.

In [36], the authors present a detailed model outlining ten levels of automation. The model ranges from complete human control, where the human must take all decisions and actions, to full automation, where the computer makes all decisions and acts autonomously without human input. The intermediate levels include varying degrees of shared control, where the system can offer alternatives, execute decisions with human approval, or act autonomously while informing or not informing the human operator. The autonomy is done along 4-stage model of human processing: (1) information acquisition; (2) information analysis; (3) decision and action selection; (4) action implementation.

Similarly, in [37], the authors provide a taxonomy specifically for driving automation, identifying six levels from no automation to full automation. At the lowest level, the driver performs all tasks. The model starts with the human performing all driving tasks (Level 0). As automation increases, the system takes over specific driving tasks (Levels 1 and 2), then all routine driving tasks under supervision (Level 3), without supervision under specific conditions (Level 4), and finally all driving tasks including fallback operations under all conditions (Level 5). This progression mirrors Parasuraman's levels [36] but is tailored to the context of vehicle automation.

Endsley and Kaber [38] explore the impact of different levels of automation on performance, situation awareness, and workload in dynamic control tasks. This framework also includes ten levels, from manual control to full automation. The model highlights how automation can improve performance under normal conditions but may hinder performance recovery if the automation fails, indicating the importance of designing for both normal and exceptional circumstances.

As mentioned earlier, in [30], the authors propose a two-dimensional framework, the Levels of Digital Twin (LoDT) framework, which includes automation characterization. The five levels of automation they proposed range from no automation, where humans perform tasks without DT support, to non-routine autonomy, where DTs can autonomously handle dynamic situations through learning and adaptation without human involvement.

Based on the existing levels of autonomy frameworks described above, a simplified six-level scale of autonomy for STS, particularly focusing on DTs, is proposed. This scale ranges from no autonomy to full autonomy, capturing key stages of autonomy development.

- **Level 0: No Autonomy**: The system provides no assistance. Humans make all decisions and actions independently without any support from the system. For example, a DT that only serves as a static reference model without any interactive functions.
- **Level 1 – Independent Functions**: The system automates specific, isolated functions that operate independently. The human manages the overall process, integrating outputs from these functions manually. For example, a DT that monitors temperature but does not interact with other system components.
- **Level 2 – Interdependent Functions**: The system includes multiple automated functions that interact and depend on each other, coordinating their actions to achieve more complex tasks. Human supervision is required to oversee the integration and intervene when necessary. For example, a DT that integrates temperature monitoring with humidity control requires human oversight.
- **Level 3 – Routine Autonomy**: The system can autonomously handle routine tasks without human supervision. These tasks are predictable and repetitive, allowing the system to operate independently under normal conditions. For example, a DT that autonomously manages routine maintenance schedules based on predefined rules.
- **Level 4 – Non-Routine Support**: The system can assist humans in handling non-routine, dynamic situations that

require adaptation and learning. It suggests actions or executes tasks with human oversight, helping to manage unexpected scenarios. For example, a DT that supports operators in diagnosing and responding to unexpected equipment failures.

- **Level 5 – Fully Autonomous**: The system operates independently in all conditions, managing both routine and non-routine tasks without human intervention. It adapts to new situations, learns from experiences, and makes autonomous decisions to maintain optimal performance. For example, a DT that autonomously optimizes an entire production process, adapting to changing conditions and making decisions without human input.

3.3 | Extrinsic Dimension

The extrinsic dimension of DTs captures how these systems, along with their functionalities, are perceived and contextualized within broader situations, moving beyond isolated technical perspectives to embrace more integrated views. This dimension focuses on understanding the multifaceted interactions and impacts of these systems within their operational environments.

- **Technical (T)**: At the core, the technical perspective prioritizes the engineering and operational aspects of the system. It focuses on the system's architecture, components, and functionalities from a purely technical standpoint, without any human or social considerations. This view is essential for ensuring that the system meets specified performance criteria, reliability, and efficiency [39]. However, it represents just the starting point of understanding such a system, as it ignores the roles of users and the societal context in which these systems operate.
- **Human (H)**: Transitioning to a more user-centered perspective, this facet emphasizes understanding the system from the standpoint of its users. It incorporates psychological and ergonomic considerations [40, 41], recognizing that the design and functionality of DT need to align with human capabilities, limitations, and needs. This approach necessitates considering user experience (UX) design, human-computer interaction (HCI) [42], and the psychological impact of technology on users. By focusing on the human aspect, it aims to make systems more accessible, intuitive, and supportive of user well-being, thereby enhancing the effectiveness and acceptance of technology.
- **Social (S)**: The social perspective broadens the scope further to consider the system within the context of society and organizational structures [41]. It explores how DT integrates with and impacts social groups, work processes, and societal norms. This view is critical for understanding the broader implications of technology deployment, including issues of social equity, digital divide, organizational change, and cultural adaptation. It highlights the importance of interoperability between different systems and social cohesion, emphasizing that technological solutions should foster positive social outcomes, facilitate communication, and support collaborative work environments.

By transitioning through these perspectives, the extrinsic dimension elucidates a view of STS that encompasses not only their technical makeup but also their usability, accessibility, and social integration. It highlights the necessity of designing and evaluating these systems with an eye towards holistic integration into human lives and societal structures, ensuring that technological advancements contribute positively to individual experiences and societal progress. This holistic approach is vital for developing systems that are not only technically proficient but also socially responsible and aligned with human values.

3.4 | Reflexive Dimension

The reflexive dimension of the framework examines the self-awareness of these systems, especially in how they perceive and react to external complexity. This is important for distinguishing the System of Interest from the World of Interest, where DTs play a key role. DTs replicate physical systems to enable simulation, prediction, and responsive actions through sensor data and internal modeling, representing the start of a deeper reflexive capability. This need is highlighted by Hetherton et al. [43], who discuss the importance of self-awareness in DTs, focusing on the higher-order challenges that arise during the operationalization of DTs. This work emphasizes the criticality of self-awareness for practical applications of DTs in real-world settings.

DTs can model and understand both their operational parameters and the humans and social structures they interact with. This change from being passive to active, self-aware entities allows DTs to adjust to their operational context proactively. By using advanced simulation models, DTs can perform predictive maintenance, optimization, and strategic adaptation, improving their functionality and integration within human and social frameworks. By including models of human behavior and social dynamics, DTs can anticipate user needs, customize interactions for safety and efficiency, and foresee the societal impacts of their deployment. This shift towards self-modeling capabilities marks an important phase in the development of DTs, giving them the ability to evolve, learn, and potentially make autonomous decisions. These capabilities suggest a future where DTs are not only technically proficient but also aware of the complex interactions between technology, humanity, and societal needs, aiming to bridge the gap between mechanical systems and the human-social ecosystem.

The four facets of the reflexive dimension are:

- **Absent (-)**: The DT is not self-aware and lacks a model of its internal functioning. This facet is not particularly relevant for systems composed of human agents, as individual agents may have self-awareness, but there is no model of the overall system. In practice, most complex STS will exhibit some level of self-awareness; this level is mainly applicable to purely technical systems without any form of self-reflective capability.
- **Technical (t)**: The DT has a model of its technical components, enabling it to understand and manage its physical and operational elements. This includes awareness of hardware, software, and their interactions, such as a PID controller

managing a process. This facet allows the system to perform tasks like predictive maintenance and optimization of its technical functions.

- **Human (h)**: The DT is aware of its human aspects, incorporating user models that reflect the behaviors, preferences, and interactions of its users. This level of self-awareness allows the system to tailor interactions for improved usability, safety, and efficiency, enhancing the user experience by anticipating and meeting user needs.
- **Social (s)**: The DTs understands its social context, including interactions between agents and its integration within its World of Interest. This facet involves awareness of social dynamics, organizational roles, and the broader societal impact of the system deployment. It enables the system to anticipate and respond to social implications, improving integration and cooperation within its operational environment.

3.5 | Additional Insights

The framework originates from systems engineering and human-systems integration perspectives, which promote integrative approaches that go beyond purely technical aspects and support the joint consideration of technical, human, and societal dimensions. In this context, each higher level of the framework inherently includes the aspects of the lower levels. Therefore, when a system represents social aspects, it also encompasses human and technical aspects. This hierarchical structure means that an DT cannot solely represent social aspects without also including technical components. However, this systems engineering-centric view may differ from approaches in fields such as Ergonomics, Sociology, and Politics, where the integration and prioritization of these aspects might not follow the same order.

This framework helps designers to clearly articulate, understand, and ensure the human-centered and social-centered aspects of their design approach. By breaking down the system into intrinsic, extrinsic, and reflexive dimensions, designers can systematically analyze how a DT of an STS functions not only from a technical perspective but also in terms of its interactions with users and society.

The intrinsic dimension, focusing on autonomy, allows designers to assess how independent the system is and how it interacts with human users. Understanding this helps ensure that the system is designed with user needs and capabilities in mind, making it more accessible and usable.

The extrinsic dimension expands this view by considering how the system fits into a broader social context. It encourages designers to think about how the system integrates with human activities and social structures. This perspective helps designers create systems that are not only technically sound but also socially relevant and responsible.

The reflexive dimension adds another layer by considering the system's ability to be self-aware and to understand its role within the human and social context. This enables the system to adapt and respond to user needs and social changes more effectively.

By using ***FIRE***, designers can ensure that their approach is not just technically robust but also aligned with human and social values. It leads to the development of systems that are more likely to be accepted, trusted, and effectively used by people and society at large.

4 | DISCUSSIONS

In this section, the usability and relevance of ***FIRE*** are discussed and illustrated through:

- its application to an academic example involving the representation of a coffee machine and its associated DT, analyzed under various design hypotheses that are more or less human- or STS-centered.
- its use in representing and evaluating different DT systems proposed in the scientific literature.

4.1 | FIRE as Guiding Tool

The ***FIRE*** framework enables design teams to deliberately incorporate sociotechnical dimensions when developing DTs for complex systems. To illustrate how this framework can guide system engineers in designing and developing DTs, we propose a practical example: the DT of an offshore oil and gas production platform. This example begins with a technically centered system and progressively integrates human and social complexity, showing how ***FIRE*** supports the evolution toward full sociotechnical integration.

In this case, we explore the redesign of an offshore platform's pigging system—initially limited to isolated SCADA (supervisory control and data acquisition) functionalities or even standalone sensor readouts—into a fully autonomous DT capable of managing and remotely the system. The transformation highlights the increasing need for integrated reflexivity, social interaction, and operational autonomy in complex industrial systems. As stated before, Figure 4 introduces the notation I_r^E to describe the framework. In this notation:

- I represents the *Intrinsic* dimension, rated on a scale from 1 to 5 (see Section 3.2),
- E represents the *Extrinsic* dimension, which can be Technical (T), Human (H), or Social (S) (see Section 3.3),
- r represents the *Reflexive* dimension, which can be Absent (−), Technical (T), Human (H), or Social (S) (see Section 3.4).

Below, the levels of autonomy are outlined, demonstrating the progression from technical systems to sociotechnical entities with reflexive capabilities, from human-operated machines **H** to systems embedded within social contexts **S**, culminating in the emergence of highly autonomous, socially integrated systems. The final aspect, the reflexive dimension, is illustrated by DTs that enhance predictive maintenance, supply management, and user experience through advanced modeling and simulation.

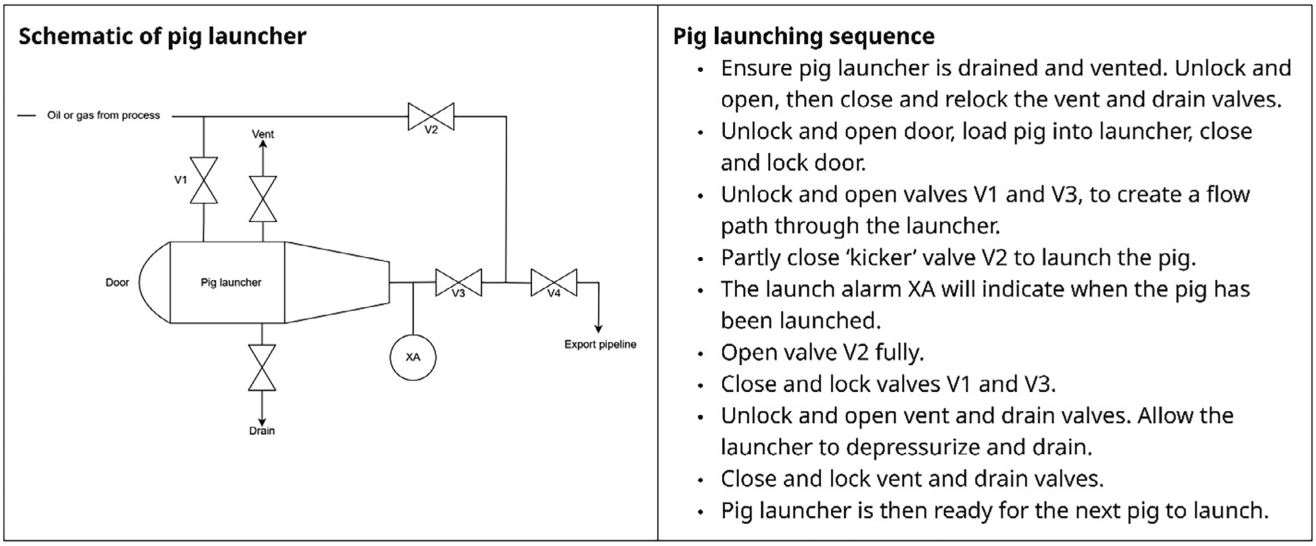

FIGURE 5 | Technical functioning of pig launcher.

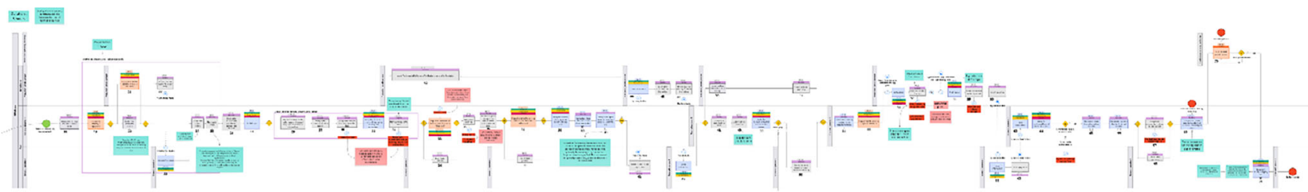

FIGURE 6 | BPMN model of human activities during pig launching sequence [32].

At its most basic, the pigging operation is a process used to clean or inspect pipelines without stopping the flow of the product in the pipeline. In a traditional configuration, this process involves inserting a scrapers or pig into the pipeline via a launch station and using the flow of product to push it to the receiving end. Initially, a purely technical model of the pigging operation can be taken. For example, the Wikipedia description of the pig launching sequence[1] represents a 1^{T}_{-} scenario (Figure 5).

This configuration is an example of a technical-only system. It performs a single, narrowly defined function—launching the pig—without integrating upstream planning, co-activity coordination, or downstream processing. Preparatory tasks such as transporting the pig to the site, safety verification, or resource scheduling are not digitally captured. Likewise, the system does not engage with concurrent operations (e.g., process supervision or crew management) nor consider downstream impacts such as data logging, residue handling, or pig inspection. It lacks contextual awareness, self-assessment, and interaction with human or organizational actors. There is no model of itself embedded in its design—hence, this scenario represents a 1^{T}_{-} scenario.

Intelligent or "smart" pigs can be viewed as a 2^{T}_{-}, as they manage multiple technical functions such as internal inspection, The transition to an 2^{H}_{-}-type System requires the integration of these functions from a human perspective. One such approach could be to use a BPMN as proposed in [32] (Figure 6) to represent the field operators, production panel operators, and authority.

Advancing to level 3 autonomy, the pigging system evolves with the introduction of a DT that goes beyond basic monitoring. At this stage, the system can be viewed as an advanced SCADA-like environment that not only collects data but also models and simulates the pigging process in real time. It integrates data on flow rates, valve states, and pipeline conditions to simulate operational scenarios and track the position of the pig throughout its journey. This simulation capability supports predictive maintenance and operational optimization. The DT anticipates wear on seals, identifies potential anomalies such as unexpected pressure drops or friction zones, and estimates inspection intervals. The system now holds a reflexive model of the technical process itself — a 3^{H}_{t} configuration — allowing operators to project its future states and optimize accordingly. This model can be rule-based (e.g., alert thresholds triggered by abnormal flow behaviour) or physically grounded using hydrodynamic simulations and geometric representations of the pig and pipeline.

As modelling capabilities expand, the DT begins to incorporate user patterns and scheduling practices — for instance, it learns that pigging is usually scheduled after production peaks or adjusted around crew rotations. These insights reflect a 3^{H}_{h} configuration, where the DT adapts to human routines and anticipates operational preferences.

At level 4, the DT uses historical patterns and user models to autonomously schedule pigging operations in operators planning, ensuring minimal disruption to production. This corresponds to a 4^{H}_{h} configuration. When integrated with broader organizational

TABLE 1 | Synthesis of the redesign example of pigging system using ***FIRE***.

Global evaluation	Description	Example
1^{T}_{-}	Basic functionality focused solely on the mechanical execution of pigging without integration or awareness of surrounding operations.	Manual pig launch procedure with SCADA indicators for valve states and no coordination logic.
2^{T}_{-}	Technical improvement through smart pigs; no contextual awareness, but multiple integrated physical functions.	Smart pig used for internal inspection during flow, with basic data collection capabilities.
2^{H}_{-}	Introduction of human-oriented modeling and task integration, such as operator workflows and procedural representations.	Process modeled using BPMN to represent coordination between field operators and control room.
$3^{T}_{\mathbf{t}}$	Reflexive technical modeling via a DT; supports simulation of pigging operation (flow, valve states, pig location) and basic operational forecasting.	SCADA-extended system simulating pig behavior and flow to anticipate wear or blockage.
3^{H}_{h}	Human-adaptive modeling where the DT learns from human planning practices (e.g., pigging after peak production).	DT adjusts scheduling patterns based on historical crew routines and shift rotations.
$4^{H}_{\mathbf{h}}$	Autonomous scheduling and coordination with internal actors based on predictive human models.	DT proposes and schedules pigging in coordination with platform operations.
4^{S}_{h}	Sociotechnical integration with external actors (contractors, regulators); the system manages logistics and compliance collaboratively.	DT coordinates with third-party service providers, manages documentation, and updates ERP.
$5^{S}_{\mathbf{s}}$	Full autonomy and socio-reflexivity; DT anticipates regulatory and societal changes, optimizes inspection lifecycle and coordinates stakeholder communication.	DT modifies inspection plans in response to ESG trends, policy shifts, and public perception.

systems — such as coordinating with external maintenance contractors, accounting for supply chain delays, or updating compliance records — the DT now operates in a 4^{S}_{h} mode. It becomes a sociotechnical agent, sharing its functions across multiple stakeholders. For example, a third-party service provider may deliver the pig and execute the operation based on the DT's recommendations, while internal staff receives compliance dashboards and cost projections.

At level 5^{S}, the system reaches full autonomy, evolving into a socio-reflexive operational intelligence. The DT manages the entire extended lifecycle of pigging operations, including risk assessments, budget planning, stakeholder communication, and adaptation to regulatory shifts. To perform effectively at this level, it must anticipate external and internal variables — such as seasonal inspection cycles, offshore crew fatigue, public scrutiny after an incident in another facility, or changes in ESG (Environmental, Social, and Governance) reporting standards — thus embodying a 5^{S}_{S}, configuration. The system no longer merely reacts to events but shapes its environment through proactive decision-making, negotiation with external actors, and alignment with evolving organizational norms.

This example, synthesized in Table 1, illustrates the utility of the ***FIRE*** framework in supporting the work of designers by representing and making explicit their design hypotheses within the dimensions of the framework. Through this structured understanding, designers can ensure that human and social requirements are adequately addressed and identify pathways to enhance the autonomy, reflexivity, and sociotechnical integration of their systems.

4.2 | FIRE as Descriptive Tool

To evaluate the relevance and usability of the proposed framework, seven references from the scientific literature on DTs explored for this study were analyzed through the ***FIRE*** lens. Due to the increasing interest in DT research in recent years, an exhaustive validation approach is not feasible. Therefore, the selected references aim to represent the diversity of design approaches and applications of DTs, though this selection is subjective and reflects the authors' perspectives. The purpose of Table 2 is to illustrate how the ***FIRE*** framework can be used as a descriptive tool to analyze the chosen DT. It demonstrates how ***FIRE*** can help interpret and compare DTs by identifying their intrinsic, extrinsic, and reflexive characteristics based on the information provided in the original publications. This exercise supports the usability of the framework and helps clarify how the values of each dimension can be derived from textual descriptions of DTs.

In addition to demonstrating the usability of ***FIRE***, this exercise reveals several insights into recent research trends concerning DTs (DT).

TABLE 2 | Application of the ***FIRE*** framework to existing DTs from literature.

Reference	Proposed DT	Global evaluation	Detailed evaluation per dimension		
[14]	DT of aerospace vehicle	4_t^T	**I**	4	DT is autonomous for all routine tasks but not for mission reconfiguration
			E	T	DT considers technological aspects
			R	t	DT is self-aware of its technological components
[44]	DT of manufacturing system	4_t^H	**I**	4	DT is autonomous for all routine tasks but not for unexpected event
			E	H	DT considers technological and user aspects
			R	t	DT is self-aware of its technological components
[23]	Agent-based DT for trauma management	3_s^S	**I**	3	DT is autonomous for some routine tasks
			E	S	DT considers technological, human and organizational aspects
			R	s	DT is self-aware of its technological, human and organizational components
[19]	Environment DT	3_s^S	**I**	3	DT is autonomous for some routine tasks
			E	S	DT considers technological, human and organizational aspects
			R	s	DT is self-aware of its technological, human and organizational components
[30]	DT of crane installation	3_-^H	**I**	3	DT is autonomous for some routine tasks
			E	H	DT considers technological and (some) human aspects
			R	—	No reflexive capability is described
[45]	DT of production system	2_h^H	**I**	2	DT is used to support human activities without real autonomy
			E	H	DT considers technological and human aspects
			R	h	DT is self-aware of its technological and human components
[11]	DT of oil-and-gas industrial site	4_h^H	**I**	4	DT is autonomous for all routine tasks but not for unexpected event
			E	H	DT considers technological and human aspects
			R	h	DT is self-aware of its technological and human components

For the intrinsic dimension, most of the studied DTs are autonomous for all [11, 14, 44] or some [19, 23, 30] routine tasks but do not consider non-routine or unexpected events. This highlights a common challenge in achieving full autonomy.

In the extrinsic dimension, the system modeled in the DT varies based on the designer's goals. DTs designed to monitor technological systems often do not integrate human (and organizational) aspects [14], or include them only partially [30]. Conversely, DTs designed to monitor STS (e.g., industrial or healthcare systems) always consider human aspects [11, 44, 45] and sometimes integrate organizational aspects as well [19, 23].

For the reflexive dimension, there is a correlation between the scope of the extrinsic dimension and the reflexive capabilities. DTs that consider more aspects (technological, human, organizational) in their extrinsic dimension tend to have higher reflexive capabilities [19, 23]. DTs with a narrower focus in the extrinsic dimension have reflexive capabilities limited to those specific aspects [11, 14, 45]. Some exceptions exist where extrinsic considerations do not fully translate into reflexive capabilities [30, 44], highlighting areas for potential improvement in DT design.

5 | Conclusion

FIRE (Framework for representing Intrinsic, Reflexive, and Extrinsic dimensions of DT) offers a structured approach to the conceptualization and design of Digital Twins (DTs) for Sociotechnical Systems (STS). By incorporating the intrinsic (autonomy), extrinsic (integration), and reflexive (introspection) dimensions, ***FIRE*** addresses a gap in the literature: integrating human perspectives into DT design for complex sociotechnical environments. The framework aligns with established STS principles such as joint optimization and adaptability, extending these concepts into DT design. This makes ***FIRE*** a useful tool for diverse fields like manufacturing, healthcare, and smart cities, where the interaction between technical systems and social structures is fundamental.

The application of ***FIRE*** to existing DTs has provided key insights. One notable finding is that many current DTs struggle with achieving full autonomy, particularly in handling unexpected events, revealing limitations in the intrinsic dimension. Additionally, there is a correlation between the scope of a DT's extrinsic dimension and its reflexive capabilities, suggesting that more comprehensive DTs tend to exhibit higher levels of self-awareness. ***FIRE*** also offers practitioners a structured way to evaluate and improve DT designs, potentially leading to systems that are more intuitive and responsive to stakeholders. Although not discussed in detail in this paper, the potential alignment of the ***FIRE*** framework with established assessment tools such as Technology Readiness Levels (TRL) [46] and Human Readiness Levels (HRL) [47], by including social and organizational factors in the assessment, could be explored in future work. As STS DTs evolve, applying ***FIRE*** can help identify gaps, foster iterative improvement, and support balanced decision-making across all dimensions.

However, several limitations should be acknowledged. The framework's structure reflects a simplifying choice, which may introduce a hierarchical view not shared by all disciplines. This does not reflect a limitation of SE itself, but a modeling choice within the framework. The framework's roots in systems engineering may introduce a hierarchical bias that might not fully align with perspectives from fields like ergonomics or sociology. The analysis of existing DTs was also limited in scope and involved some subjectivity in evaluation. Additionally, further investigation is needed to ensure that ***FIRE*** can be effectively integrated into industry practices and standards. Despite these challenges, ***FIRE*** serves as a stepping stone for advancing DT design in sociotechnical contexts, ensuring that technological advancements are paired with human-centered considerations.

Looking ahead, further research should focus on validating ***FIRE*** across a wider range of DT applications, exploring its practical implementation in real-world projects, refining the framework to incorporate interdisciplinary perspectives, developing quantitative metrics for each dimension, and investigating how it can be integrated with existing industry standards. As DTs for STS continue to develop, frameworks like ***FIRE*** will help guide thinking about human and social dimensions, ensuring that future DTs are not only technically sophisticated but also responsive to the complex environments they aim to represent.

Data Availability Statement

Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

Endnotes

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