Human–Twin Interaction (HTI): A Position Paper on Human-Centered Digital Twin Collaboration

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Abstract

Digital twins have matured from static simulation artifacts into continuously evolving, data-driven counterparts of physical systems. Yet, a review of current literature reveals that the field remains profoundly system-centric, emphasizing fidelity, prediction accuracy, and automation, while under-theorizing the role of the human. Although high-level concepts like human-centricity and explainability are widely discussed, the technical approaches to implementing them—such as ontological foundations, unified models, human-environment interaction, and federated semi-supervised learning—remain siloed and address interaction challenges in isolation. This position paper introduces *Human–Twin Interaction (HTI)* as a unifying, interaction-focused framework for understanding and designing human-centered digital twin systems. HTI is proposed as an umbrella construct that consolidates these fragmented technical efforts under a single, coherent interaction paradigm. We argue that training-oriented digital twins provide a revealing context where the limitations of current paradigms become visible. The paper articulates the conceptual foundations of HTI, situates it within a history of human-system failures and current digital twin research, proposes a conceptual framework, and illustrates its application through a training-oriented case. We conclude by outlining research directions for developing digital twin systems that do not merely optimize performance, but actively support human learning, judgment, and responsibility.

1. Introduction

The promise of complex, automated systems has always been shadowed by a peril: they are only as reliable as the humans who interact with them. History is replete with costly failures rooted not in faulty hardware, but in brittle human-system interaction. The crew of Eastern Air Lines Flight 401 became fixated on a faulty landing gear indicator, a failure of perception that led to a fatal crash into the Everglades (National Transportation Safety Board, 1973). The

Therac-25 radiation therapy machine delivered lethal overdoses because its interface allowed a rapid sequence of inputs that operators could not possibly comprehend, a catastrophic failure of system design and feedback (Israelski & Muto, 2004). In the Clapham Junction rail disaster, a latent wiring error made during maintenance persisted through multiple safety checks, a systemic failure where the "human-in-the-loop" was not empowered to see or correct the fault (Rail Accident Investigation Branch, 2023). From the Piper Alpha oil rig explosion, caused by a breakdown of the permit-to-work safety procedure, to the more recent Boeing 737 MAX accidents (Jamieson et al., 2022), we see a devastating pattern: technical systems that create "error traps" for their human operators.

As Endsley (2024) argues, these accidents occur not just from technical failures, but from a lack of socio-technical design features, processes, and training that support people when automation fails. Even in the digital age, this pattern persists. The 2021 global Facebook outage, caused by a routine maintenance command that an audit tool failed to stop, starkly illustrates that as systems grow in complexity, the cost of poor interaction design rises exponentially (Reuters, 2021).

This historical pattern of brittle interaction is echoed in modern digital twin research. While the concepts of human-centered design are gaining traction, the technical approaches are often fragmented, creating powerful systems that, like their predecessors, are not designed with the human as a true partner. Foundational work has established their technical maturity, focusing on high-fidelity representation and semantic interoperability (Wilson et al., 2024). However, a review of this literature reveals that the field remains profoundly system-centric, emphasizing prediction and optimization while under-theorizing the human's role (Browning et al., 2022). Without an explicit, interaction-first design philosophy, we risk creating a new generation of systems that are more powerful but just as brittle, repeating the mistakes of the past.

This paper advances the position that the next stage of digital twin research must break this cycle. We must move from system-centric to human-centered. We introduce Human–Twin Interaction (HTI) as a domain-agnostic conceptual framework that foregrounds the reciprocal, evolving relationship between humans and digital twins across the system lifecycle, directly addressing the pattern of interaction failure that has plagued complex systems for decades.

2. Background and Related Literature

Digital twins have emerged as a key enabling technology for Industry 4.0 and beyond, promising to revolutionize how we design, monitor, and maintain complex systems. At its core, a digital twin is a virtual representation of a physical system or process that is continuously updated throughout its lifecycle (Grieves & Vickers, 2016). Foundational systematic reviews describe a digital twin as comprising three essential parts: a physical entity, a virtual entity, and a bidirectional data connection that links the two (Jones et al., 2020). This connection allows the twin to mirror the state of its physical counterpart in real-time, enabling a wide range of applications, from predictive maintenance and optimization to simulation-based training and decision support. While the technical capabilities of digital twins are well-established, their interaction with human users remains a less-defined and fragmented area of research, which this paper seeks to address.

A detailed analysis of the literature reveals several distinct technical approaches for building human-centered digital twins, as well as a dominant application philosophy that prioritizes system performance. While each makes valuable contributions, they often address specific aspects of the interaction problem in isolation, leaving critical gaps.

2.1 The Ontological Foundation Approach

At the most fundamental level, a critical challenge for digital twins is the lack of a clear, shared definition of what a "digital twin" is, which can lead to ambiguity and hinder interoperability between systems. The Ontological Foundation approach seeks to solve this by creating a standardized, semantic framework. As Wilson et al. (2024) introduce, this involves creating precise "characterizations of digital twins within the Common Core Ontologies" to resolve "semantic interoperability challenges associated with the growing reliance on digital twins across various industries and domains."

In this context, the human's role is that of a stakeholder in standardization—a researcher, engineer, or legislator who uses the ontological framework to ensure clear communication, integrate systems from different vendors, and build more sophisticated and reliable twin representations. This approach is a foundational enabler for meaningful interaction. Before a human can effectively interact with a digital twin, they must have a shared, unambiguous understanding of what the twin represents. By providing this "common language," it ensures that when a human sees data or a model in the twin, they interpret it correctly, preventing the misunderstandings that can lead to critical errors.

2.2 The Autonomous Control & Predictive Asset Management Philosophy

In contrast to foundational work, a dominant application philosophy, particularly in engineering and manufacturing, centers on using digital twins for autonomous control and predictive asset management. This approach develops the twin as a tool to reduce operational costs and risks by integrating live sensor data, physics models, and AI to enable remote monitoring and unattended operation. Browning et al. (2022) exemplify this with a digital twin for nuclear reactors that can "compute predictive results of operational status with artificial intelligence (AI) to aid in optimizing asset use, and apply asset control accordingly."

Here, the human's role is defined as a supervisor and optimizer. They use the twin's predictive insights to make high-level strategic decisions, while the system handles moment-to-moment control autonomously. This philosophy defines a specific mode of interaction: a high-level feedback loop focused on supervision and optimization. While effective for asset management, this narrow framing of the human as a passive monitor limits the potential for more collaborative, hands-on engagement.

2.3 The Unified Foundation Model Approach

Recognizing that digital twins often focus on only one aspect of a system (e.g., just static data or just physics), the Unified Foundation Model approach proposes a more holistic architectural blueprint. It seeks to create a comprehensive, high-fidelity digital twin by unifying different types of information—static, physical, and interactional—into a single, cohesive framework. Li et al. (2022) proposed such a "foundation model for building digital twins which realizes the unification of building static information, physical mechanisms and interaction patterns," designed to "coevolve with the physical building throughout its lifecycle."

The human in this model is an informed decision-maker who benefits from a holistic view, allowing them to understand not just 'what' is happening, but 'why' it's happening based on the interplay of physical laws and dynamic patterns. This approach acts as a quality enhancer for interaction. By providing a richer, more causally complete model, it allows the human to interact with the twin on a deeper level, asking "why" questions and understanding underlying mechanisms, rather than just observing surface-level data.

2.4 The Human-Environment Interaction Modeling Approach

A more direct approach focuses specifically on modeling the interaction between humans and their immediate physical environment. The goal is to create a digital twin of an interactive space at a micro-level (e.g., a single room) to study and enhance the human-environment relationship. Prasetyo et al. (2023) introduce "a new approach for producing a Digital Twin of the interactive space based on the 4Rs paradigm of Digital Twins," focusing on "Human to Environment Interaction in Interactive Spaces" at the room level.

In this approach, the human is an active participant whose presence, actions, and interactions with the environment are the central subject being modeled by the twin. This is the most explicit approach in the literature, as it makes the interaction itself the direct subject of the digital twin. The interaction is not just a feature; it is the system being modeled, allowing for applications in architecture, asset management, and user experience design. However, its scope is often narrow, and its generalizability across domains remains an open question.

2.5 The Federated Semi-Supervised Learning Approach

From a machine learning perspective, the Federated Semi-Supervised Learning approach focuses on enhancing human-machine collaboration by making the "twin" side of the interaction more intelligent and responsive. It leverages the digital twin to generate large amounts of synthetic training data, which is then combined with limited real-world data to create a highly accurate and efficient interaction model. Alam et al. (2024) introduce a "federated semi-supervised Digital Twin framework for enhanced human-machine interaction in Industry 5.0" that "utilizes synthetic data generated through Digital Twin technology alongside real-world data, enhancing the detection and classification of interactions."

The human is a collaborator with an intelligent machine, working in tandem in a smart manufacturing environment. This approach serves as a loop enhancer. By using the digital twin to generate synthetic data, it trains an AI model to better understand and classify human actions in real-time, leading to a smoother, safer, and more effective interaction. The human interacts with a system that is more perceptive and responsive, but the approach focuses on the technical loop rather than the broader socio-technical dimensions of trust and skill development.

2.6 Synthesis and Research Gap

A detailed analysis of the literature reveals five distinct approaches that are fundamentally related to Human-DT Interaction, but they address it from different angles and at different levels of abstraction. Table 1 provides a high-level overview of these approaches, categorizing their core function and relationship to interaction.

Table 1

High-Level Overview of Human-DT Interaction Approaches

Approach	**Relationship to Human-DT Interaction**	**Core Function**
Ontological Foundation	Enabler	Creates a shared language for meaningful interaction.
Autonomous Control	Mode of Interaction	Defines a supervisory, optimization-focused interaction.
Unified Foundation Model	Quality Enhancer	Deepens the interaction by providing a more holistic model.
Human-Environment Modeling	Direct Subject	Models the human's interaction with the environment as the core focus.
Federated Semi-Supervised Learning	Loop Enhancer	Makes the system more intelligent and responsive to improve collaboration.

The analysis of these five distinct approaches reveals a critical synthesis gap. The literature provides powerful building blocks: the Ontological approach gives us a shared language, the Unified Model gives us architectural depth, the Human-Environment approach gives us a direct focus on interaction, and the Federated Learning approach gives us intelligent responsiveness. However, these approaches exist in silos. They address specific facets of the interaction problem in isolation.

An approach may define the human's role (Autonomous Control), another may provide richer data (Unified Model), and a third may enhance the AI loop (Federated Learning), but no single approach provides a comprehensive framework that integrates these dimensions. What is missing is an interaction-first construct that treats the relationship between human and twin as a first-class system component, unifying these disparate efforts under a single, coherent design philosophy. This gap motivates the introduction of Human–Twin Interaction (HTI).

3. Human–Twin Interaction (HTI): Concept and Scope

3.1 Defining Human–Twin Interaction

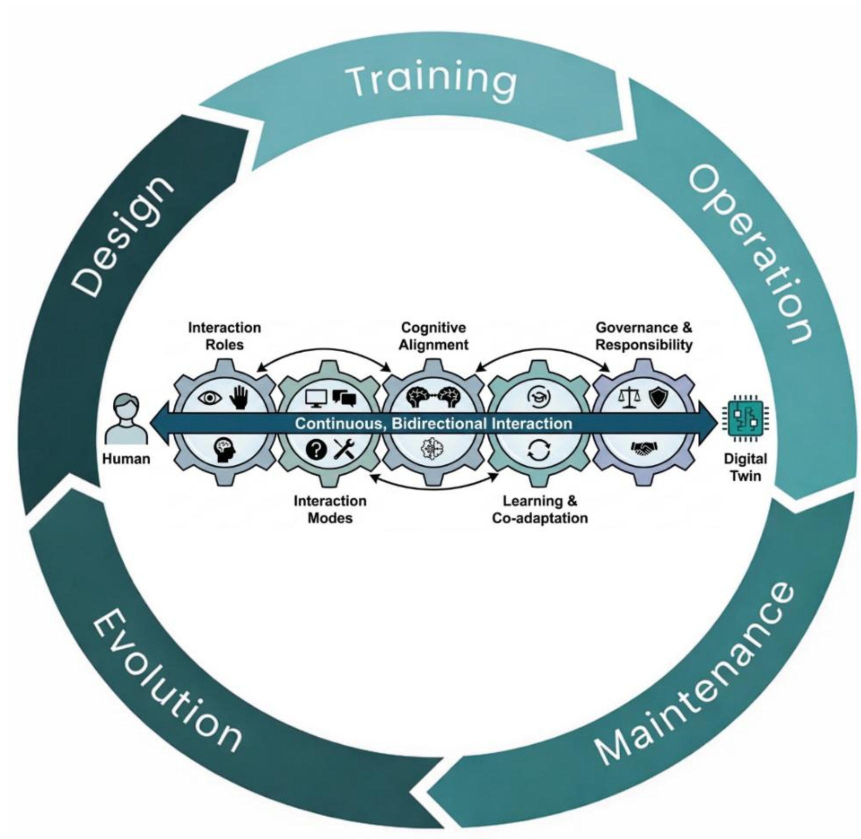
We define Human–Twin Interaction (HTI) as the structured, reciprocal, and evolving interaction between human actors and digital twin systems, through which humans influence, interpret, learn from, and remain accountable for twin-mediated decisions across the system lifecycle.

HTI is proposed as an umbrella construct that consolidates the fragmented efforts of various technical approaches—from ontological foundations to federated learning—under a single, interaction-centered philosophy.

3.2 Conceptual HTI Framework

The proposed HTI framework consists of five interacting dimensions that cut across lifecycle phases (design, training, operation, maintenance, evolution). These dimensions are designed to directly address the collective limitations of the five distinct approaches identified in the literature.

Figure 1



The HTI Framework, showing the five dimensions interacting across the digital twin lifecycle phases.

1. **Interaction Roles** – observer, supervisor, collaborator, learner, and decision-maker.

This dimension directly addresses the narrow, static roles defined in current approaches. The Autonomous Control approach defines the human only as a "supervisor," while the Human-Environment approach defines them as a "participant." HTI provides a fluid, context-aware model that integrates these and other roles, allowing the human to be a supervisor in one context and a learner in another.

2. **Interaction Modes** – monitoring, exploration, explanation, intervention, and reflection.

This dimension provides a structured vocabulary that is missing from the literature. Current approaches imply modes (e.g., the "monitoring" in Autonomous Control or the "intervention" in Human-Environment Modeling) but do not define them as a coherent set. HTI offers a complete toolkit for designing the how of interaction, moving beyond a single, predefined pathway.

3. **Cognitive Alignment** – mental model alignment, explicability, and predictability.

This dimension elevates the goal of "understanding." While the Ontological Foundation approach provides a prerequisite for shared understanding (a common language) and the Unified Foundation Model provides richer data, HTI makes cognitive alignment an explicit design goal. It ensures the twin is not just transparent, but its behavior is predictable and aligned with the human's mental model, addressing the "why" behind the "what."

4. **Learning and Adaptation** – human learning, twin adaptation, and co-evolution.

This dimension addresses the one-sided nature of learning in current approaches. The Federated Semi-Supervised Learning approach focuses heavily on twin adaptation, but the literature consistently identifies a gap in supporting human learning. HTI places human skill development on equal footing with model improvement, framing the interaction as a long-term partnership of co-evolution.

5. **Governance and Responsibility** – accountability, trust calibration, and ethical oversight.

This dimension directly confronts the most critical, cross-cutting gap in the literature. Every one of the five approaches—from Ontological Foundations to Federated Learning—has documented challenges related to trust, accountability, or ethics. HTI makes these socio-technical dimensions a core, non-negotiable part of the design process, providing a structure to address them head-on.

A detailed analysis of the literature reveals four distinct, yet fragmented, approaches to human interaction in digital twin systems. Table 2 synthesizes the specific characteristics, strengths, and documented limitations of each approach. It demonstrates how, while valuable, these approaches address interaction challenges in isolation and leave critical gaps. The HTI framework is then presented as a comprehensive solution that directly overcomes these specific, documented limitations.

Table 2

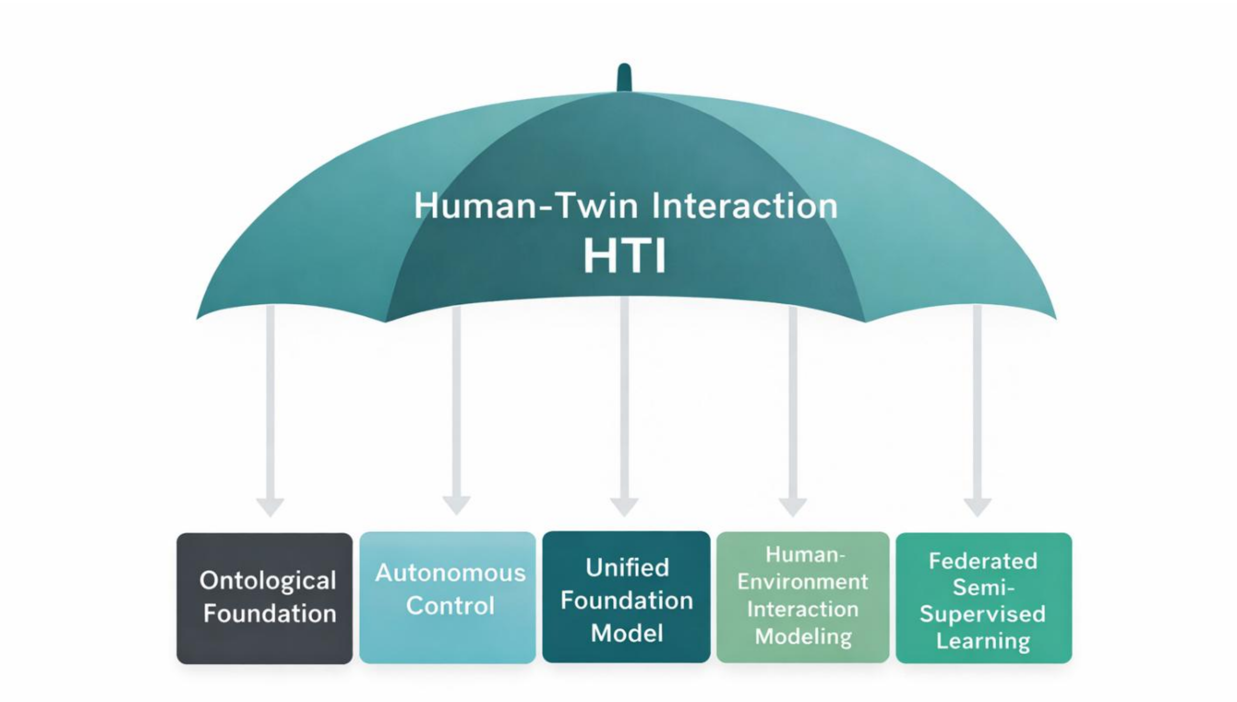
A Synthesis of How Existing Approaches Address Interaction Challenges

Interaction Challenge / Dimension	Ontological Foundation	Unified Foundation Model	Human-Environment Interaction Modeling	Federated Semi-Supervised Learning	Autonomous Control & Predictive Asset Mgmt (Philosophy)	HTI (Our Framework)
Defining the Human's Role	Stakeholder in standardization.	Informed decision-maker.	Active participant being modeled.	Collaborator with an intelligent machine.	Supervisor and optimizer.	Defines multiple, fluid roles that change with context and expertise.
Structuring Interaction	Enabled by a shared	Structured by a comprehensive	Structured by directly modeling the	Structured by a sophisticate	Structured as a high-level feedback loop	Defines distinct interaction

	semantic foundation.	architectural blueprint.	human-environment relationship.	d AI learning framework.	for supervision.	modes for designing any type of interaction.
Achieving Understanding	Foundational prerequisite for unambiguous explanations.	Achieved by a holistic, causal view.	Achieved by modeling the interaction itself.	Achieved through improved system performance and accuracy.	Derived from predictive outputs and performance metrics.	Centers on Cognitive Alignment, ensuring behavior is predictable and understandable.
Supporting Skill Development	Supports learning at a systems engineering level.	Supports deep, causal learning.	Supports skill development via a virtual environment.	Supports the human's collaborative skill.	Supports skill in high-level strategic supervision.	Frames Learning and Co-adaptation as a core dimension, making the twin a partner in skill development.
Trust, Governance, & Accountability	Addresses trust at a foundational, semantic level.	Challenge: Implementation of interaction models is still in development.	Challenge: Needs more empirical data on effectiveness and scalability.	Challenge: Limitations of synthetic data and scalability are open questions.	Challenge: Ethical, privacy, and cybersecurity considerations are critical gaps.	Embeds Governance and Responsibility, making trust an active design goal and clarifying accountability.

Figure 2 visually synthesizes the core argument of this paper. It illustrates how the five distinct technical approaches, while powerful, exist in silos, each addressing specific facets of the human-twin interaction problem in isolation. The HTI framework is then presented as a unifying structure that bridges these silos, providing a comprehensive and integrated solution to the challenges identified in the literature.

Figure 2



A conceptual diagram showing the fragmentation of current digital twin approaches and the unifying role of the HTI framework.

4. Case Illustration: A Concrete Scenario in Aerospace Maintenance

To make HTI tangible, consider a training scenario for diagnosing a faulty hydraulic pump in an aircraft's landing gear system. We contrast a standard digital twin approach with an HTI-oriented approach for two trainees: a novice and an expert. We explicitly map the interactions to the five dimensions of our framework.

Standard Digital Twin Approach: The twin detects a pressure anomaly and displays an alert: "HYD PUMP 3 PRESSURE LOW - SCHEDULE MAINTENANCE." Both the novice and the expert receive the same static alert. The novice is confused by the technical jargon. The expert knows from experience that this alert is often a false positive caused by a faulty sensor. The system offers no way to investigate this suspicion, forcing the expert to either trust the potentially flawed alert or disregard it, undermining trust and failing to teach the novice the nuances of diagnosis.

HTI-Oriented Approach:

For the Novice Trainee (Role: Learner):

1. Interaction Roles: The system identifies the user as a "Learner" based on their profile and tailors the interaction accordingly.
2. Interaction Modes: The primary mode is Explanation and Intervention. The twin detects the anomaly but presents a simplified dashboard: "Warning: Landing Gear System Needs Attention." It prompts the novice: "Would you like to run a diagnostic test to isolate the pump from the sensor?" The novice clicks "Yes," and the twin simulates the outcome.
3. Cognitive Alignment: The twin provides a layered explanation to align with the novice's developing mental model: "I think the pump might be failing because its pressure is low. However, the sensor reporting this pressure has a history of being inaccurate. Let's check another source." It then displays data from a redundant sensor, making its reasoning process transparent.
4. Learning and Adaptation: The system logs the novice's actions and provides a summary in a Reflection mode: "Good job. You correctly isolated the problem. In 70% of cases like this, the issue is the sensor, not the pump." This creates a feedback loop for human learning.
5. Governance and Responsibility: Before the trainee can "sign off" on the virtual repair, the system presents a final check: "Based on your diagnosis, you are recommending replacing Sensor S7. As the technician, you are responsible for this decision. Please confirm." This reinforces human accountability and creates an audit trail of the interaction.

For the Expert Trainee (Role: Collaborator):

1. Interaction Roles: The system identifies the user as a "Collaborator" and provides a richer, more open-ended interface.
2. Interaction Modes: The primary mode is Exploration and Intervention. The twin presents the same raw data but with full technical detail and confidence intervals. The expert is not prompted but given tools to immediately access a "what-if" sandbox to test their own hypothesis.
3. Cognitive Alignment: The twin provides a concise summary that respects the expert's existing mental model: "Pump 3 pressure is low, but confidence is 40% due to sensor S7's known drift. My model suggests two hypotheses: (1) Pump failure, (2) Sensor failure." This provides a starting point for joint reasoning.
4. Learning and Adaptation (Co-adaptation): The twin observes the expert's diagnostic path (e.g., prioritizing cross-referencing temperature data). It learns from this interaction and

updates its future recommendations for this user, becoming a more effective partner over time.

5. Governance and Responsibility: When the expert proposes a non-standard intervention, the twin flags it: "Warning: This action is outside standard procedure. It will require a supervisor's override. Please document your justification below." This maintains procedural safety while respecting expert judgment, clearly delineating the boundaries of responsibility.

5. Novelty and Contributions

The novelty of this position paper lies in reframing digital twins as interaction systems rather than purely technical artifacts, directly addressing the interaction gap and fragmentation identified in the current literature (Ali et al., 2024; Dalibor et al., 2022). This paper is, to our knowledge, the first to explicitly position interaction as the primary organizing principle of digital twin design and to unify human-centric, explainable, and system-centric perspectives under a single, domain-agnostic framework.

This paper makes three contributions:

1. Introduces HTI as a unifying, domain-agnostic interaction framework for digital twin systems.
2. Synthesizes fragmented literature across DTs to demonstrate the need for an interaction-first approach.
3. Demonstrates the relevance of HTI through a concrete training-oriented digital twin case illustration.

6. Discussion and Future Directions

HTI opens several critical research avenues, directly addressing the under-developed areas identified in both historical precedent and current digital twin literature.

1. Interaction Metrics: Current digital twin literature often focuses on system-level outcomes like prediction accuracy (Browning et al., 2022). HTI requires new methods to quantify the "health" of the human-twin relationship, moving beyond simple usability scores to capture trust and learning gain, factors that were missing in the human factors analysis of past disasters like Therac-25.

2. Adaptive Explanations: While the Unified Foundation Model approach proposes richer data, its practical implementation is nascent (Li et al., 2022). HTI requires adaptive explanations that change based on the user's role and expertise. This directly addresses the lack of operational transparency that was a central factor in the Boeing 737 MAX accidents (Jamieson et al., 2022).
3. Human–Twin Co-learning: The literature notes that twins can adapt, but not how they can co-adapt with humans. How does a twin learn from a human without reinforcing their biases? This raises fundamental challenges in safe and robust reinforcement learning, requiring new algorithms that maintain the verifiable safety constraints that were absent in the system design of incidents like Piper Alpha.
4. Ethical and Governance Tensions: The Ontological Foundation approach provides a shared language, but the literature highlights a stark lack of clarity on accountability when an autonomous system fails (Browning et al., 2022). This is a gap that exists across all approaches but is most pronounced under the Autonomous Control philosophy. HTI demands new frameworks for accountability that are as dynamic as the systems themselves.

7. Conclusion

As digital twins increasingly mediate critical operations, we stand at a crossroads. We can either repeat the historical pattern of creating powerful but brittle systems that fail in predictable, human-centric ways, or we can forge a new path. By learning from the lessons of Eastern Flight 401, Therac-25, and Piper Alpha, and by addressing the gaps in the fragmented technical approaches and the dominant system-centric philosophy, we can see that technical sophistication is not enough. Human–Twin Interaction offers a conceptual lens to guide this shift. By centering interaction, learning, and responsibility, HTI reframes digital twins as collaborative socio-technical systems capable of supporting human judgment rather than replacing it, ensuring that the next generation of critical systems is not only more powerful, but also more trustworthy, resilient, and humane.

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