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CHARACTERIZING DIGITAL FACTORY TWINS: DERIVING ARCHETYPES FOR RESEARCH AND INDUSTRY

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ABSTRACT

The concept of the digital twin has evolved to a key enabler of digital transformation in manufacturing. The adoption of digital twins for factories or digital factory twins remain fragmented and often unclear, particularly for small and medium-sized enterprises. This study addresses this ambiguity by systematically deriving archetypes of digital factory twins to support clearer classification, planning, and implementation. Based on a structured literature review and expert interviews, 71 relevant DFT use cases were identified. The result of the conducted cluster analysis is four distinct archetypes: (1) Basic Planning Factory Twin, (2) Advanced Simulation Factory Twin, (3) Integrated Operations Factory Twin, and (4) Holistic Digital Factory Twin. Each archetype is characterized by specific technical features, data integration levels, lifecycle phases, and stakeholder involvement.

1 INTRODUCTION

The digital twin concept was first introduced by Michael Grieves in 2003 in the context of product lifecycle management (Grieves 2003). In 2012, NASA formally defined the term, recognizing its potential for aerospace (Glaessgen and Stargel 2012). This led to initial industrial applications and broader visibility through a white paper in 2014 (Grieves 2014).

From 2014 onwards, the concept gained traction across industries. In Germany and Europe, the term “Digital Twin” became central to the Industry 4.0 initiative, while in the US, CESMII led efforts under the Smart Manufacturing umbrella, focusing on AI, cloud, and CPS integration (Shao et al. 2019; Song and Le Gall 2023). In China, Digital Twins are part of the national "Made in China 2030" strategy (Hofbauer et al. 2024).

However, adoption remains slow, especially among small and medium-sized enterprises. This is due to conceptual confusion, lack of standards, and resource constraints. Many companies lack guidance on where to start and how to implement a digital twin. Even within the simulation community, new demands for real-time and data-driven modeling require a significant mindset and skills shift (Shao et al. 2019; Kattenstroth et al. 2024).

To address the confusion of how *digital factory twins* (DFT) can be used in manufacturing, we develop archetypes of DFTs. Archetypes are universal patterns, models, or symbols that appear across cultures, stories, and human experiences (Liddell et al. 1925) and are very popular in IS research and computer system research. They represent fundamental themes, behaviors, or characteristics.

To do that, we address these research questions (RQ):

RQ1: What use cases for DFTs can be identified in the recent scientific literature?

RQ2: What characteristics of those use cases can be derived from research and industry?

RQ3: What are the archetypes of DFTs?

2 FACTORY PLANNING AND FACTORY OPERATIONS

The two overarching management tasks in the context of the factory, which must ensure the best possible fulfillment of the factory target criteria, are factory planning and factory operations (Schenk et al. 2014). In the following, the two are analyzed in more detail.

The engineering discipline of factory planning creates the structures for production operations in a factory (VDI 5200:2011). It plans the factory from a construction perspective and from the perspective of the production system (Burggräf et al. 2021). Factory planning is often event-driven and is therefore carried out in the form of projects. A distinction is made between greenfield planning, i.e. the planning of a new factory, and brownfield planning, which reorganizes existing factories or components (Wiendahl et al. 2023).

Definition 1 Factory planning is the engineering discipline of planning the structures of a factory to ensure optimized factory operations.

In the operation of a factory, several organizational tasks must be fulfilled, which can be summarized under the term production management (Schuh and Schmidt 2014). As an object of planning and control, production management deals with a production process that is already in regular operation and can be understood as the steering instance of a control loop. The execution instance is the production process as such. Production management has the task of planning, monitoring, and controlling this control loop (Vahrenkamp and Siepermann 2014; Adam 2013).

Definition 2 Factory operations, also called production management, is the engineering discipline of planning, managing, and optimizing the production steering and control loop.

3 RELATED WORK: DIGITAL TWINS IN FACTORY PLANNING AND FACTORY OPERATIONS

Digital concepts in the context of manufacturing have a long history. Initially, however, computer support was limited to islands of the factory, e.g., in the form of individual production plants or production areas (Westkämper et al. 2013; Bracht et al. 2018). As IT performance improved, computer-integrated manufacturing (CIM) was introduced. CIM, which predates Industry 4.0, aimed to integrate computer systems into manufacturing operations. Although CIM promised fully automated and digitally integrated production, its potential was constrained by heterogeneous IT systems, a lack of standardization, and high implementation costs. Nevertheless, CIM paved the way for modern production management systems and established the foundation for data-driven production decisions, with many of its principles later incorporated into more advanced concepts such as the digital factory (Thorade and Erdogan 2024).

With the increasing performance of IT, more advanced concepts emerged in recent years and continue to emerge. For example, the term Industry 4.0 describes the overarching process of digital transformation for industry (Hänisch 2017; Bauernhansl et al. 2016). Within this context, the term digital factory was introduced by the VDI at the beginning of the 2000s (VDI 4499:2008). Its concept focuses mainly on planning purposes and emphasizes the importance of linking data and tools during the production system lifecycle. (Bracht et al. 2018). While CIM is focused on computer system integration into manufacturing processes, the digital factory concentrates more on an overarching planning and optimization of a production system. However, the integration of different IT systems remains a challenge. The digital factory allows for more precise planning and optimization of production processes by using virtual models of production facilities. These models help to analyze different scenarios and identify the best solution for efficient processes. (Westkämper et al. 2013; Bracht et al. 2018; VDI 4499:2008)

An essential component of the digital factory is material flow simulation. By using simulative methods, production systems can be realistically modeled, bottlenecks can be identified, and production efficiency can be improved. According to the studies by Zhang et al. and Kattenstroth et al., material flow simulation contributes significantly to flexibility and increased efficiency in production systems. (Zhang et al. 2024; Kattenstroth et al. 2024)

Another evolution in this field is the smart factory. It describes the transfer of the smart environment concept to the factory and thus the use of cyber-physical systems in the production context (Westkämper et al. 2013). The DFT then describes a mapping of all relevant aspects of the overall factory system in a digital mirror image (Burggräf et al. 2023). Several organizations working on standardization in the context of the smart factory and the digital factory and the efforts are gaining traction (notable examples are the ISO 23247 'Digital Twin Framework for Manufacturing' or the Asset Administration Shell). The relevant and used phrases are structured in Figure 1. We focus on the DFT because it covers all phases of the production system lifecycle, and not separately the planning phase, like the digital factory does.

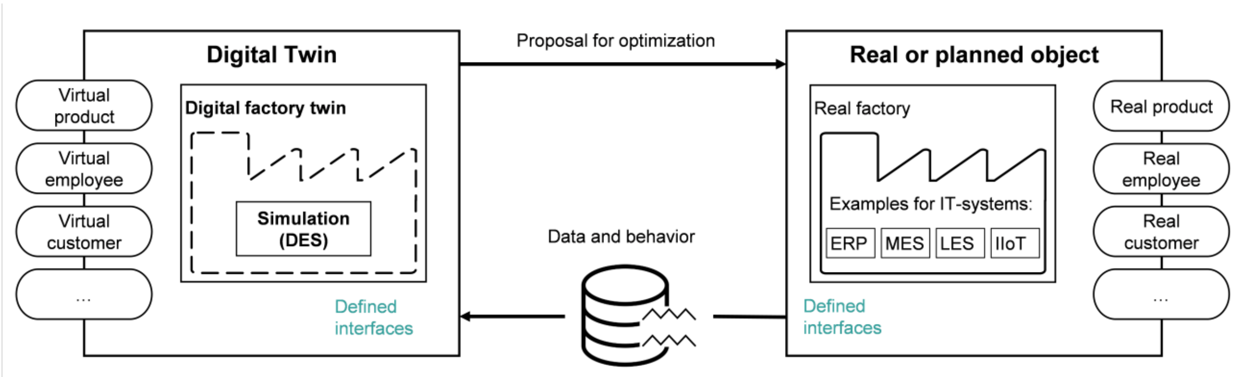

Figure 1: Illustrating the relationship of the DFT and discrete event simulations.

While other studies focus more on a generic digital twin characterization and archetype development (see for example (Van der Valk et al. 2022; Gillani et al. 2024; Minerva et al. 2020)), we focus on the specific context of the digital factory and connected topics described above.

4 RESEARCH METHODS

We use an archetype development process successfully developed and applied in van der Valk et al. to answer our research questions (Van der Valk et al. 2022). According to the standardized procedure, we go through a total of six steps: Research Preparation, Object Phase, Cluster Type Phase, Synthetization Phase, Designation Phase, and, finally, Finalization Phase.

The first phase deals with defining the general aspects of the research topic, i.e., DFTs, and identifying a working definition. Furthermore, a DFT must be used in the context of factory planning or factory operations. It needs a bi-directional data flow, yet it does not need to be fully automated. We require synchronization between the virtual side, e.g., the digital model of the factory, and the real-world shopfloor. Lastly, we present an internal data processing unit within the digital twin.

The second phase comprises the steps of object collection and documentation of the object properties according to which the archetypes are subsequently formed. We use a structured literature review (SLR) and interviews to acquire data about DFTs. We will describe the SLR procedure in the following section. The interviews took place with two industrial experts. One has multiple years of experience in applied research on the topic and works closely with manufacturers. The other expert works in the industry and is focused on utilizing digital twins for factory planning and operations.

Within the third phase, the actual clusters are derived from the data. Therefore, the various properties and configurations of the objects are coded and finally grouped with a cluster analysis. A deeper explanation of the cluster analysis is provided in Section 4.2. The descriptions of the different clusters given by the cluster analysis are then matched against the working definition from the first phase.

The different cluster types are compared with each other, and mandatory components are derived (phase 4). In the 5th phase, the cluster types are finally transferred to archetypes. For this purpose, the archetypes are named according to a template. The final phase includes the evaluation of the archetypes and the possibility of increasing the clarity of the archetypes with examples. For the evaluation, we also interviewed another industrial expert. He has over 15 years of experience in material flow simulations and works closely in the sector of production systems and logistics flow engineering.

4.1 Structured Literature Review

In order to create the database for the derivation of the clusters, an SLR is carried out according to Xiao and Watson 2019 and Lame 2019 (Xiao and Watson 2019; Lame 2019). Two different search strings are used to ensure that all relevant publications from factory planning and factory operations are considered. The first search string is ("Digital Twin" OR "Digital Shadow" OR "Digital Thread" OR “Cyber-Physical System”) AND ("production" OR "manufacturing" OR "factory" OR "operational" OR "smart manufacturing" OR "Industry 4.0") AND ("definition" OR "Use Case") AND (“data” OR “source”). It targets publications between 2018 and 2025. With this search string, 1567 publications were found in the Scopus database. However, after screening the titles and abstracts, only 60 relevant publications remained, which were reduced to only 43 objects after a full-text analysis. This is due to the fact that most of the results were not located in our target domain, i.e., manufacturing. In addition, a further subdivision had to be made within the manufacturing domain because we want to look at discrete assembly and production, and not continuous material solutions such as oil or gas. Furthermore, a large number of publications have been eliminated because they do not correspond to our working definition of a DFT.

The second search approaches the topic from within the simulation, which is why the 2nd search was formulated as follows: ("material flow simulation" OR "discrete-event simulation") AND ("Digital Twin" OR "Digital Shadow" OR "Digital Factory" OR "Virtual Factory" OR "Smart Factory") AND ("manufacturing" OR "production" OR "logistic" OR "factory" OR "operational" OR "smart manufacturing" OR "Industry 4.0") AND ("procedure" OR "method" OR "approach" OR "systematic" OR "framework" OR "feature" OR "characteristic"). A total of 208 publications were found. Three of them matched the first search and were removed as duplicates. After title screening 165 publications were remaining. After abstract screening 81 publications were left. These were subjected to a full-text analysis, and 48 publications remained. The following criteria were applied to eliminate non-matching publications. There was no relevance to the research question. The publication dealt with a non-industrial context. There was no focus on material flow simulation, and no concrete use case was derived.

4.2 Cluster Analysis and Archetype Derivation

In Phase 3, designated as the “Cluster Type Phase,” the defining characteristics of the use cases were established, with a detailed overview provided in Table 1. This phase focused on identifying the key attributes that differentiate various applications of DFTs, laying the groundwork for subsequent cluster analysis. Following the identification of use case characteristics, cluster analysis was performed to group similar use cases together. The elbow curve method, a common technique for determining the optimal number of clusters, indicated a potential bend at 3 to 4 clusters. This suggests that the data could be divided into either three or four distinct groups, each representing a different archetype of DFT. While the elbow curve suggested 3 or 4 clusters, an analysis using 3 clusters revealed limitations. Specifically, several key differences in the describing characteristics of the use cases were grouped into the same cluster. This implied that using only three clusters might oversimplify the data and fail to capture the full spectrum of variations among the use cases. The decision to explore a higher number of clusters was therefore motivated by the need to achieve a more granular and accurate representation of the data. To visualize the use cases and their assignment to clusters, a 2D representation was generated using the K-Means algorithm. This visualization aimed to provide a clear picture of how the use cases were distributed across the clusters, allowing for a qualitative assessment of the clustering results. The analysis revealed that approximately

38.6% of the variance in the characteristics could be identified with dimension 1 and dimension 2, suggesting that these two dimensions capture a significant portion of the variability in the data.

Table 1: Describing characteristics of identified DFT use cases for following cluster analysis.

Name	**Motivation for including characteristic**	**Possible values**
Lifecycle phase	Identifying use in specific phases in the factory lifecycle	Production requirements, production engineering, process planning, ramp up, production, re-use/ recycling
Hierarchy level factory	Differentiating depth of application within the factory structure	Production network, factory, production area, production line, workstation
Simulation or operations focus	Defining focus of DFT usage	Simulation, operations, both
Type of used simulation	Identifying used simulation methods	Discrete-event, continuous, agent-based, system dynamics, Monte-Carlo, hybrid, none
Properties of DFT model	Defining technical requirements and capabilities of DFT model	Real-time capability, bidirectional data connection, visualization, GUI, performant, interfaces for the integration of further models, automatic data preprocessing
Number/ type of use of DFT model	Determining frequency and pattern of model usage	Once, several times, parallel to operation (continuous)
Type of data input	Defining level of automation in data input	Fully automated, semi-automated, manual
Interval of data synchronization	Defining how often data is updated for DFT model	Real-time, batch, event-based
Transferring results to other IT systems	Defining level of automation in use of the model results in other IT systems	Automated, manual
Stakeholders	Identifying actors involved and benefitting in the use of DFT	Customer, supplier, production engineering, R&D, production planning, maintenance, operations management, quality management, logistics, works council, occupational safety, sustainability management
Involved data clusters	Clarifying relevant data groups for DFT	Product design data, production requirements, operational data, instructions and regulations, manufacturing asset configuration, manufacturing KPIs, process data, predictions of production system performance, simulation and analysis of production system behavior, layout configuration

As a final step, an initial check against the working definition was performed, leading to the identification of 4 distinct cluster types. This outcome aligned with the upper end of the range suggested by the elbow curve and indicated that four archetypes could provide a more nuanced and comprehensive classification of DFT use cases. The identification of these archetypes represents a crucial step towards a more structured and systematic understanding of the diverse applications of DFTs.

5 ARCHETYPES OF THE DIGITAL FACTORY TWIN

In Phase 4, the "Synthesization Phase," mandatory and optional elements for the cluster types were defined based on the characteristics outlined in Table 1, with a more detailed discussion presented in sections 5.1 and 5.2.

In Phase 5, the "Designation Phase," the archetypes were identified and are discussed in more detail afterward.

5.1 Archetypes 1, 2, and 3: Simulation-based Digital Factory Twins

The four DFT archetypes rise in complexity and implementation effort. Archetypes 1–3 primarily focus on simulation-based DFTs and are described below, including mandatory and optional features as per van der Valk et al. (Van der Valk et al. 2022).

The Basic Planning Factory Twin (AT1) is represented by low technical effort and little system integration, primarily due to its early planning phase and reliance on manual input data. 21.4% of the identified use cases (see section 4.1) belong to this archetype. A basic simulation functionality, not differentiated by the simulation type, is a mandatory element of AT1. It uses low or no real-time integration, so the data is rather manually or batch-based integrated. Consequently, the number of stakeholders involved is limited, which aligns with the simplified and early lifecycle phases.

In addition to these mandatory elements, the archetype may also incorporate several optional characteristics. These include enhanced data visualization capabilities, the integration of static operational data, a modest degree of automation, and the partial use of production requirements or layout data. Combined, these elements underscore the archetype's role in addressing classic planning scenarios with a focus on simplicity and low integration, making it a practical solution.

The Advanced Simulation Factory Twin (AT2) is distinguished by its robust real-time capabilities, interactive graphical interface, and advanced visualization tools, making it ideally suited for simulation applications. Representing 15.7% of the identified use cases, this archetype focuses on scenarios that emphasize high technological performance, seamless integration, and enhanced user interaction. Therefore, capabilities for real-time data processing are mandatory for this archetype to reflect time-sensitive operations. The graphical user interface allows users to control either the simulation directly or the input commands and analyze the results visually. Effective communication between the user and the system is secured. The simulation models are widely different in AT2, they can have a high fidelity, but share adaptability as a common feature. Thereby, a realistic depiction of different complexities can be handled. A bidirectional system connectivity from and to reality is key to maintaining integration and data consistency across platforms. How the bidirectionality is established can differ between automatic and manual, with the overall goal to ensure high simulation performance and responsiveness.

Adding to these mandatory elements, the Advanced Simulation Factory Twin can be further enhanced with optional characteristics, such as automated data preprocessing, visualization dashboards, broader stakeholder integration (extending beyond engineering to include logistics and planning), and cross-phase usage that supports both design and operational phases. These enhancements provide additional value through data management and extend the scope of the simulation's applicability.

The Integrated Operations Factory Twin (AT3) is designed for scenarios that require extensive utilization of operational data and robust automation, making it ideal for digital twins and production-accompanying simulation applications. With 35.7%, it represents the biggest share of the identified use cases. Five mandatory elements for this archetype were identified, including automated or sensor-based data input. The system gathers data automatically from sensors or through standardized interfaces such as SCADA, ensuring timely and accurate data capture from the operational environment. Next, the bidirectional synchronization with real systems was found. The communication between the DFT and the physical production system is established continuously. This enables a simulation to reflect real-time changes and maintain data consistency across both domains. The archetype incorporates clusters of operational data, including key performance indicators, process information, and manufacturing configuration details. This structured data supports comprehensive analysis and decision-making. Inputs from several stakeholder groups are included in day-to-day operations, production engineering, and maintenance. This enables real-time decision support functionalities, which is crucial for addressing immediate operational challenges and optimizing production processes.

Optional enhancements for this archetype cover forecasting and predictive models to anticipate future trends, interactive graphical user interfaces for improved usability, continuous simulation during production for ongoing analysis, and partial use for planning-related activities. These additional characteristics further augment the DFT's capabilities by extending its scope beyond. Overall, the Integrated Operations Factory Twin is highlighted by its comprehensive integration of operational data and automation, offering a dynamic and responsive simulation environment that supports both immediate operational needs and long-term production planning.

5.2 Archetype 4: Holistic Digital Factory Twin

The Holistic Digital Factory Twin (AT4) represents the premium setup in DFTs, offering an integrated, data-driven, and highly interactive simulation environment that is operationally relevant. Representing 27.1% of the identified use cases, this archetype is characterized by its extensive use of all data clusters and the seamless combination of various simulation kinds and actual operations. It accommodates many stakeholders and system components, ensuring that every facet of the production and logistics process is considered. The full integration of multiple data clusters is therefore a mandatory aspect. It ensures that every relevant data from design, operations, KPIs, simulation results, etc., is fully integrated, providing a comprehensive view of the system. Another key characteristic is the coverage of all lifecycle phases of a production system, including design, ramp-up, operations, and continuous improvements. The model integrates input from a wide range of departments such as planning, logistics, safety, and sustainability, making sure that all perspectives are considered in decision-making. By an automated bidirectional data flow, a seamless communication between the DFT and the physical production environment is established, ensuring consistent up-to-date data. The last mandatory aspect is the high model modularity and scalability. The system is designed with modular components that can be easily adjusted or expanded, supporting scalability and adaptation to complex and evolving production requirements.

The optional characteristics of the Holistic Digital Factory Twin are a cross-site factory integration, self-adaptive control mechanisms, multi-model orchestration and predictive analytics across domains. These features further enhance the model's capabilities by providing advanced tools for integration, control and foresight. Overall, the archetype 4 delivers a state-of-the-art, fully integrated simulation platform that combines comprehensive data utilization, extensive lifecycle coverage and broad stakeholder involvement, making it an optimal solution for modern, data-driven production environments.

5.3 Evaluation of Archetypes with Examples from Research and Industry

In the course of validating the proposed archetypes, we used an interview with an industry expert. In principle, he supports the proposed archetypes but suggests several minor adjustments. For archetype 1 Basic Planning Factory Twin, the expert emphasized that this category primarily reflects the use of digital tools commonly employed in early planning stages; such as CATIA, MicroStation, visTable, or at most code-based simulation tools with bare connectivity.

Regarding archetype 2, Advanced Simulation Factory Twin, the expert noted that many classic material flow simulation use cases fall within this category. However, caution was advised against overemphasizing the notion of 'real-time data' at this stage. Instead, it was proposed to generalize the data input aspect to include both real-time and historical data from operational systems ('field data'), thus accommodating a broader spectrum of data-driven simulation scenarios. Furthermore, the term 'bidirectional system communication' was deemed too advanced for the typical maturity level of this archetype. A more appropriate and inclusive term would be 'system communication', which captures uni- or bidirectional data flows without implying full integration. Moreover, he pointed out that the naming could be confusing and thus proposed to change it to 'Advanced Visualization and Simulation Factory Twin'. At his company, this archetype is widely used in the context of planning purposes for green- and brownfield, robot, or Programming Logic Controller simulation in particular.

For archetype 3. Integrated Operations Factory Twin, the expert found the structure and interpretation to be comprehensible, especially when bidirectional communication is understood to include both automated and manual data flows. This clarification ensures consistency with common industrial setups, where data synchronization between virtual and physical systems may not yet be fully automated. In this context, he didn't have a specific use case in mind, but is sure that this is used in another department regularly.

Lastly, in the context of archetype 4, Holistic Digital Factory Twin, the expert referred to the emerging concept of the Industrial Metaverse as a fitting real-world analogy. This vision encompasses the seamless integration of multiple tools, data domains, and use cases across the entire factory ecosystem. The Industrial Metaverse, with its immersive and collaborative capabilities, represents a future-oriented manifestation of this archetype and serves as a reference point for full-scale, cross-functional, and lifecycle-spanning digital twin implementations. This is the desired form of a DFT for him, but at the point of the interview, it's not implemented in the factory due to multiple hurdles, like, e.g., troubles with common software, issues with interconnecting different software, and high investments.

Each DFT archetype was validated through real-world research and industrial use cases, highlighting practical implementations and specific characteristics aligned with each archetype.

AT1 – Basic Planning Factory Twin:

- Research: Sommer et al. present a method for the automated creation of digital twins for built environments. It involves scanning and object recognition to assist in production planning. (Sommer et al. 2023)
- Industry: Audi's Planning Twin in Neckarsulm uses high-resolution 3D indoor mapping to support virtual layout planning and measurements remotely. The tools applied include systems like CATIA or visTABLE, typically disconnected from operational IT systems. (NavVis 2020)

AT2 – Advanced Simulation Factory Twin:

- Research: Khumbar et al. developed a DFT framework combining process mining and bottleneck detection. This simulation-based system enables performance improvements through utilization analysis. (Khumbar et al. 2024)
- Industry: The WSA 3D Digital Twin maps an entire cardboard factory's material flow in 3D. It enables what-if analyses for layout and process optimization. Tools used typically include interactive GUIs and dynamic visualization systems. (WSA 2025)

AT3 – Integrated Operations Factory Twin:

- Research: Khdoudi et al. introduce a deep learning-based DFT that supports autonomous process control in injection molding. It allows virtual decision-making with real-time data from sensors. (Khoudi et al. 2024)
- Industry: Pegatron's PEGAVERSE integrates live machine data and predictive analytics for factory monitoring. It offers bidirectional synchronization and decision support for ongoing production operations. Other tools in use include Twinzo and Azure Digital Twins for live monitoring and visualization. (NVIDIA 2023)

AT4 – Holistic Digital Factory Twin:

- Research: Garcia et al. propose a platform combining discrete-event simulation with optimization tools and AR interfaces. It uses a cloud-based input structure and supports lifecycle-spanning system validation. (Garcia et al. 2021)
- Industry: BMW's Virtual Plant in Debrecen, built with NVIDIA Omniverse, provides a unified environment for simulating and optimizing all factory aspects from layout to energy management. (NVIDIA 2022)

The mentioned tools in the provided examples for the archetypes AT1 to AT4 are described shortly afterwards.

NavVis is a platform for high-precision indoor mapping using mobile scanning devices, producing georeferenced point clouds and photorealistic digital twins. These are useful for remote production planning, facility management, and BIM integration, especially in complex industrial settings (NavVis 2020). The WSA 3D Digital Twin, developed with Warak, links automation systems with accurate 3D models. By connecting real-time sensor and machine data, it enables predictive maintenance, workflow optimization, and material handling control via a user-friendly interface (WSA 2025). NVIDIA Omniverse is a real-time collaboration and simulation platform that uses AI, GPU acceleration, and photorealistic rendering to enable multi-stakeholder factory simulation and optimization (NVIDIA 2022; NVIDIA 2023).

Other examples for tools and how they fit into our archetypes are the following: Halocline's VR software is an AT1 example: a manually updated digital twin for layout planning and process simulation in a virtual reality environment (Halocline 2025). FlexSim is a widely used material flow simulation tool that supports both AT2 and AT3 through interfaces like Python or MQTT. At Nemak, FlexSim is applied for AT3-level twins with automated input, real-time synchronization, and decision support (Nigischer et al. 2024). Twinzo and Microsoft Azure Digital Twins exemplify AT3 usage, offering real-time data integration into 3D virtual models for live monitoring and analytics, without necessarily enabling full automation (Twinzo 2025; Microsoft 2025). Dassault Systèmes' DELMIA and Siemens' digital twin platforms illustrate AT4 implementations. These systems combine real-time control, AR support, and human-machine interfaces to bridge virtual models and physical production systems (Dassault Systèmes 2025; Siemens 2025).

Our observation is, that advanced DFT tools are typically used in AT3 and AT4 but require careful consideration of ROI and technical needs. Many companies begin with AT1 and evolve toward more complex setups as infrastructure and digital maturity increase.

6 CONCLUSION, LIMITATIONS, AND OUTLOOK

This research developed DFT archetypes using a database of use cases from a Systematic Literature Review (SLR), complemented by three expert interviews. The SLR provided broad insights into DFT applications, grounding the archetypes in real-world implementations. The development followed van der Valk's method (Van der Valk et al. 2022), while the interviews added practical context to differentiate the use cases. Cluster analysis identified four types, directly matching the proposed archetypes. Each includes mandatory and optional elements derived from the use case analysis (see Section 5), providing a clear structure for classification and practical application. Table 2 outlines the formal definitions, while Table 3 offers real-world examples, confirming the framework's relevance.

While insightful, the study has limitations. SLRs and the cluster analysis itself are subject to researcher interpretation, and other studies might yield different papers are clusters. The elbow curve analysis indicated that three clusters might also fit, suggesting possible alternative archetypes. Choosing four clusters with balanced granularity and clarity, though other valid models may exist. In addition, the interviews were conducted with three experts. There is a need to challenge the clusters with more experts from different industries.

Overall, the archetypes bring structure to a complex field, supporting both research and application. For researchers, they offer a consistent language to classify and compare findings. For practitioners, the framework aids in defining DFT scope, selecting providers, and aligning implementations with strategic goals. Combined with prior contributions (Cieply et al. 2023; Lick et al. 2024a, Lick et al. 2024b, Lick et al. 2024c), this supports integrated planning across business and IT.

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