Working Paper Series

ISSN 1177-777X

A Multidimensional Activity Theory Framework for Human Computer Interaction with Digital Twins

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Working Paper: 01/2025

May 2025

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Abstract

This paper introduces a human-centred framework to address the interaction and usability challenges of complex Digital Twin (DT) systems by proposing a new generation of Activity Theory, named Pyramidal Activity Theory (PAT). Digital twins are virtual representations of physical processes, systems, or components that are continuously synchronised with real-world data. Despite their growing adoption across industries, their graphical representation remains challenging due to the diversity of application domains, where multiple models—spanning different users, phases, and scales—are typically distributed across heterogeneous software packages. These complexities often result in inconsistencies, fragmented workflows, and communication barriers across domains.
The proposed model builds upon the previous generation of activity theory, extending it into a 3D pyramidal structure while excluding motivational factors to focus exclusively on interaction mechanics. PAT provides a coherent model for designing unified, user-centred interfaces by capturing dynamic interactions among the key elements of DT systems—Users, Tools (Models), Live Data, Interfaces, and Outcomes—and their interrelationships. Two case studies are presented to demonstrate its applicability. Case Study 1 maps human–system interactions in advanced manufacturing, clarifying roles and activity flows to make the framework understandable and directly applicable for practitioners. Case Study 2 validates PAT through an implemented prototype for industrial energy optimisation.
The proposed model introduces a novel 3D interaction paradigm, providing a scalable and adaptable framework for digital twin interface design. It improves usability, standardisation, and decision-making by clarifying stakeholder roles, reducing cognitive load through "black-box" model integration, and ensuring consistent logic from regional planning to unit-level control. The paper concludes with future research directions, including usability testing, interface refinement, and alignment with interoperability and accessibility standards.

Keywords: Digital Twins, Human-Computer Interaction, User-Centred Design, Activity Theory, Interface Design and Industrial Systems

1 Introduction

As industries advance toward digitisation, Digital Twins (DTs) have emerged as powerful tools for simulating, monitoring, and optimising real-world systems (Giberna et al., 2025). A Digital Twin continuously synchronises with its physical counterpart using real-time data, enabling dynamic decision-making across various operational scales. DTs have been successfully implemented in sectors such as manufacturing, energy, healthcare, and smart cities, where they contribute to improved efficiency, automation, and operational reliability, by accurately mirroring real-world behaviour (Adamenko et al., 2020).

As DT adoption expands into more complex and interdisciplinary industrial settings, the demand for a standardised, model-independent interface is increasing (Soman et al., 2025). User centric DT interfaces (Barricelli et al., 2019) must be black-box, supporting multi-user collaboration across diverse domains, while remaining adaptable and scalable (Park & McKilligan, 2018). However, current DT interfaces are often case-specific (Sharma et al., 2022) and model-dependent (Juarez et al., 2021), limiting their usability across applications (Barricelli & Fogli, 2024). They frequently lack cross-domain interoperability, are designed for single-user interactions, and cater to narrowly defined industrial use-cases. This fragmentation poses significant challenges for engineers, operators, and decision-makers, who must interact within shared DT environments, as shown in Figure 1.

To address the above challenges and to better understand human-computer interaction (HCI) issues in these complex systems, this paper draws on traditional Activity Theory (AT) (Nardi, 1998) as a foundational framework. AT is a socio-cultural model (Vygotsky & Cole, 1978) that emphasises the relationship between individuals (subjects), the tools they use, the goals they pursue (objects), and the broader social and organisational context in which activities occur. Over time, AT has evolved through several generations (Khayyat, 2016). Building on this foundation, this paper introduces Pyramidal Activity Theory (PAT) as a new generation of AT. PAT extends traditional AT by offering a three-dimensional view that captures the multi-directional interactions among core DT elements: Users (Subjects), Models (Tools), Live Data, User Interface, and Outcomes (Objects) (Wu et al., 2021). Unlike the fourth generation of AT (Khayyat, 2016), PAT excludes motivational and emotional factors in order to focus on the structural dynamics of user-system interactions. As described later in Section 3.1, the faces of the pyramid represent distinct interaction pathways, forming a comprehensive model designed

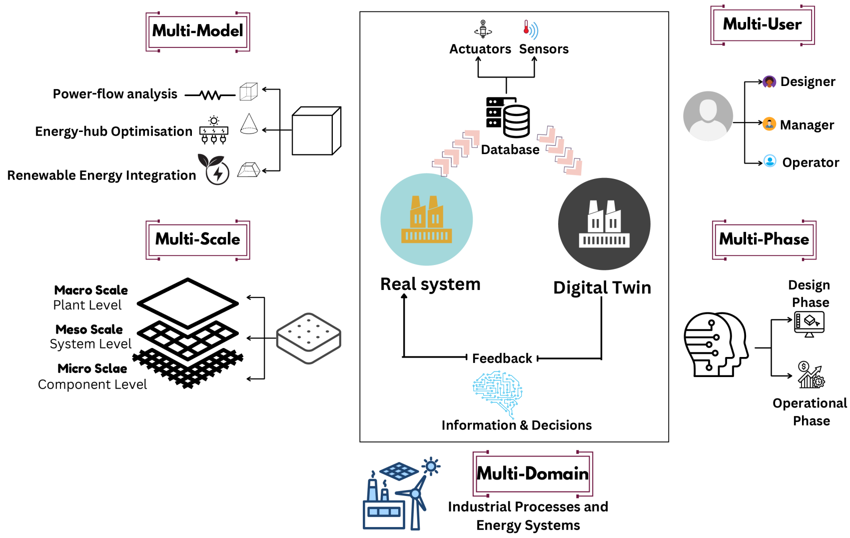

Figure 1: Design and Interaction Challenges with Digital Twins

to guide the development of user-centred, scalable, and model-agnostic interfaces, that ensure alignment between system behaviour and human decision-making.

In Section 3.2, two conceptual case studies demonstrate the application of the PAT framework in industrial contexts, addressing both manufacturing operations and energy management. The first example applies PAT to an advanced manufacturing system, showing how the framework models collaborative human–machine interactions, dynamic workflows, and proactive decision-making supported by digital twin systems. The second example focuses on energy optimisation, where a DT integrates multiple simulation models to manage energy usage efficiently. These examples illustrates how PAT structures complex interaction flows, clarifies user roles, and validates the framework through an implemented prototype, thereby supporting informed decision-making. Together, the two case studies highlight PAT's ability to capture multi-scale interactions and to bridge human expertise with automated processes, ultimately enhancing efficiency, adaptability, and sustainability across industrial systems.

This research contributes to the field of Human-Computer Interaction (HCI) by providing a structured and adaptable model for interaction design in DT environments and other complex systems. It supports enhanced usability, system coherence, and informed decision-making, while enabling human-centred workflows within increasingly complex industrial ecosystems.

2 Background

2.1 Evolving Digital Twin Design Approaches: From Technology-Driven to Human-Centred Systems

The Digital Twin (DT) concept, introduced by Grieves et al. (Grieves & Vickers, 2017), has evolved into a powerful paradigm for modeling, simulating, and analysing real-world systems. Its applications now span a variety of domains including manufacturing, construction, aerospace, healthcare, and energy (Attaran & Celik, 2023; Singh et al., 2022). DTs have become central to Product Lifecycle Management, where they enhance product design, support informed decision-making, and enable virtual prototyping (Lo et al., 2021; Tao et al., 2019).

In recent years, there has been a growing focus on integrating Human-Computer Interaction (HCI) into DT systems. HCI enhances usability, efficiency, and adaptability by prioritising the user's role in interacting with complex digital environments (Barricelli & Fogli, 2024). Building on this, DTs are also seen as platforms for collaborative design and co-creation, supporting broader stakeholder engagement across the product development lifecycle (Wagner et al., 2019). In this context, End-User Development approaches are becoming increasingly relevant, enabling non-technical users to contribute to DT customisation and functionality (Batty, 2018).

Despite these advancements, significant challenges persist. These challenges include the lack of interdisciplinary collaboration strategies (Barricelli et al., 2019), insufficient attention to user-centred design and customisation (Singh et al., 2021), and the absence of standardised frameworks for integrating DTs with Product-Service Systems (Donoghue et al., 2018).

To overcome these barriers, researchers advocate for the development of standardised frameworks, deeper user involvement, and collaborative design methodologies that support scalable and user-friendly DT systems (Hananto et al., 2024). Notably, Park and McKilligan (2018) explored how HCI design principles intersect with DTs, while Vainionpää et al. (2022) highlighted the growing importance of HCI in shaping DT development and adoption. Reinforcing this perspective, Wu et al. (2021) proposed an integrated five-dimensional framework that systematically captures the relationships among physical and virtual entities, services, data, and their dynamic interconnections, laying the groundwork for comprehensive and adaptive DT ecosystems.

2.2 Human-Computer Interaction and Digital Twins

The integration of Human-Computer Interaction (HCI) with Digital Twin (DT) technology represents a transformative shift in how humans interact with digital representations of physical systems. Digital Twins are no longer confined to being static, data-driven models; they are evolving into interactive, adaptive, and human-centred platforms that support real-time decision-making. Research by Dingli and Haddod (2019) and Josifovska et al. (2019) highlights the development of intelligent interfaces and multimodal adaptation frameworks, enabling users to interact with DTs more intuitively. The human-centred perspective is further emphasised by Onan Demirel et al. (2021) and George et al. (2023), who underscore the role of ergonomics, user involvement, and sustainability objectives in DT design. Advanced HCI technologies, as discussed by Lv et al. (2023) and Yigitbas et al. (2021), leverage AR/VR, adaptive systems, and immersive environments to enhance user engagement, creating interfaces that are both context-aware and responsive to human needs. Furthermore, emerging studies, including Soman et al. (2025), introduce the concept of human twin interfaces, where DTs integrate human attributes to improve system adaptability and performance. Applications in construction (Long et al., 2024; Su et al., 2023) and product design (Medina & Hernandez, 2025) reveal that DTs, when coupled with robust HCI frameworks, enhance collaboration, visualisation, and lifecycle management.
To clarify the evolving landscape of Digital Twin design, the frameworks introduced above are grouped into five categories: intelligent interfaces, human-centric digital twins, AR/VR and immersive digital twins, interactive digital twins, and domain-specific applications. Table 1 evaluates each category against five core capabilities—multi-user, multi-model, multi-domain, multi-scale, and multi-phase (design and operational). This categorisation reflects the thematic focus of each work and helps position its contribution within the broader Digital Twin literature. For each capability, Table 1 indicates whether support is full, partial, or absent.

Table 1: A Comparison of digital twin frameworks showing their level of support for five key capabilities (● Full support ◐ Partial support ○ No support)

Framework	References	Multi User	Multi Model	Multi Domain	Multi Scale	Multi Phase
Intelligent Interfaces	Dingli and Haddod, 2019	○	◐	◐	○	○
Human-Centric Digital Twins	Asad et al., 2023; George et al., 2023; Onan Demirel et al., 2021	●	●	◐	◐	●
AR/VR & Immersive DT	Lv et al., 2023; Yigitbas et al., 2021	●	●	○	◐	◐
Interactive DT	Adamenko et al., 2020; Carlin et al., 2024; Kong et al., 2020	◐	◐	◐	●	●
Domain-Specific Applications	Long et al., 2024; Medina and Hernandez, 2025; Su et al., 2023	◐	◐	○	◐	◐

Building on this perspective, Human-Computer Interaction (HCI) plays a critical role in the development of Digital Twin (DT) interfaces by ensuring their usability, interactivity, and adaptability. Rather than functioning solely as real-time data replicas, DTs are increasingly conceptualized as interactive systems that actively enhance user engagement and support informed decision-making processes (Barricelli & Fogli, 2024). This shift highlights the necessity of embedding HCI principles into DT design. Previous studies have introduced methodological frameworks that reinforce this approach, aiming to strengthen real-time user interaction and data integration within DT systems (Adamenko et al., 2020; Carlin et al., 2024; Kong et al., 2020). Similiarly, the *Human-Centric Digital Twin (HCDT)* paradigm emphasises embedding user-centric interactions to improve both usability and decision support (Asad et al., 2023). Collectively, these developments advocate a transition from passive data representations to systems that are actively engaging and responsive. To clarify the structural composition of such systems, Figure 2 presents a Venn diagram that captures the three core components of the Interactive Digital Twin Framework under consideration here: a User Interface (conceived as a black-box abstraction for simplified interaction), Live Data (ensuring real-time consistency), and a Simulation Model (providing domain-flexible modeling capabilities).

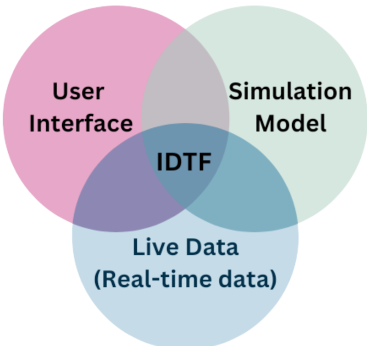

Figure 2: Components of the Interactive Digital Twin Framework

2.3 Activity Theory (AT): Evolution and Limitations

AT originated within psychology, particularly through the work of Soviet psychologists (Leont'ev, 1978; Vygotsky & Cole, 1978), who conceptualised human cognition as a socially and culturally mediated process. Initially grounded in developmental and educational psychology, AT was later embraced by the HCI community (Nardi, 1998) as a powerful framework for analysing how users engage with technology within broader social and organisational contexts. Over time, AT has evolved through multiple generations (Khayyat, 2016).

The first generation, led by Vygotsky and Cole (1978), emphasised mediated action through tools and signs but focused primarily on individual cognition, with limited attention to social or collective activity. The second generation, developed by Leont'ev (1978), broadened the scope to collective activity systems, but did not fully address the complexities of multi-user or digital interactions. Engeström (2001, 2014) added elements for example rules, community, and division of labour, to reflect the collective nature of human activity, yet AT continued to struggle with scaling to complex, interdisciplinary digital systems. The fourth generation of AT incorporated motivational factors (Khayyat, 2016), but even these advances do not fully satisfy the requirements for modelling complex, simulation-based digital environments. Consequently, AT remains an emerging approach without a widely accepted or standardised framework for application to complex socio technical systems.

According to Clemmensen et al. (2016), Activity Theory (AT) serves as a structured framework for analysing and designing user interactions within digital environments. They also noted that "Traditional AT models have limitations when applied to large-scale, distributed, technology-mediated systems", citing frequent difficulties in analysing environments involving multiple actors, tools, and continuous real-time feedback. Similarly, Spinuzzi and Guile (2019) conclude that "Even fourth-generation models struggle to incorporate the full complexity of modern digital systems, especially regarding real-time data, layered user roles, and dynamic interaction with computational models". This is also emphasised in a systematic review by Barricelli and Fogli (2024), who highlight the absence of a standardised, user-centred framework for digital twins in HCI and emphasise the need for scalable, adaptive models that can accommodate the increasing complexity of industrial ecosystems. Consequently, AT remains an emerging approach for complex systems such as digital twins. The following challenges remain unresolved:

- Digital twin ecosystems require seamless and structured integration of multiple models (Sharma et al., 2022).
- Many DT systems do not fully embrace user-centred design, which effects usability and system adoption (Barricelli et al., 2019).
- There is a need for consistent and standardised framework for designing digital twin interfaces (Soman et al., 2025).
- Real-time adaptation based on live sensor data and ongoing system changes is essential for digital twins (Bilberg & Malik, 2019).
- Existing approaches often lack robust strategies for mediating between users and systems, limiting usability and interactive decision-making (Barricelli & Fogli, 2024; Märtin et al., 2019; Spinuzzi & Guile, 2019).

These limitations highlight the need for a new theoretical framework that is scalable, adaptable, and explicitly interactive, in order to effectively support Human Computer Interaction (HCI) within digital twin ecosystems.

3 Methodological Approach

3.1 Conceptual Modeling

This research introduces Pyramidal Activity Theory (PAT) as a conceptual framework for understanding interactions within Digital Twin (DT) environments. Building upon the foundations of the fourth generation of Activity Theory (AT) (Khayyat, 2016) as shown in Figure 3(a), PAT extends the model into a third dimension and repositions the user at the apex of a triangular pyramid structure, emphasising a user-centred design approach. Unlike earlier AT models, PAT moves beyond linear relationships by embedding real-time responsiveness, dynamic roles, and multi-layered system interaction, within a single unified structure. The model incorporates key elements from the Interactive Digital Twin Framework, which identifies the User Interface, Live Data, and Simulation Model as core components as illustrated in Figure 2 and discussed in Section 2.2. By incorporating these elements in a multi-dimensional framework, PAT facilitates multi-faceted interactions and supports both the design and operational phases of digital twin systems. The PAT model consists of five key vertices—Subject (User),

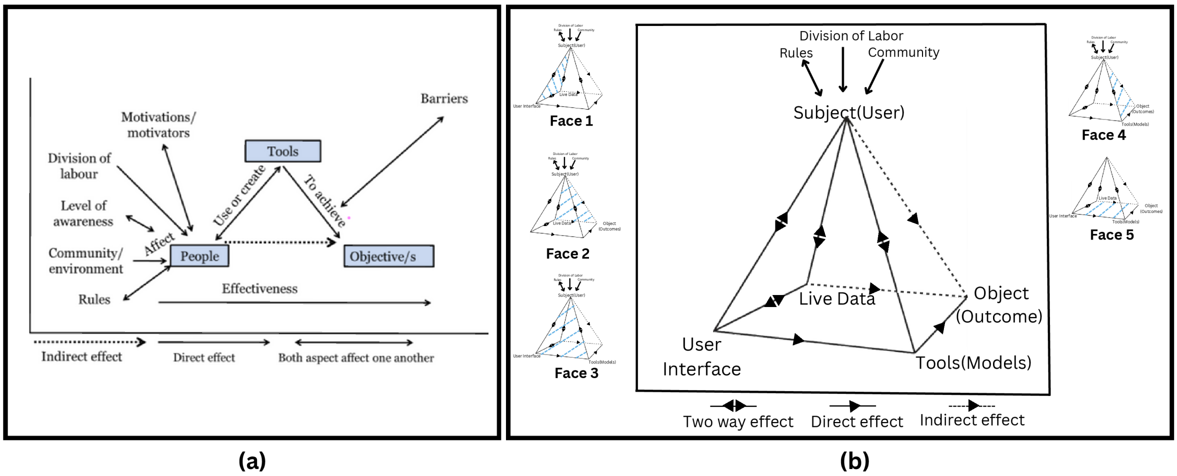

Figure 3: (a) Fourth generation of Activity Theory Model (Khayyat, 2016); (b) Proposed Pyramidal Model.

User Interface, Tools (Models), Live Data, and Object (Outcomes)- which form five triangular faces, each representing a distinct interaction pathway essential for Digital Twin (DT) functionality. As shown in Figure 3(b), these faces support both the design and operational phases of DT systems, enabling a seamless transition from conceptual planning to real-time deployment. The user remains central in this structure, positioned at the apex and influenced by rules, division of labour, and the broader stakeholder community. Motivational factors, level of awareness, and perceived barriers have been excluded in this model to maintain a focus on interaction mechanics rather than external influences. The User Interface functions as a mediation layer, simplifying system complexity and allowing intuitive engagement with the underlying computational models. Simultaneously, Live Data plays a pivotal role in continuously informing both users and models, supporting real-time responsiveness and system adaptability. The Object signifies the intended outcomes resulting from this dynamic interaction.

Each of the five faces of the pyramid reveals a unique perspective within the activity system. As shown in Figure 3(b), Face 1 connects the User, Live Data, and User Interface, highlighting how users perceive and respond to real-time information. Face 2 illustrates the user's indirect influence on Outcomes through engagement with Live Data, emphasising feedback loops and observational learning. Face 3 captures the direct interaction between the User and Tools via the Interface, where system logic is configured and deployed. Face 4 preserves the classic AT triad—User, Tools, and Outcomes—representing mediated actions aimed at purposeful activity. Finally, Face 5 links Live Data, Tools, and Outcomes, showcasing the autonomous and computational functions that generate outputs. Together, these faces form a comprehensive, multidimensional representation of interaction flows within a Digital Twin, supporting continuous optimisation and human-computer collaboration.

3.2 Case Study Application

To demonstrate the practical relevance and versatility of the proposed Pyramidal Activity Theory (PAT) framework, two case studies are presented. Case Study 1 is a conceptual scenario that explains and illustrates how PAT works in practice, focusing on its theoretical application in a manufacturing environment. Case Study 2 applies PAT to clarify and structure decision-making processes for energy optimization within a manufacturing plant, supporting both strategic planning and operational efficiency across multiple scales, and guiding the design and development of a fully functional prototype interface.

3.2.1 Case Study 1: Applying PAT to Advanced Manufacturing Systems

Consider an advanced manufacturing facility producing precision automotive components using a combination of robotic assembly lines, additive manufacturing (3D printing), and real-time quality inspection systems. The digital twin in this scenario continuously synchronises with physical machines and sensors, providing as virtual representation of the production process. Operators, process engineers, and maintenance staff interact with the DT interface to monitor equipment health, predict failures, and dynamically adjust production parameters. To systematically analyse the interactions within a digital twin-enabled manufacturing environment, the core elements can be mapped onto the PAT (Pyramidal Activity Theory) framework, as illustrated in Figure 4. In this framework, system users oversee production, scheduling, and maintenance activities. Their decisions and actions are supported by an integrated dashboard interface that delivers real-time visualisations of process flows, equipment status, maintenance forecasts, and operational alerts. Analytical and predictive tools, such as simulation engines, machine learning algorithms, and optimisation solvers, process incoming information to enhance workflow efficiency and detect anomalies. These digital resources rely on a continuous influx of live data streams originating from IoT (Internet of things) sensors, automated controllers, and environmental monitoring systems. This case study helps to understand the dynamic interaction of these elements contributes to improved product quality, reduced equipment downtime, and optimised throughput of the assembly line.

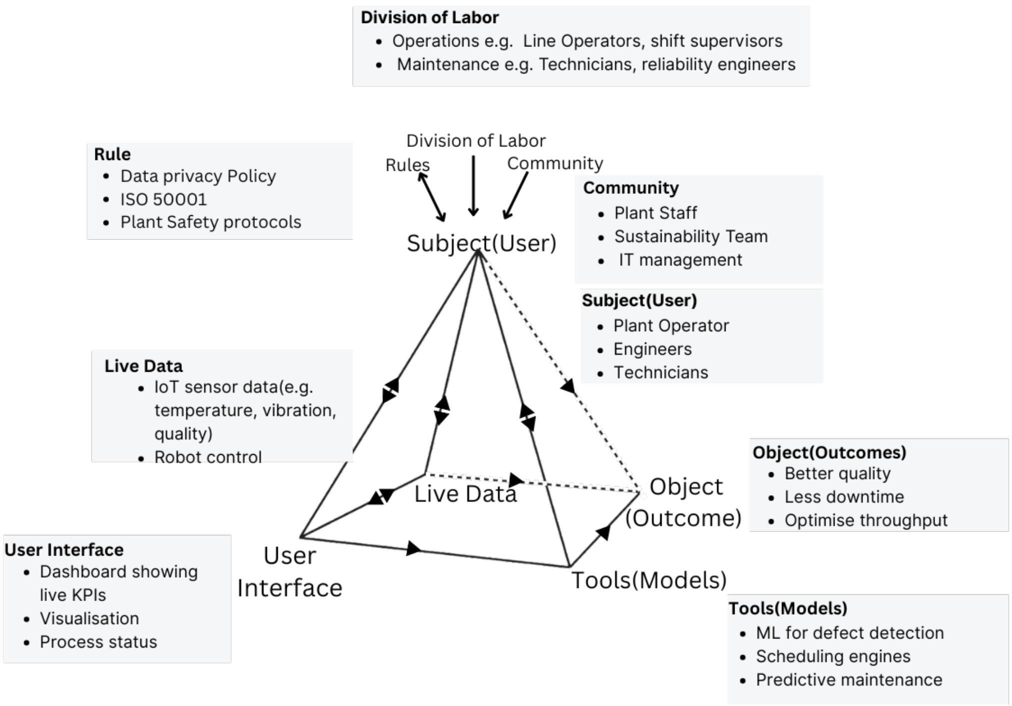

Figure 4: Mapping the key elements and interaction pathways of an advanced manufacturing system within the Pyramidal Activity Theory (PAT) framework.

The PAT model organises the interactions among the elements shown in Figure 4 to facilitate proactive decision-making and system adaptability. Faces are described here using the Face designations from figure 3b.

- **Face 1 (User–Live Data–User Interface):** Operators receive instant feedback on machine performance and can adjust process variables in response to anomalies detected by the digital twin.

- **Face 2 (User–Live Data–Outcome):** Process engineers observe the impact of workflow adjustments, such as changes to production speed or tooling configurations, through real-time performance metrics and quality outcomes.
- **Face 3 (User–User Interface–Tools):** Maintenance staff interact with predictive maintenance models via the interface, scheduling repairs before failures occur, thereby reducing unplanned downtime.
- **Face 4 (User–Tools–Outcome):** The collaboration between human expertise and digital tools drives continuous process optimization, leading to higher product consistency and lower operational costs.
- **Face 5 (Live Data–User Interface-Tools–Outcome):** Autonomous digital twin functions, such as defect detection and automatic process adjustments, operate in the background, further improving system robustness.

While this case study does not include an implemented prototype, it provides a clear conceptual map of how PAT can be applied in industrial contexts.

3.2.2 Case Study 2: Applying PAT to Industrial Energy Optimization with Prototype Implementation

In this case study, the Pyramidal Activity Theory (PAT) framework is applied to guide the development of a Digital Twin (DT) prototype for energy optimisation in a medium-scale manufacturing plant. This moves PAT from a conceptual framework to an operational implementation, with every interface screen and workflow mapped to PAT's vertices and faces. The scenario demonstrates how PAT structures human–system interactions to enable effective industrial energy management.

In this example, the DT monitors, simulates, and optimises energy usage across the plant. It integrates real-time sensor data, user inputs, predictive models, and external energy pricing to support informed decision-making and adaptive control. The Subject (User) is an energy systems engineer responsible for decisions such as balancing demand, reducing peak loads, and integrating renewable sources. The User Interface provides a real-time dashboard with interactive simulation controls, energy-consumption trends, and system alerts, mediating between the user and complex system data. The Tools (Models) include load-forecasting algorithms, optimisation models, and machine-learning components for anomaly detection. Live Data streams continuously from IoT sensors (e.g., electricity usage, equipment runtime, temperature). The Object (Outcome) is defined as optimal energy use, cost reduction, and emission targets. These objectives are realised through interactions that align with PAT's five faces, illustrated in Figure 3(b). The corresponding interface screens are presented as screenshots in Appendix A.

- **Face 1 (User–Live Data–User Interface):** The energy systems engineer interacts with real-time IoT sensor data e.g. temperature through the interface as shown in Figure A1. They can also adjust setpoints and trigger optimisation routines based on metrics such as electricity usage and equipment runtime. For example, they may modify process setpoints or activate load-shifting routines when peak demand alerts are triggered, directly shaping live plant operations.
- **Face 2 (User–Live Data–Outcome):** Engineer monitors the effects of the models through feedback summaries displayed in the flowsheet, as shown in Figure A2. For instance, they can observe changes in peak load reduction, renewable energy contribution, or cost savings without directly modifying the backend models.
- **Face 3 (User–User Interface–Tools):** User configures the compressor model by setting operational parameters to calculate the energy required for its operation, as shown in Figure A3. Compressor configuration, with unspecified parameters highlighted in red, as shown in Figure A7. In the same way, other industrial unit models such as turbines, mixers, and heaters can be configured and digitised within the DT environment, enabling the engineer to explore different operational scenarios and energy impacts.
- **Face 4 (User–Tools–Outcome):** User engages with the optimisation and forecasting models to achieve defined outcomes, such as configuring unit operations (e.g., integrating solar energy)

within the manufacturing plant, as illustrated in Figure A4. For example, the engineer may adjust turbine efficiency settings, reschedule heater loads, or reconfigure mixer operations to minimise peak electricity demand and reduce overall energy costs.

- **Face 5 (Live Data–User Interface-Tools–Outcome):** Live sensor data from the manufacturing plant (e.g., compressor mechanical work) is continuously streamed into the models to calculate the resulting pressure increase as shown in Figure A5. The interface then visualises outcomes such as electricity cost, renewable use, and emissions in real time. Machine learning models as shown in Figure A6 can be integrated for forecasting, anomaly detection, and predictive maintenance, leveraging historical and live data to support proactive optimisation.

Together, these faces show how PAT structures user–system interactions at different operational levels. Table 2 maps PAT elements (Activity, Subject, User Interface, Models, Live Data, and Object) across multiple operational scales in DT environments—from regional planning (Figure A9) to unit-level control (Figure A3).

Table 2: Multiscale structure of PAT Framework
(All referenced figures are in Appendix A)

Scales	Activity	Subject	UI	Live Data	Model	Object
Regional Level	Long-term energy planning and scenario evaluation.	Energy Managers Policy Makers	-	Smart meters Regional demand sensors Weather data	Regional energy planning models Scenario analysis tools	Regional energy balance and policy outcomes
Industry Level	Policy enforcement and performance optimisation.	Plant Managers Energy Analysts	-	Emission sensors Process-level energy meters	Industrial process optimisation models Load forecasting	Reduce costs and improve energy efficiency of industrial processes
Unit Level	Real-time control and fault diagnosis.	Machine Operators Process Supervisors	-	Sensor data (temperature, pressure, flow) Machine status Control system feedback	Process control models Fault detection systems	Energy efficient unit operations

This multi-scale mapping as shown in Table 2 demonstrates how the PAT framework can be systematically applied across different levels of operation—regional, industry, and unit—within a Digital Twin environment. By linking each scale to specific UI screens, data sources, models, and intended outcomes, the table highlights how PAT supports both high-level strategic planning and detailed real-time operational control. This ensures that decision-making remains consistent and coherent, regardless of the scale at which the user interacts with the system, while maintaining a unified, user-centred interface design.

This case study confirms that PAT is not only a conceptual framework but also a practical design methodology for building Digital Twin interfaces. By mapping user interactions to PAT's vertices and faces and aligning them with real prototype screens, the framework ensures that interface design is theoretically grounded, operationally coherent, and scalable across multiple levels of decision-making. The integration of live data, predictive models, and user-centred controls demonstrates how PAT can bridge human expertise with automated system intelligence, enabling smarter decisions, greater flexibility, and improved energy efficiency.

4 Discussion

The application of the Pyramidal Activity Theory (PAT) framework across the two case studies demonstrates its adaptability as both a conceptual lens and a practical design methodology for complex industrial systems.

In Case Study 1, PAT's multidimensional structure effectively modelled human–system interactions in an advanced manufacturing context, showing how the integration of live data, user interfaces, and computational tools can support real-time responsiveness and informed decision-making. This validated PAT's role as a conceptual model for structuring digital twin interactions in ways that prioritise usability and system adaptability.

In Case Study 2, the framework was extended from conceptual mapping to the design of an operational prototype. Each PAT vertex and face was directly linked to specific digital twin functionalities and user interface components, showing a clear translation from theory to implementation. This progression demonstrated PAT's scalability—from regional-level energy planning to unit-level control—while ensuring consistency in decision-making logic across operational contexts.

A comparative review of existing frameworks, summarised in Table 1, highlights the limitations that PAT overcomes. Previous approaches—such as intelligent interfaces, immersive AR/VR systems, and domain-specific applications—tend to focus on isolated dimensions, with only partial support for multi-user, multi-domain, or multi-phase interactions. Similarly, while the Human-Centric Digital Twin (HCDT) paradigm emphasises usability, it often lacks scalability across different operational levels. By contrast, PAT consolidates these fragmented perspectives into a single multidimensional framework. Its integration of Activity Theory principles with digital twin design pathways provides conceptual clarity, while the prototype implementation demonstrates practical applicability. In this respect, PAT can be regarded as a more comprehensive and established approach compared with earlier frameworks, bridging the gap between theoretical models and operational practice.

A key insight from both case studies is that PAT's structured, multi-scale approach reduces cognitive load and encourages adoption by enabling "black-box" integration of diverse models. This allows users to interact meaningfully with the system without requiring deep knowledge of model internals, which is a critical usability factor in multi-domain industrial environments. Such an approach aligns with current HCI priorities of lowering barriers to interaction with complex systems.

Implementing PAT in a fully functional interface requires careful translation of theoretical constructs into practical UI components, demanding close collaboration between domain experts and interface designers. In real-world deployment, additional considerations—including cybersecurity, interoperability with legacy infrastructures, and training for non-expert operators—will be critical. These issues underline the importance of iterative refinement and empirical validation to ensure that PAT achieves robustness and acceptance across diverse industrial contexts.

5 Conclusion and Future Outlook

This paper has introduced Pyramidal Activity Theory (PAT) as a multidimensional framework for designing, analysing, and optimising user interactions in digital twin environments. By extending traditional activity theory into three dimensions, PAT incorporates live data, computational models, and intuitive interfaces into a structured form that reflects the complexity of modern industrial ecosystems. Its pyramidal structure clarifies stakeholder roles, enhances usability, and supports continuous system optimisation.

The two case studies illustrated PAT's versatility: from modelling collaborative interactions in advanced manufacturing (Case Study 1) to guiding the design of a fully implemented energy-optimisation prototype (Case Study 2). Across both contexts, PAT structured complex interaction flows, strengthened alignment between human decision-making and technical system behaviour, and demonstrated scalability across multiple operational levels.

When compared with existing frameworks outlined in Section 2, PAT addresses several persistent limitations. Earlier approaches often provide only partial support for multi-user, multi-domain, or multi-phase contexts, while others focus narrowly on intelligent interfaces or immersive technologies. PAT, by contrast, unifies these dimensions within a single, coherent structure. Its integration of Activity Theory principles with practical design pathways, combined with validation through prototype implementation, positions it as a more comprehensive and established framework than those previously proposed.

Future research should focus on validating PAT through usability studies in real industrial environments, refining interface components for greater intuitiveness, and ensuring alignment with interoperability and accessibility standards. Beyond digital twins, PAT has the potential to serve as a foundational framework for other complex socio-technical systems, providing a structured, user-centred approach that bridges human expertise with automated intelligence.

Disclosure of Potential Conflicts of Interest

No potential conflict of interest was reported by the authors.

Additional Information

Acknowledgements

The authors used ChatGPT (GPT-4, developed by OpenAI) to assist with the initial drafting of some sections of the manuscript and to refine the clarity of language. The AI tool was not used to generate original scientific ideas, analyse data, or interpret results. All content generated with AI assistance was critically reviewed, edited, and approved by the authors.

Funding

The research described in this paper was supported by the MBIE Strategic Science Investment Fund grant, Ahuora: Delivering Sustainable Industry through Smart Process Heat Decarbonisation (Grant ID: CONT-69342-SSIFAETP-UOW).

References

1. Adamenko, D., Kunnen, S., Pluhnau, R., Loibl, A., & Nagarajah, A. (2020). Review and comparison of the methods of designing the digital twin. *Procedia CIRP*, *91*, 27–32. https://doi.org/10.1016/j.procir.2020.02.146
2. Asad, U., Khan, M., Khalid, A., & Lughmani, W. A. (2023). Human-centric digital twins in industry: A comprehensive review of enabling technologies and implementation strategies. *Sensors*, *23*(8), 3938. https://doi.org/10.3390/s23083938
3. Attaran, M., & Celik, B. G. (2023). Digital twin: Benefits, use cases, challenges, and opportunities. *Decision Analytics Journal*, *6*, 100165. https://doi.org/10.1016/j.dajour.2023.100165
4. Barricelli, B. R., Casiraghi, E., & Fogli, D. (2019). A survey on digital twin: Definitions, characteristics, applications, and design implications. *IEEE Access*, *7*, 167653–167671. https://doi.org/10.1109/ACCESS.2019.2953499
5. Barricelli, B. R., & Fogli, D. (2024). Digital twins in human-computer interaction: A systematic review. *International Journal of Human-Computer Interaction*, *40*(2), 79–97. https://doi.org/10.1080/10447318.2022.2118189
6. Batty, M. (2018). Digital twins. *Environment and Planning B: Urban Analytics and City Science*, *45*(5), 817–820. https://doi.org/10.1177/2399808318796416
7. Bilberg, A., & Malik, A. A. (2019). Digital twin driven human–robot collaborative assembly. *CIRP Annals*, *68*(1), 499–502. https://doi.org/10.1016/j.cirp.2019.04.011
8. Carlin, H. M., Goodall, P. A., Young, R. I. M., & West, A. A. (2024). An interactive framework to support decision-making for digital twin design. *Journal of Industrial Information Integration*, *41*, 100639.
9. Clemmensen, T., Kaptelinin, V., & Nardi, B. (2016). Making HCI theory work: An analysis of the use of activity theory in HCI research. *Behaviour & Information Technology*, *35*(8), 608–627. https://doi.org/10.1080/0144929X.2016.1175507
10. Dingli, A., & Haddod, F. (2019). Intelligent digital twins. *International Conference on Human-Computer Interaction*, 3–15. https://doi.org/10.1007/978-3-030-23541-3_1
11. Donoghue, I., Hannola, L., Papinniemi, J., & Mikkola, A. (2018). The benefits and impact of digital twins in product development phase of PLM. In P. Chiabert, A. Bouras, F. Noël, & J. Ríos (Eds.), *Product lifecycle management to support industry 4.0* (pp. 432–441, Vol. 540). Springer International Publishing. https://doi.org/10.1007/978-3-030-01614-2_40
12. Engeström, Y. (2001). Expansive learning at work: Toward an activity theoretical reconceptualization. *Journal of Education and Work*, *14*(1), 133–156. https://doi.org/10.1080/13639080020028747
13. Engeström, Y. (2014). *Learning by expanding: An activity-theoretical approach to developmental research*. Cambridge University Press.
14. George, M. W., Gaikwad, N., Duffy, V. G., & Greenwood, A. G. (2023). Digital twin modelling for human-centered ergonomic design. *International Conference on Human-Computer Interaction*, 58–69.
15. Giberna, M., Voos, H., Tavares, P., Nunes, J., Sorg, T., Masini, A., & Sanchez-Lopez, J. L. (2025). On digital twins in defence: Overview and applications. *arXiv preprint arXiv:2508.05717*.
16. Grieves, M., & Vickers, J. (2017). Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems. In F.-J. Kahlen, S. Flumerfelt, & A. Alves (Eds.), *Transdisciplinary perspectives on complex systems: New findings and approaches* (pp. 85–113). Springer International Publishing. https://doi.org/10.1007/978-3-319-38756-7_4
17. Hananto, A. L., Tirta, A., Herawan, S. G., Idris, M., Soudagar, M. E. M., Djamari, D. W., & Veza, I. (2024). Digital twin and 3d digital twin: Concepts, applications, and challenges in industry 4.0 for digital twin. *Computers*, *13*(4), 100. https://doi.org/10.3390/computers13040100
18. Josifovska, K., Yigitbas, E., & Engels, G. (2019). A digital twin-based multi-modal UI adaptation framework for assistance systems in Industry 4.0. *International Conference on Human-Computer Interaction*, 398–409.
19. Juarez, M. G., Botti, V. J., & Giret, A. S. (2021). Digital twins: Review and challenges. *Journal of Computing and Information Science in Engineering*, *21*(3), 030802. https://doi.org/10.1115/1.4050244
20. Khayyat, M. (2016). A proposed model for the fourth generation of activity theory to be applied on the smart city research. *Proceedings of the Thirty Seventh International Conference on Information Systems (ICIS)*, 1–9. https://iot-smartcities.lero.ie/wp-content/uploads/2016/12/A-proposed-model-for-the-fourth-generation-of-Activity-Theory-1.pdf

21. Kong, L. C. W., Harper, S., Mitchell, D., Blanche, J., Lim, T., & Flynn, D. (2020). Interactive digital twins framework for asset management through internet. *2020 IEEE Global Conference on Artificial Intelligence and Internet of Things (GCAIoT)*, 1–7. https://doi.org/10.1109/GCAIoT51063.2020.9345942
22. Leont'ev, A. N. (1978). *Activity, consciousness, and personality* [Translated by Marie J. Hall]. Prentice-Hall.
23. Lo, C. K., Chen, C. H., & Zhong, R. Y. (2021). A review of digital twin in product design and development. *Advanced Engineering Informatics*, *48*, 101297. https://doi.org/10.1016/j.aei.2021.101297
24. Long, W., Bao, Z., Chen, K., Ng, S. T., & Wuni, I. Y. (2024). Developing an integrative framework for digital twin applications in the building construction industry: A systematic literature review. *Advanced Engineering Informatics*, *59*, 102346.
25. Lv, Z., Wu, J., Chen, D., & Gander, A. J. (2023). Advanced human–computer interaction technology in digital twins. In *Artificial intelligence in iot and cyborgization* (pp. 99–123). Springer.
26. Märtin, C., Herdin, C., Engel, J., & Kampfer, F. (2019). A structured approach for designing adaptive interactive systems by unifying situation-analytics with model- and pattern-based user interface development. In *Computer-human interaction research and applications: First international conference, chira 2017, funchal, madeira, portugal, october 31–november 2, 2017, revised selected papers 1* (pp. 45–65). Springer.
27. Medina, F. G., & Hernandez, V. M. (2025). Product digital twins: An umbrella review and research agenda for understanding their value. *Computers in Industry*, *164*, 104181.
28. Nardi, B. A. (1998). Activity theory and its use within human-computer interaction. *The Journal of the Learning Sciences*, *7*(2), 257–261.
29. Onan Demirel, H., Irshad, L., Ahmed, S., & Tumer, I. Y. (2021). Digital twin-driven human-centered design frameworks for meeting sustainability objectives. *Journal of Computing and Information Science in Engineering*, *21*(3), 031012. https://doi.org/10.1115/1.4050684
30. Park, H., & McKilligan, S. (2018). A systematic literature review for human–computer interaction and design thinking process integration. In A. Marcus & W. Wang (Eds.), *Design, user experience, and usability: Theory and practice* (pp. 725–740, Vol. 10918). Springer International Publishing. https://doi.org/10.1007/978-3-319-91797-9_50
31. Sharma, A., Kosasih, E., Zhang, J., Brintrup, A., & Calinescu, A. (2022). Digital twins: State of the art theory and practice, challenges, and open research questions. *Journal of Industrial Information Integration*, *30*, 100383. https://doi.org/10.1016/j.jii.2022.100383
32. Singh, M., Fuenmayor, E., Hinchy, E. P., Qiao, Y., Murray, N., & Devine, D. (2021). Digital twin: Origin to future. *Applied System Innovation*, *4*(2), 36. https://doi.org/10.3390/asi4020036
33. Singh, M., Srivastava, R., Fuenmayor, E., Kuts, V., Qiao, Y., Murray, N., & Devine, D. (2022). Applications of digital twin across industries: A review. *Applied Sciences*, *12*(11), 5727.
34. Soman, R. K., Farghaly, K., Mills, G., & Whyte, J. (2025). Digital twin construction with a focus on human twin interfaces. *Automation in Construction*, *170*, 105924. https://doi.org/10.1016/j.autcon.2024.105924
35. Spinuzzi, C., & Guile, D. (2019). Fourth-generation activity theory: An integrative literature review and implications for professional communication. *2019 IEEE International Professional Communication Conference*, 37–45.
36. Su, S., Zhong, R. Y., Jiang, Y., Song, J., Fu, Y., & Cao, H. (2023). Digital twin and its potential applications in the construction industry: State-of-the-art review and a conceptual framework. *Advanced Engineering Informatics*, *57*, 102030.
37. Tao, F., Sui, F., Liu, A., Qi, Q., Zhang, M., Song, B., Guo, Z., Lu, S. C.-Y., & Nee, A. Y. C. (2019). Digital twin-driven product design framework. *International Journal of Production Research*, *57*(12), 3935–3953.
38. Vainionpää, F., Kinnula, M., Kinnula, A., Kuutti, K., & Hosio, S. (2022). HCI and digital twins – a critical look: A literature review. *Proceedings of the 25th International Academic Mindtrek Conference*, 75–88. https://doi.org/10.1145/3569219.3569376
39. Vygotsky, L. S., & Cole, M. (1978). *Mind in society: The development of higher psychological processes.* Harvard University Press.
40. Wagner, R., Schleich, B., Haefner, B., Kuhnle, A., Wartzack, S., & Lanza, G. (2019). Challenges and potentials of digital twins and Industry 4.0 in product design and production for high performance products. *Procedia CIRP*, *84*, 88–93. https://doi.org/10.1016/j.procir.2019.04.219

41. Wu, C., Zhou, Y., Pereira Pessôa, M. V., Peng, Q., & Tan, R. (2021). Conceptual digital twin modeling based on an integrated five-dimensional framework and TRIZ function model. *Journal of Manufacturing Systems*, *58*, 79–93.
42. Yigitbas, E., Karakaya, K., Jovanovikj, I., & Engels, G. (2021). Enhancing human-in-the-loop adaptive systems through digital twins and VR interfaces. *2021 International Symposium on Software Engineering for Adaptive and Self-Managing Systems (SEAMS)*, 30–40.

Appendix A.

User Interface Screenshots

This appendix provides screenshots referenced in the main body of the paper illustrating the implementation of PAT's five interaction faces and their mapping to practical user interface elements within the digital twin environment. Each screen demonstrates how specific components—User Interface, Models, Live Data, and Outcomes—are integrated into workflows at different operational levels.

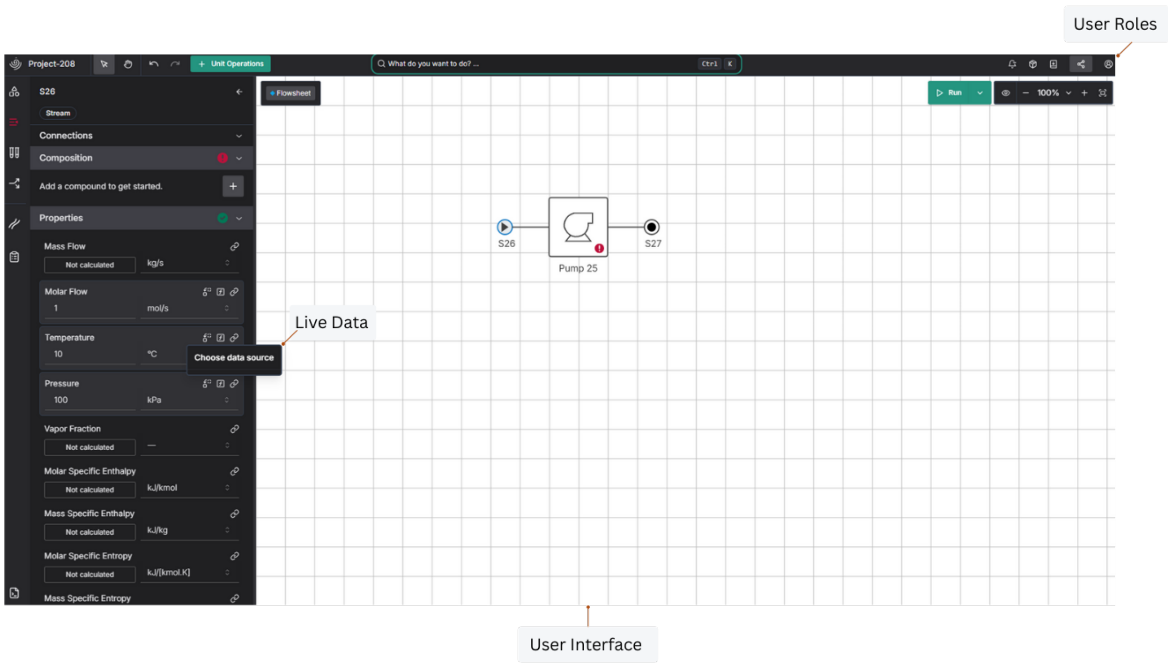

Figure A1: User interface of the flowsheet editor showing PUMP unit operation setup (Pump 25) with live data configuration options, where properties such as temperature and pressure can be linked to external data sources(Face 1).

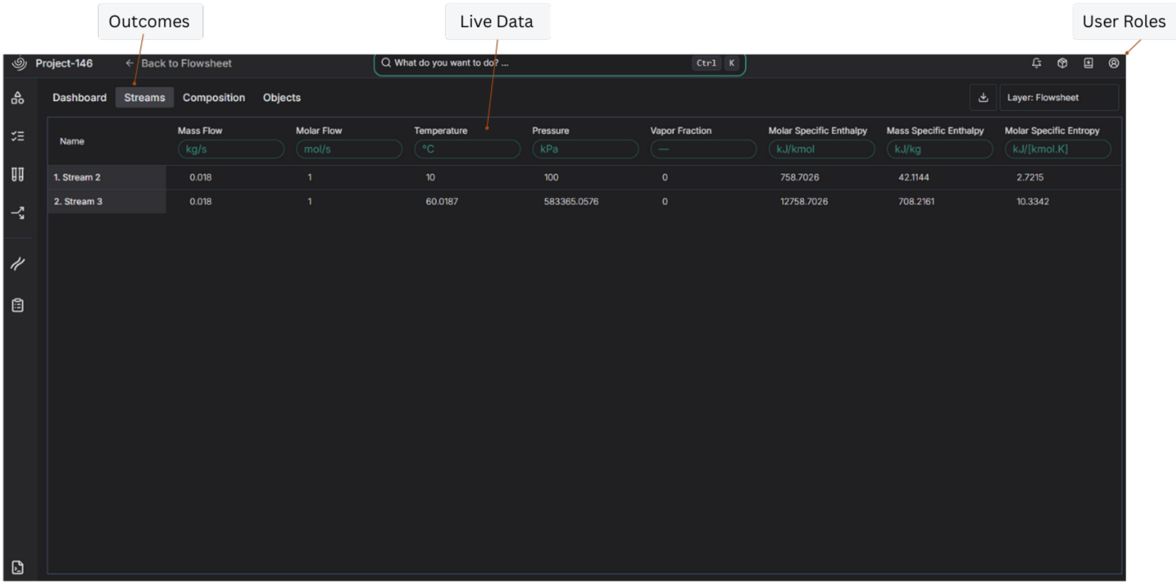

Figure A2: The interface dashboard displays live data (temperature, pressure, enthalpy, etc.) and their resulting outcomes, enabling users to observe the impact of system stream behaviours (inputs and outputs) (Face 2).

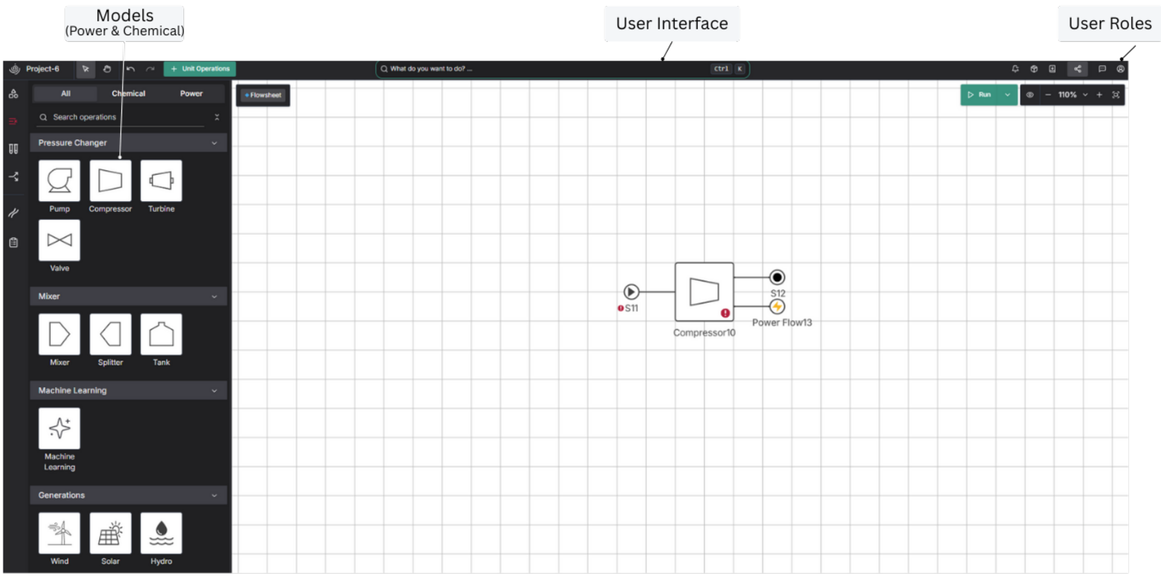

Figure A3: Flowsheet editor allows users to interact with chemical and power system models (e.g., compressor's power load) through the interface (Face 3).

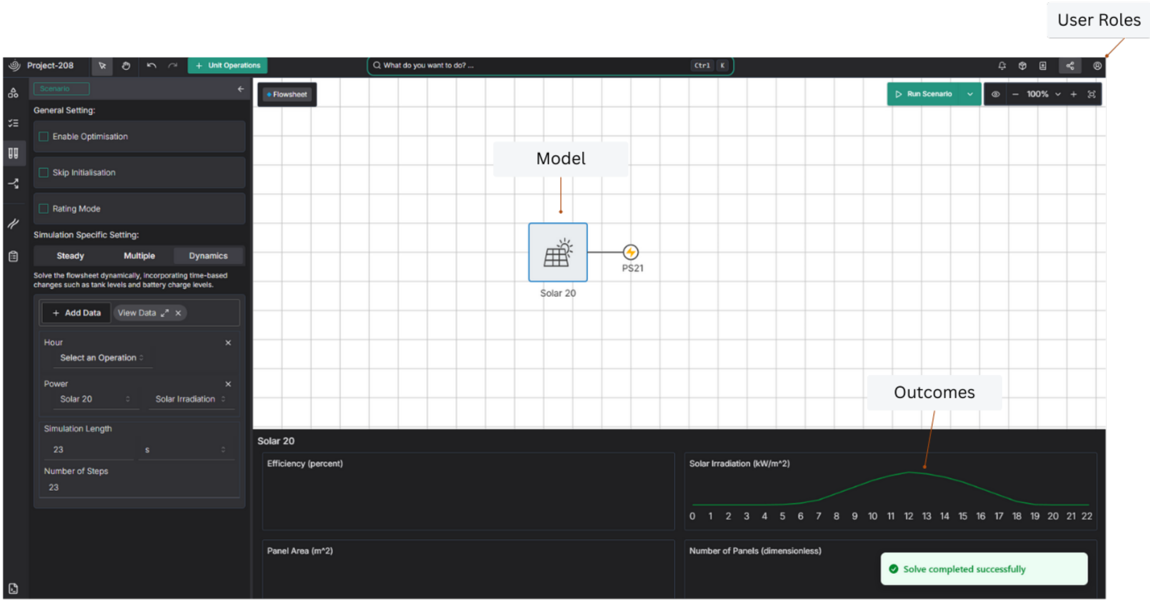

Figure A4: Solar unit model is configured and simulated through the interface, where live inputs drive model execution and users observe the resulting outcomes e.g. solar irradiation profile (Face 4).

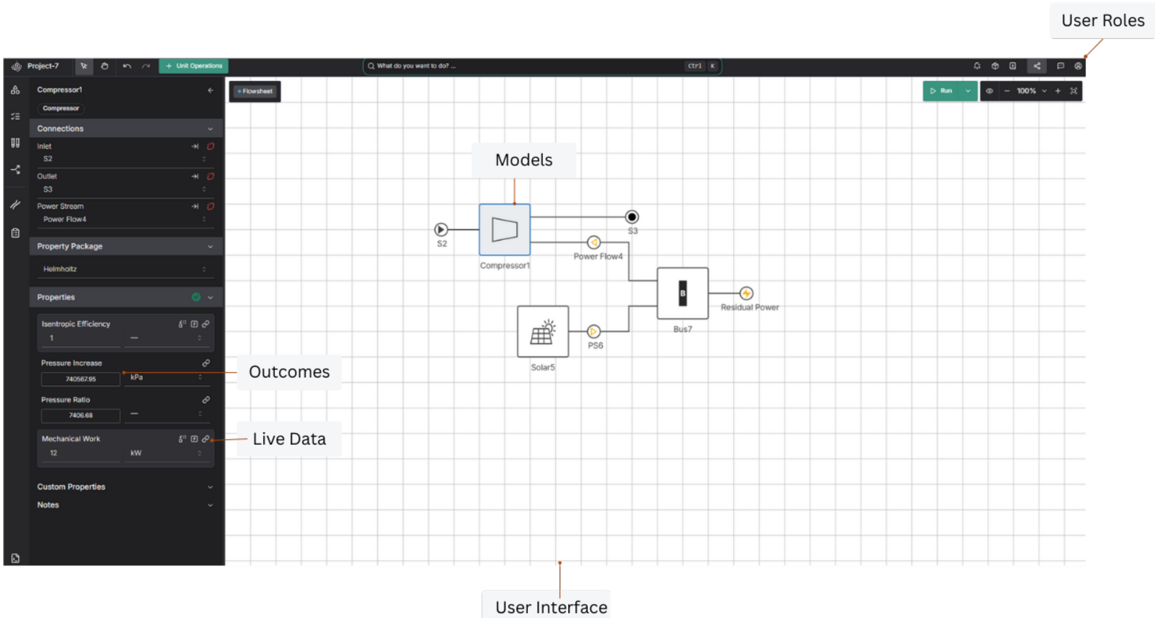

Figure A5: Flowsheet integrates multiple models, where the compressor's power load is supplied by solar-generated electricity. Live data such as mechanical work is sensed in real time, and the model computes the resulting pressure increase (Face 5).

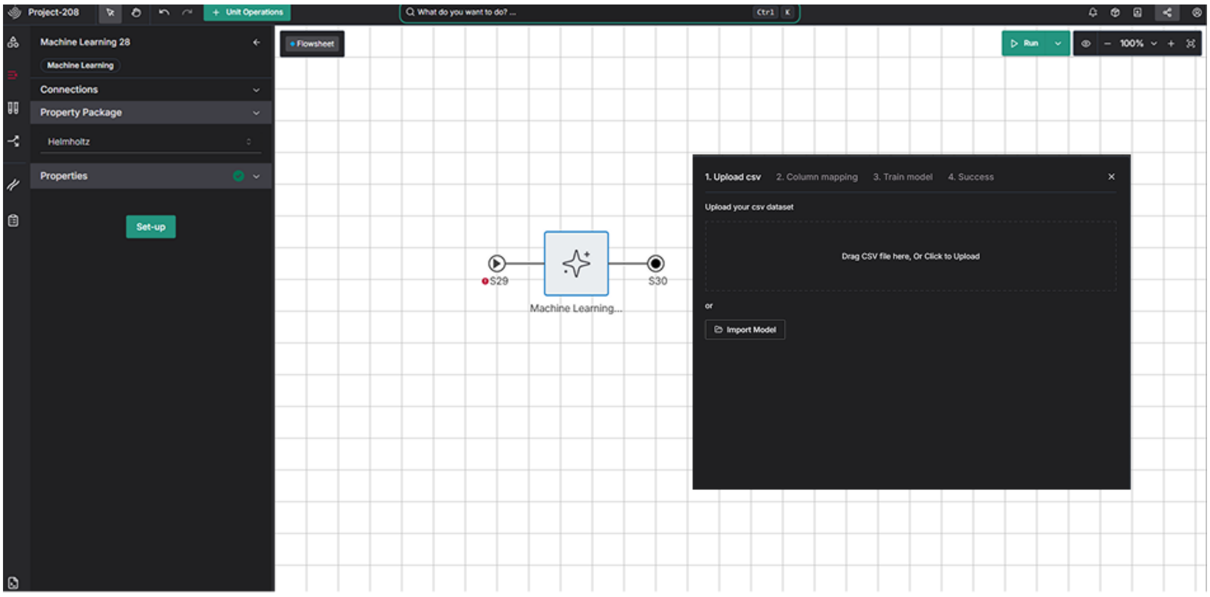

Figure A6: Integration of a machine learning unit in the DT environment, where users can upload datasets (CSV) or import models for training and predictive analysis.

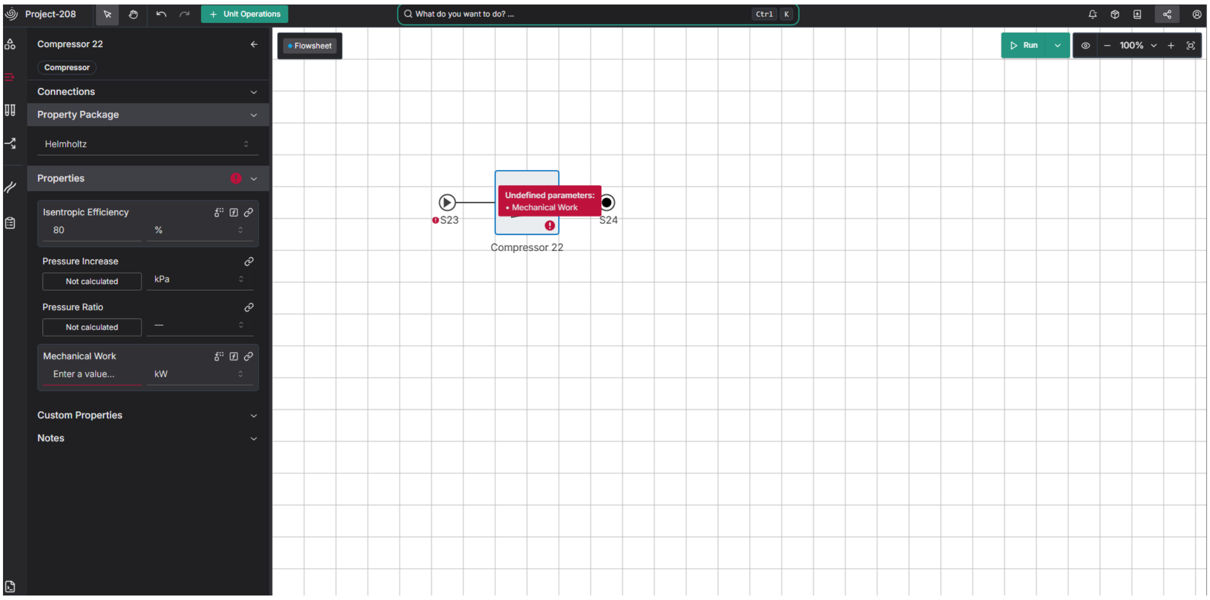

Figure A7: Configuration of the compressor unit in the Digital Twin environment, with unspecified input parameters highlighted in red (e.g., mechanical work) to indicate missing values.

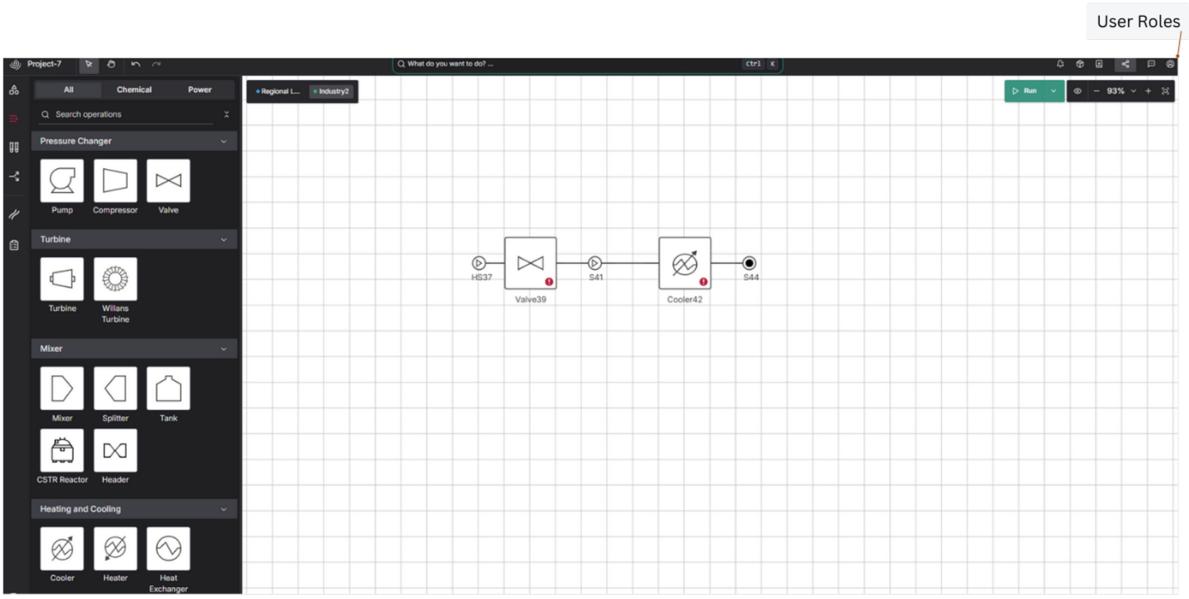

Figure A8: Industry-level operations group multiple unit operations (e.g., valve and cooler) within the flowsheet, simplifying complex processes to reduce cognitive load for users.

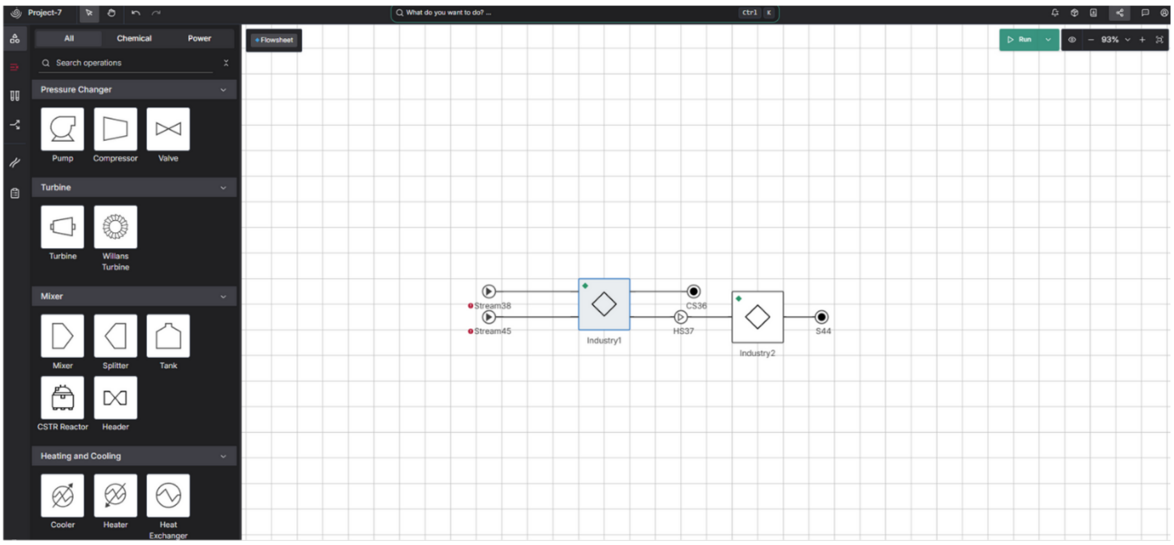

Figure A9: Regional-level operations consolidate multiple processes into higher-level unit blocks (e.g., Industry 1 and Industry 2), providing a streamlined representation of complex systems and reducing cognitive load for users.