Tu, Xinyi; Ala-Laurinaho, Riku; Yang, Chao; Autiosalo, Juuso; Tammi, Kari

Architecture for data-centric and semantic-enhanced industrial metaverse : Bridging physical factories and virtual landscape

Published in:
Journal of Manufacturing Systems

DOI:
10.1016/j.jmsy.2024.05.016

Published: 01/06/2024

Document Version
Publisher's PDF, also known as Version of record

Journal of Manufacturing Systems 74 (2024) 965–979

Contents lists available at ScienceDirect

Journal of Manufacturing Systems

journal homepage: www.elsevier.com/locate/jmansys

Technical paper

Architecture for data-centric and semantic-enhanced industrial metaverse: Bridging physical factories and virtual landscape

Xinyi Tu *, Riku Ala-Laurinaho, Chao Yang, Juuso Autiosalo, Kari Tammi

Department of Mechanical Engineering, Aalto University, Otakaari 4, Espoo, 02150, Finland

ARTICLE INFO

Keywords:
Industrial metaverse
Virtual–physical continuum
Digital twins
Extended reality
Architecture
Industry 5.0

ABSTRACT

The metaverse paradigm has recently captured increasing scholarly and industrial attention, particularly within the scope of human-centric Industry 5.0. In this context, the metaverse promises a transformative confluence of the physical and digital realms, offering unparalleled avenues for human augmentation in industrial applications. Yet, while several conceptual metaverse architectures and illustrative case studies have emerged, they scarcely delve deep into the nuanced practice of cultivating the industrial metaverse for factory-scale applications. Addressing this research gap, this work introduces a novel architecture for a data-centric and semantic-enhanced industrial metaverse. The architecture intricately weaves the physical factory domain with the metaverse, fortified by a suite of ten modules, facilitating data flow and knowledge synchronization with the integration of digital twins and semantic models. The practical application and relevance of this architecture are further accentuated through a case study focused on in-plant material flow tracking. Emerging results underline that our architecture encapsulates the essential components for constructing a factory-scale industrial metaverse. Future research will be geared towards a comprehensive validation of the proposed metaverse architecture, culminating in tangible implementations across diverse industrial contexts.

1. Introduction

The metaverse paradigm has recently gained great attention, underpinned by its transformative potential in integrating physical and digital worlds. While consumer sectors such as online retail, social media, and gaming have seen early adoption spearheaded by companies like Meta, the industrial metaverse is rapidly coming into focus as an arena of enormous potential. ABI Research predicts that the industrial metaverse market can grow to nearly 100 billion dollars by 2030, overshadowing its consumer counterpart pegged at about 50 billion. Bearing testament to a paradigm shift in contemporary industry, the industrial metaverse promises to reshape the industrial chain and usher in unparalleled value for diverse stakeholders in the foreseeable future [1]. Within the paradigm of human-centric Industry 5.0, the metaverse is posited as a revolutionary force, seamlessly integrating the physical and digital worlds [2,3]. Such integration can pave the way for innovative manufacturing frameworks characterized by interactive, immersive, and tailored experiences, thereby facilitating enhanced human augmentation in industrial scenarios [4].

The term "metaverse" has been at the forefront of both technological and cultural discourses, often bringing along with it a medley of interpretations. Drawing from the perspectives of [5,6], the metaverse is envisioned as an interconnected web of social, networked, perpetual, and persistent multi-user immersive environments that combines physical reality and digital virtuality. To bring clarity to our discussion, we define the metaverse as "a continuum of physical and virtual systems, interconnected and intertwined in ways that allow for seamless transitions and interactions, which stands distinct from merely virtual environments in its depth of connection to the physical world, and its constant synchronization and reflection of real-world dynamics".

Transitioning from this foundational understanding of the metaverse, this article delves into the concept of the "industrial metaverse", a nuanced adaptation tailored for the industrial domain. According to [7], the industrial metaverse not only incorporates core features of the metaverse, such as man-in-the-loop, digital assets, and social networks, but it also distinguishes itself through a unique focus on the industrial process value, and the capability to simulate and connect with various industrial factors including machines, humans, materials, processes, and activities. Notably, [7] posits the industrial metaverse as a novel digital twin system, centered on human-in-the-loop dynamics, adeptly simulating industrial processes, facilitating industrial value transactions, and fostering human–machine collaborations. This conceptualization aligns with [8], which perceives the industrial metaverse as a workspace's digital twin, a cornerstone in augmenting interactions

* Corresponding author.
E-mail address: xinyi.tu@aalto.fi (X. Tu).

https://doi.org/10.1016/j.jmsy.2024.05.016
Received 14 February 2024; Received in revised form 6 May 2024; Accepted 16 May 2024
Available online 23 May 2024

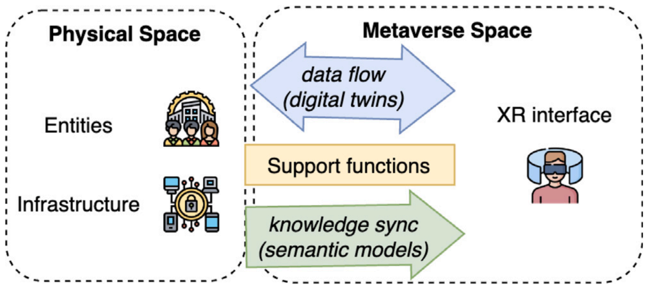

Fig. 1. Condensed overview of the proposed industrial metaverse architecture: This architecture seamlessly bridges the physical space, encompassing entities and infrastructure, with the metaverse space. Within the metaverse space, digital twins ensure bi-directional data flows, while semantic models drive knowledge synchronization. The architecture also encompasses the XR interface and support functions.

with physical entities and enhancing visualizations in a cyber–physical ecosystem. This represents a significant evolution from conventional digital twins or standalone extended reality (XR) technologies, or a disparate collection of technologies. Instead, the industrial metaverse synthesizes various enabling technologies into a sophisticated, cohesive, interoperable, and scalable framework, extending beyond traditional software platforms to offer a multifaceted solution tailored to meet the complex demands of modern industry.

The industrial metaverse offers a communal space for interdisciplinary teams and customers to interact and collaborate seamlessly with highly personalized experiences [9]. The applications of the industrial metaverse manifest along multiple phases of a plant's life cycle: facilitating collaborative simulations for product and plant layout designs during the design phase, offering intuitive training arenas for novice workforce during the onboarding phase, and enhancing operational efficiency while minimizing quality risks during the manufacturing phase. By structurally integrating various technologies, the industrial metaverse represents a significant advancement over existing methods, not only providing a dynamic approach to digitalizing manufacturing processes but also offering interactive interfaces that empower human workers to interact with complex manufacturing environments effectively. In essence, it promises a transformative shift in factory personnel's engagement, ushering in collaborative and tailored machine interfaces pivotal for control, monitoring, and upkeep.

Despite these promising potentials, there are notable gaps in the industrial metaverse development. Current metaverse architectures, as underscored by [6,10–12], predominantly cater to consumer applications, often overlooking the bespoke challenges and intricacies posed by industrial contexts. Furthermore, literature targeting industrial metaverse [7,8] while enlightening, are largely conceptual, lacking the granular technical guidelines for tangible, real-world implementations. Moreover, prevailing case studies [8,13–15], though rich in insights, tend to overemphasize XR that consists of virtual reality (VR), augmented reality (AR), and mixed reality (MR). This focus, though important, often neglects the holistic, platform-centric approach pivotal to the essence of the metaverse — a seamlessly interconnected digital–physical continuum. Such studies sideline imperatives like data integration, and semantic enrichment. In our prior research endeavors [16–22], the attention was primarily on integrating the foundational technologies underpinning the industrial metaverse: digital twins and XR. While these explorations provided invaluable insights, they predominantly gravitated towards specific machine applications, bypassing the wider spectrum of metaverse components encompassing personnel, materials, and the environment. Collectively, these research gaps accentuate an urgent need for an interconnected, scalable, and pragmatic industrial metaverse architecture, a challenge this article aspires to address.

Fig. 1 illustrates a condensed representation of our proposed industrial metaverse architecture. At its core, this architecture bridges the physical factories, consisting of entities and infrastructure, with their metaverse counterparts. Within the metaverse space, digital twins form the backbone for dynamic bi-directional data flows. Simultaneously, semantic models ensure knowledge synchronization. The architecture also emphasizes the criticality of the XR interface for end-users and highlights the encompassing support functions that represent various capabilities within the metaverse. Building on this premise, this work elucidates the following pivotal contributions:

1. Introducing a novel industrial metaverse architecture, seamlessly linking physical factories with their metaverse counterparts.
2. Orchestrating data flow and knowledge synchronization through the integration of digital twins and semantic models.
3. Affirming the efficacy and viability of the proposed architecture through a case study focused on in-plant material flow tracking.

The rest of the article is structured as follows: Section 2 analyzes existing literature on prevailing metaverse and industrial metaverse architectures, case studies of industrial metaverse applications, and the interplay of digital twins and XR. Section 3 introduces our proposed industrial metaverse architecture, detailed across ten pivotal modules, and underscored by the principles of data flow and knowledge synchronization. Section 4 illustrates the practical application of our architecture through a case study focused on in-plant material flow tracking. Discussions on the implications, challenges, and future research are presented in Section 5. The article culminates in Section 6, summarizing our findings and contributions to the field.

2. Related works

This section delves into a literature review across three pivotal domains: prevailing metaverse and industrial metaverse architectures, case studies of industrial metaverse applications, and the authors' previous works focusing on digital twins and XR as the foundational pillars of the industrial metaverse. Through a critical examination of the related works, we highlight existing gaps and shortcomings, thereby establishing the research motivation of this work.

2.1. Existing metaverse architectures

The metaverse development is still at an early stage, therefore its architecture has not reached a consensus. [10] proposed a seven-layered architecture that described the value chain of the metaverse development stages: The seven layers from bottom to top were infrastructure, human interface, decentralization, spatial computing, creator economy, discovery, and experience; The sequence of the layers indicated that the realization of the metaverse should start from infrastructure and equipment, then move to development tools, and eventually reach application products and operation ecosystems [6]. Based on the seven-layered architecture, [11] described the metaverse at a more macro level with only three layers: the infrastructure layer that corresponded to the physical world, the ecosystem layer that corresponded to the virtual world, and the interaction layer in the middle that corresponded to the intersection between these two worlds. [12] introduced three sequential stages of the metaverse development as a "digital twins-native continuum" considering the experience-duality: The first stage focused on creating a digitalized real world; It was followed by the phase of "digital natives", which led to various virtual worlds with content from their digital creators; The final phase featured the forming of a self-sustaining and persistent metaverse, with the co-existence of physical–virtual reality that was interoperable yet independent of each other.

Despite their advancements, these metaverse architectures predominantly focus on consumer applications, neglecting the distinctive requirements and challenges presented by industrial settings. In contrast to consumer-oriented metaverses, industrial metaverses demand significantly higher levels of reliability to ensure consistent performance, stringent security measures to protect sensitive data and operations, and comprehensive interoperability to facilitate seamless interaction among a variety of systems and devices. This interoperability becomes particularly critical when considering the need to integrate with existing industrial systems. Recognizing these unique requirements, researchers have proposed specific architectures tailored to the needs of the industrial metaverse.

For instance, [7] proposed a primary architecture specific for building the industrial metaverse, consisting of four layers. The basic layer includes five essential elements (personnel, equipment, raw material, environment, and principle), along with data, storage, and network resources. These provided all the basis and support for generating and operating the industrial digital space. The perception layer, equipped with the capabilities to link, detect, percept, obtain, and abstract, ensured stable and real-time perception of multi-source industrial information from physical elements and human participants. The service layer was divided into three platform-as-a-service (PaaS) sub-layers: foundation, engine, and analyze PaaS. This layer provided various services around the requirements of a high-fidelity industrial environment, immersive user experience, and a decentralized social system. Finally, the application layer provided users with multiple functions that fulfill the needs of the industrial metaverse across various industrial system granularities along the product lifecycle.

Similarly, [8] proposed the cyber–physical industrial metaverse systems based on the "5C" framework: The connection layer focused on data acquisition using hardware; The conversion layer processed raw data into information; The cyber layer conducted time-machine and fleet-sourced data management; The cognition layer focused on information visualization to enhance human–machine interaction; The configuration layer enabled multi-sourced information to be viewed simultaneously in the metaverse to realize different purposes including remote interaction, remote instruction, remote indoctrination, as well as remote investigation and control.

Despite the emergence of these specialized architectures, the current body of literature often remains conceptual, falling short of providing concrete guidance for the implementation of an industrial metaverse on a factory scale. Furthermore, much of the existing work emphasizes building an entirely new metaverse ecosystem from scratch, rather than focusing on how to establish a meaningful and seamless connection between the metaverse space and existing physical factories. A critical aspect often overlooked is the integration of information technology (IT) and operational technology (OT) systems. IT systems facilitate the secure processing and storage of data, supporting essential functions such as user interaction, system monitoring, and analytics. Meanwhile, OT systems directly manage the physical elements of industrial operations, playing a vital role in automating and optimizing manufacturing processes. This integration is essential for a fully functional and efficient industrial metaverse that can operate in harmony with legacy infrastructures.

2.2. Industrial metaverse case studies

Several case studies have been conducted around industrial metaverse applications. For instance, [13] explored the metaverse's applications in fluid machinery, focusing specifically on pumps and fans. Their study highlighted that current metaverse applications in this field were primarily relegated to enabling remote operation and monitoring of machinery within virtual environments. [8] studied the application of the metaverse in machine health and process monitoring, control, and maintenance of a ball screw for remote manufacturing. Their work underscored the real-time data connectivity, through which users could not only access real-time machine status but also engage with experts for instructions on remote maintenance. [14] shifted the focus to data-driven intelligent transportation systems, demonstrating metaverse applications that employed AR for data visualization and VR for remote operation of vehicles. [15] investigated the concept of a "digital factory metaverse", emphasizing the incorporation of VR and online multi-user experiences to facilitate factory operations.

Despite the valuable insights offered by existing case studies in the realm of the industrial metaverse, several research gaps are evident. Predominantly, these studies often portray XR as the centerpiece, neglecting a holistic platform-oriented approach that integrates multiple technological components. Consequently, they fall short of capturing the core essence of the metaverse, which is fundamentally an interoperable and dynamically linked digital–physical space. This myopic focus on isolated XR applications overlooks crucial elements such as seamless data integration, and semantic enrichment, thereby limiting the architecture's versatility and potential for transformative impact across diverse industrial settings.

2.3. Interplay of digital twins and extended reality

In the realm of the industrial metaverse, digital twins and XR emerge as key technological enablers. Digital twins offer dynamic digital representations of physical entities, facilitating a seamless integration between physical and virtual domains. Concurrently, XR serves as the visual interface, offering users a rich, immersive, and interactive experience, epitomizing the metaverse's human-centric approach. Drawing upon the authors' prior research, particular attention has been given to how digital twins and XR can interplay effectively in industrial contexts.

Initially, [16] introduced a feature-based digital twin framework (FDTF) enumerating ten key features. These guiding principles were expanded in [17] and demonstrated with an industrial crane, where digital twins provided data interfaces leveraging twin description documents. While the FDTF was initially designed to articulate the structure and components of digital twins, its implications extended to shaping the architecture of the industrial metaverse. Guided by this insight, our present article incorporates pivotal elements from FDTF, adapting its well-defined features to suit the specific requirements of the industrial metaverse. Next, the importance of connectivity, extendability, and interoperability of digital twins was investigated through the Digital Twin Web (DTW) [18]. This expansive network of digital twins enabled streamlined management and distribution of twin description documents that captured the metadata of digital twins with common data ontology. Building upon this, [19] introduced the TwinXR method, leveraging DTW and twin description documents to customize XR applications to varied physical setups. While this approach amplifies prior research on singular XR applications tailored for digital twin-based industrial cranes [20,21], it remains constricted in scope, emphasizing single-machine applications and overlooking broader considerations such as personnel, materials, and the environment. Finally, our most recent work introduced the industrial production workflow ontology (InPro) [22], which complements our efforts to achieve a holistic view of the industrial metaverse, particularly in terms of understanding intricate processes across different layers of industrial activities, thus integrating existing industrial systems and allowing knowledge synchronization.

2.4. Research motivation

The examination of current metaverse architectures, industrial case studies, and the integration of digital twins and XR technologies reveals significant gaps and opportunities for advancement in the industrial metaverse domain. Existing frameworks largely cater to consumer applications, neglecting the complex needs of industrial environments, especially the system integration aspect. Moreover, most case studies focus narrowly on XR applications, missing the broader perspective needed for a fully integrated digital–physical ecosystem. Our prior work on digital twins and XR has laid a foundational understanding but remains limited in scope, emphasizing single-machine applications without fully addressing broader industrial components. This identified

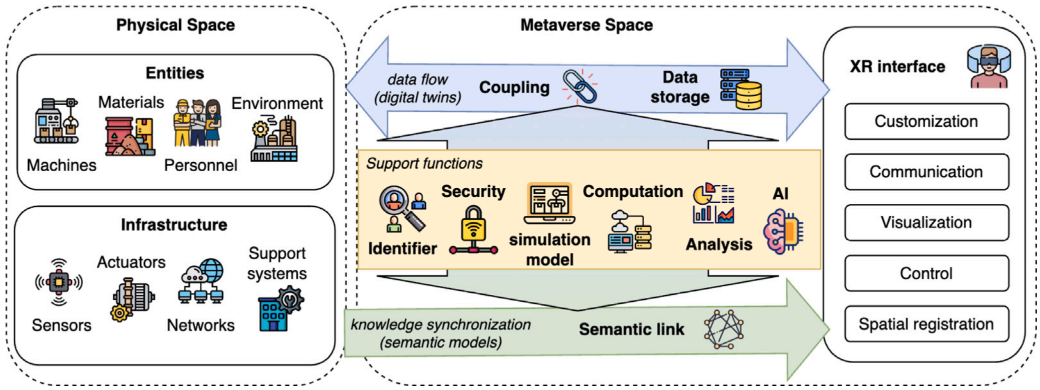

Fig. 2. Schematic representation of the proposed industrial metaverse architecture tailored for smart factories: The architecture delineates between the physical space, comprising tangible entities and infrastructure, and the metaverse space across ten comprehensive modules, namely, coupling, data storage, semantic link, XR interface, identifier, security, simulation model, computation, analysis, and AI, with data flow and knowledge synchronization enabled by digital twins and semantic models.

need for a holistic, scalable, and adaptable industrial metaverse architecture that bridges these gaps and facilitates a more integrated approach to digital–physical interactions in industrial settings motivates our research.

3. Proposed industrial metaverse architecture

This section delineates a novel industrial metaverse architecture designed for the intelligent orchestration of smart factories, as illustrated in Fig. 2. The architecture comprises two interconnected domains: the physical space and the metaverse space. The physical space represents the foundation of a smart factory, encompassing not only the tangible entities – machines, materials, personnel, and the environment – but also the infrastructure elements including sensors, actuators, networks, and support systems. These elements interact and collaborate to create an efficient and intelligent production environment. The metaverse space is a virtual representation of the physical space, centered around ten key modules: the coupling and data storage modules for data flow through digital twins, the semantic link module for knowledge synchronization through semantic models, the XR interface module for user interaction, as well as support functions including the modules of identifier, security, simulation model, computation, analysis, and artificial intelligence (AI). This section delves into the essential components of the physical space alongside the critical modules constituting the metaverse space. Additionally, we elucidate the principles of the data flow and knowledge synchronization across the physical and metaverse spaces.

3.1. Physical space: entities

The core entities in the physical space of a smart factory setup encompass machines, materials, personnel, and the environment. These entities are integral to industrial processes and form the basis for creating their digital twins and semantic models in the metaverse space. As they engage and evolve dynamically, these entities generate a continuous stream of real-time data and knowledge for the metaverse space to capture, process, analyze, visualize, and interact.

Machines in the physical space include production equipment, automation systems, robots, and other tools used to carry out manufacturing and assembly tasks. These machines are often interconnected and communicate with each other and the data is captured through the Internet of Things (IoT) devices to enable smart manufacturing processes.

Materials refer to raw materials, work-in-progress items, and finished products that are involved in the production processes. Proper tracking and management of these materials are crucial for optimizing inventory levels, reducing waste, and ensuring timely delivery of products to customers.

Personnel encompasses the workforce managing and operating production processes. Industry 5.0 highlights the integration of human expertise with technology, fostering innovation and enhancing system performance, which is achieved by enhanced human–machine collaboration, training and tools for their efficiency and safety. Personnel's skills and well-being are key to a smart factory's success, and integrating their knowledge into the metaverse can boost decision-making and collaboration.

The **environment** encompasses the factory's physical layout, ambient conditions, and external factors that can impact the production process. Monitoring and controlling environmental factors, such as temperature, humidity, air quality, and lighting, contribute to maintaining optimal working conditions and minimizing the potential for equipment failure or product defects.

3.2. Physical space: infrastructure

Comprising sensors, actuators, networks, and support systems, the infrastructure not only supports manufacturing processes but also facilitates the seamless integration of the physical and metaverse spaces.

Sensors gather real-time data from various sources in the physical space, such as temperature, humidity, pressure, vibrations, machine operation status, and process parameters. This data is used for creating accurate digital twins within the metaverse space.

Actuators convert digital commands from the metaverse space into physical actions. They implement control strategies and adjustments based on insights gained from the analysis of data, driving improved efficiency and performance.

The **network** infrastructure facilitates seamless data transmission between the physical space and the metaverse space, ensuring real-time synchronization between the two domains. Implementing reliable and high-speed connectivity solutions, such as 5G, Wi-Fi 6, or other industrial communication protocols, is essential for supporting the data-intensive requirements of the industrial metaverse.

In addition to these components, the infrastructure also encompasses **support systems** like power distribution systems, data centers, building facilities, pneumatic air or water systems. These systems contribute to the overall stability and efficiency of the industrial metaverse framework.

3.3. Metaverse space: coupling and data storage modules for data flow

This section explores the foundational modules that are pivotal to the orchestration of data flow within the metaverse space: the coupling and data storage modules. These modules work in tandem to facilitate the seamless transfer and preservation of digital twins, which is essential for the real-time representation and interaction within the metaverse. The coupling module acquires and channels data between the physical and metaverse spaces, while the data storage module encapsulates the state of the metaverse, ensuring data integrity and accessibility for ongoing operations and analysis.

3.3.1. Coupling module

The coupling module creates a two-way data connection between a physical entity and its digital twin, facilitating real-time interaction and synchronization. Coupling relies on the sensors, actuators, and network infrastructure in the physical space to establish and maintain connections between the physical entities and their digital twins in the metaverse space. The module is closely integrated with the security and identifier modules of our architecture, which is essential for maintaining data integrity and security across the interface between physical and digital entities. Coupling plays several essential roles from data acquisition, data transmission, to control and actuation.

During **data acquisition**, the coupling module leverages the sensors in the physical space to gather real-time data from the physical entities, including their states, behaviors, and contextual information. This data is then used to create and update the corresponding digital twins in the metaverse space, ensuring accurate and up-to-date representations. For **data transmission**, the module utilizes the network infrastructure in the physical space to facilitate efficient, secure, and reliable data transfer between the physical entities and their digital twins, ensuring seamless communication and synchronization between the physical and metaverse spaces. Communication protocols such as Open Platform Communications Unified Architecture (OPC UA), Message Queuing Telemetry Transport (MQTT), and Constrained Application Protocol (CoAP), facilitate the data transfer between physical entities and their digital twins. The choice of communication protocols should be aligned with the specific requirements of each use case, considering factors such as security, reliability, and real-time performance [23,24]. In terms of **control and actuation**, the coupling module works with the actuators in the physical space to translate digital commands from the metaverse space into physical actions, allowing for precise and responsive control of the physical entities and real-time feedback to the digital twins.

To augment the coupling module's capability, we propose the *data link* [17] integration as a potential enhancement. This linkage facilitates centralized access to various data systems through an application programming interface (API) gateway, offering a streamlined approach to merging scattered data for digital twin creation. Capabilities as such enable the metaverse to integrate new IoT technologies as they emerge, expand to support a broader range of physical entities, and adapt to changes in the industrial environment.

3.3.2. Data storage module

The data storage module manages and preserves digital twin models of machines, materials, personnel, and the environment, while being able to communicate with the physical space through a bi-directional data flow enabled by the coupling module. The digital twin models stored in this module are further accessed, processed, enriched, and updated through feedback loops by the support functions of simulation model, computation, analysis, and AI. To ensure the confidentiality and integrity of the stored data, the data storage module is enhanced by the security and identifier modules' capabilities, as detailed in their respective sections.

Data storage relies on databases, which provide the capability to store, organize, and retrieve large amounts of data efficiently. While relational databases – often regarded as the classic model – support structured data storage, the industrial metaverse demands specialized solutions, based on the specific use case requirements, such as data volume, velocity, variety, and veracity: Real-time databases are pivotal when immediate data reflection is required; Time-series databases are ideal for storing sequences of data points indexed in time order [25]; Document-based NoSQL databases, like MongoDB, stand out for their adaptability in managing varied data structures without a rigid schema, offering more flexibility as data needs evolve [26]; Distributed databases ensure data consistency across diverse network nodes [27]; Meanwhile, graph databases, designed to treat relationships between data points with as much priority as the data itself, emerge as especially relevant for ontological applications [28]. Furthermore, the storage solution must be capable of accommodating growing data volumes in the metaverse context, which can be achieved through cloud-based storage solutions. Cloud storage provides on-demand access to a shared pool of computing resources, including storage, processing power, and networking, typically offering high availability, data redundancy, and data backup capabilities [29].

3.4. Metaverse space: semantic link module for knowledge synchronization

This section examines the semantic link module that underpin the knowledge synchronization within the metaverse space. This module connects the metaverse space to the physical space by extracting knowledge from the physical entities of machines, materials, personnel, and the environment, and representing it with semantic models.

Semantic models represent complex attributes and relationships of physical entities, adhering to recognized standards such as the Digital Twin Definition Language (DTDL) [30], the Web of Things Thing Description (WoTTD) [31], and the Asset Administration Shell (AAS) [32]. These models leverage linked data formats like JavaScript Object Notation for Linked Data (JSON-LD) [33] to enable encoding of data in a machine-readable manner, which is essential for linking the data within semantic models to other external data sources, and forming the basis for a comprehensive global data space [34]. The information from these linked datasets can be precisely extracted using semantic query languages like SPARQL Protocol and Resource Description Framework (RDF), shortly as SPARQL.

Key to the module's efficacy are domain ontologies that provide a common vocabulary for knowledge representation and organization. Based on prevailing machine-readable ontologies such schema.org [35], the Smart Applications REFerence (SAREF) [36], and GS1 Web Vocabulary [37], this module develops customized ontologies to enable domain knowledge representation. The ontology customization requires an in-depth understanding of unique industrial processes, terminologies, and workflows, demanding collaboration with industry experts to tailor ontologies accurately. These ontological models enable assimilation of both structured and unstructured data from varied OT and IT sources, thus facilitating the integration of the industrial metaverse with pre-existing industrial systems.

3.5. Metaverse space: XR interface module for user interaction

This section explores the XR interface module for immersive engagement within the industrial metaverse. Serving as the connection for user and digital twins, the XR interface transcends traditional interfaces by enabling intuitive, real-world analogous experiences. It plays a critical role in allowing users to navigate, manipulate, and communicate within the integrated digital–physical continuum of the metaverse, establishing a seamless conduit for the multidimensional exchange of information and control.

When integrating XR technologies – VR, AR, and MR – into industrial applications, it is crucial to tailor the approach to each technology's strengths and specific use cases: VR offers complete immersion in a digitally simulated environment, making it ideal for scenarios where replicating real-world conditions is beneficial but physically impractical or risky. Industries utilize VR for creating detailed training simulations, conducting safety protocols, and showcasing product designs in a risk-free, cost-effective manner [38–40]. For these applications, digital twins must deliver high-fidelity recreations of actual environments, embodying precise spatial, behavioral, and visual attributes to ensure simulations are both realistic and effective. AR and MR, conversely, augment the user's real-world view with digital overlays, providing invaluable tools for on-the-ground tasks like maintenance, assembly, and quality inspections [41–43]. These applications demand digital twins that supply immediate, context-aware data and visualizations, offering users pertinent information and guidance seamlessly integrated with their physical environment. This blend of digital and physical elements enhances efficiency and accuracy in complex industrial operations.

We propose five key function blocks for the XR interface: communication, visualization, control, spatial registration, and customization. **Communication** enables bi-directional data exchange between the XR interface and various digital twins in the data storage module, which eventually link to the physical entities. This function also distributes acquired data to the visualization and spatial registration functions, as well as collects digital commands from the control function and reflects them back to the digital twin models. **Visualization** renders the virtual environment and displays relevant information to the user. This function ensures that the XR interface provides accurate, up-to-date, and context-aware visualizations of the digital twins with analytics, and other essential data, allowing users to make informed decisions based on real-time insights. **Control** facilitates user interaction with digital twins and other virtual elements within the metaverse space. By providing intuitive control mechanisms, such as gestures, voice commands, or haptic feedback, users can navigate, manipulate, and operate the virtual environment and the physical entities through their corresponding digital twins. **Spatial registration** aligns and anchors the virtual content within the physical space. By mapping digital twins and other virtual elements to their corresponding real-world locations, the function enables the visualization function to place virtual objects at their designed locations, and the control function to accurately execute the intended commands. In multi-user or multi-device scenarios, this function also ensures a coherent and consistent XR interface across various devices and perspectives. **Customization** utilizes the knowledge synchronization from the semantic link module to customize the XR interface and provide a context-aware and personalized experience for users. The preliminary principles and workflows are detailed in the TwinXR method [19]. First, the function queries the semantic models of machines, materials, personnel, the environment in the semantic link module. Based on retrieved knowledge, the function customizes the XR interface to accurately reflect the current user profile, as well as the overall situation of the factory floor and production process. This approach enhances the scalability and resilience of XR interface development for evolving factory conditions and physical setups. It also enables each user to interact with the interface according to their skill level, specific needs, and preferences.

3.6. Metaverse space: support functions

The support functions of the metaverse space comprise six modules: identifier, security, simulation model, computation, analysis, and AI. This section explicates how each module underpins the metaverse operation, enabling identity verification, data protection, sophisticated simulations, computational efficiency, insightful analytics, and intelligent decision-making.

3.6.1. Identifier module

The identifier module allocates unique and persistent identifiers for each digital twin in the network. These identifiers streamline the location, access, and interaction of digital twins, facilitating data exchange and collaboration within the industrial metaverse. By providing a distinct identifier to each digital twin model in the data storage, access and modification privileges are restricted to authorized users.

Key aspects of the identifier module include generation, resolution, management, and integration of identifiers. The generation of globally unique identifiers is pivotal for the unambiguous identification of entities, ensuring smooth metaverse interactions. The module enables the resolution of identifiers to their corresponding entities, maintains a registry or directory of identifiers and metadata, and provides APIs or query mechanisms for identifier resolution. Effective management and maintenance of identifiers keep the identifier system up-to-date, secure, and accurate. Seamless integration with other modules in the industrial metaverse architecture ensures that entities are consistently identified and accessed across the entire system. We propose the following technological enablers for the identifier module: Uniform Resource Identifiers (URIs) [44] that offer distinct addresses and consistent referencing for digital resources, the blockchain technology that features distributed ledger capability and the cryptographic principles of immutability [45], as well as the Decentralized Identifiers (DIDs) [46] that grant users complete self-sovereignty over their digital identifiers, which becomes particularly salient within the vast expanse of the metaverse.

3.6.2. Security module

The security module safeguards the industrial metaverse's integrity, focusing on protecting the digital twin models within the data storage module. The significance becomes evident given the convergence of physical and digital spaces and the central role of humans.

The module employs a suite of advanced security technologies to prevent unauthorized access, data breaches, and cyber threats. The technologies encompass the Advanced Encryption Standard (AES) [47] like AES-256 for data at rest, and the Transport Layer Security (TLS) protocol [48] relying on Secure Hashing Algorithms (SHAs) like SHA-256 for data in motion, ensuring comprehensive encryption across all data states. Authentication mechanisms are reinforced with multi-factor authentication and digital certificates [49] to authenticate user and system identities rigorously. Access control is meticulously managed through Role-Based Access Control (RBAC) [50] or Attribute-Based Access Control (ABAC) [51], delineating user permissions in alignment with their designated roles and attributes. The network's security infrastructure is bolstered by sophisticated firewalls, employing Stateful or Deep Packet Inspection [52] to establish a resilient defense against external threats. Intrusion detection systems, including Snort [53] for network-level surveillance and OSSEC [54] for host-level monitoring, are deployed to vigilantly identify and respond to security anomalies. Notably, the integration of humans into the metaverse introduces unique challenges. The module employs technologies like differential privacy and homomorphic encryption and adheres the principle of "secure by design" [55] to protect individual privacy during data processing [56]. Additionally, the security module advocates for the development of intuitive and fail-safe XR interfaces to mitigate the impact of human errors.

3.6.3. Simulation model module

The simulation model module shapes the representation of digital twins. Aided by various modeling techniques, the module creates high-fidelity digital twins that capture the graphical, numerical, or behavioral essence of their physical counterparts. Once these simulation models are crafted, a dynamic feedback loop becomes active, allowing the data storage module to maintain and update the digital twin models by integrating the output of the simulation models.

We propose selecting modeling techniques based on the complexity and behavior of the physical system: Mathematical modeling, encapsulating the behavior and attributes of entities, such as fluid flow or mechanical movement [57], are often used to anticipate system responses that is dictated by well-defined physical laws; On the other hand, 3D modeling, providing intricate visual replicas of physical assets or environments via Computer-Aided Design (CAD) software, such as a factory floor or a piece of equipment, should be selected to visualize the system, simulate its behavior, and test changes to the system before they are implemented in the physical world [58]; Finite Element Analysis (FEA), assessing product responses to physical forces, vibration, and thermal effects [59], is especially advantageous when dealing with complex geometries and material properties; Lastly, system dynamics, rooted in control engineering, focuses on understanding the nonlinear behaviors of complex systems over time using stocks, flows, feedback loops, and delays [60]. The application of digital twins further extends into dynamic scenarios for real-time responsiveness to changes in the environment or production needs, enhancing flexibility and efficiency [61]. Furthermore, the selection of simulation models, whether static, dynamic, continuous, discrete, deterministic, or stochastic, is vital as each type is suited for different industrial scenarios [62]. It is important to ensure that the simulation models are accurate and validated against real-world data to ensure the models' credibility and their effective representation within digital twins.

3.6.4. Computation module

The computation module executes algorithms that process and transform digital twin data in the data storage module. A key emphasis within the industrial metaverse is on spatial computing, which ensures the spatial alignment between physical space and its metaverse counterpart [63,64]. The integration of the spatial computing with the XR interface module provides intuitive and immersive visualizations of spatial data. An integral part of spatial computing is indoor positioning, enabled by Wi-Fi positioning system [65], Bluetooth [66], ultra wideband (UWB) [67], markers [68], object detection [69], or spatial anchors [70], which rely on different sensor technologies in the physical space for initial data acquisition.

We propose employing "edge-cloud continuum" [71] principles in the computation module, effectively integrating the capabilities of both edge and cloud computing. Situating computations on the edge, especially in spatial computing, allows for more instantaneous reactions to dynamic changes in the environment [72], while cloud computing leverages remote servers on the internet to manage, process, and store data [9], offering expansive computational capabilities. Furthermore, the module should consider leveraging parallel computing and distributed processing techniques that optimize resource utilization and reduce computation time for time-critical metaverse use cases.

3.6.5. Analysis module

The analysis module extracts valuable insights from digital twin data in the data storage module. It encompasses descriptive, predictive, and prescriptive analysis to understand the current state of the system, predict its future behavior, and recommend optimal actions to achieve desired outcomes.

The selection of suitable methods and algorithms must align with the data type, desired outcomes, and specific use-case requirements [73]: For instance, time-series analysis, essential for understanding temporal dynamics, enables regression and classification analyses, often crucial in predictive modeling [74]; Clustering techniques facilitate the segmentation of complex industrial data into meaningful groups, enhancing understanding of diverse data sets [75]; Anomaly detection algorithms identify outliers or unexpected events, critical for maintaining system integrity [76]. Data quality and accuracy are paramount - Mechanisms for data cleansing, validation, and enrichment are necessary parts of this module to ensure data integrity. Furthermore, integration of the analysis module with other modules are beneficial. For instance, analysis performed on the simulation models allows for scenario modeling [77], essential for strategizing and aligning efficient decision making with human-centric principles.

3.6.6. Artificial intelligence module

The AI module enables intelligent decision-making based digital twin data in the data storage module. It uses control, optimization, and prediction algorithms to enhance the efficiency and effectiveness of the industrial metaverse, while fostering a collaborative environment between humans and machines.

The module leverages machine learning, or deep learning, which are trained on large amounts of data to identify patterns, make predictions, and learn from experience [78]. Reinforcement learning can also be employed to adapt to changing conditions and optimize decision-making based on the observed outcomes of previous actions, especially in the context of industrial metaverse with robotics applications [79]. Additionally, natural language processing and computer vision can be incorporated to facilitate interaction between humans and AI-powered systems, further promoting human-centric design [80]. The module can also incorporate Generative AI and large language models (LLMs) that excels in creating new content across text, visuals, and audio. One metaverse-specific use case is dynamically generating contextual instructions for XR users [81]. Notably, embedding AI module in the metaverse context enables the human-in-the-loop principles [82] for augmenting human expertise and allowing real-time oversight and validation of AI-driven actions.

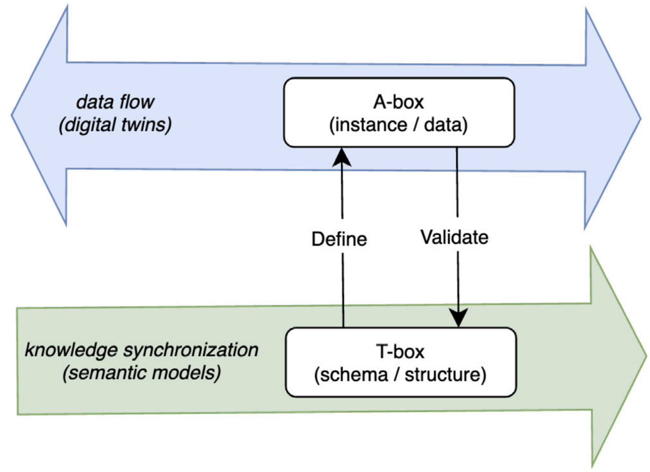

Fig. 3. Interaction between the T-box and the A-box in the context of data flow and knowledge synchronization within an industrial metaverse architecture: The T-box, representing the schema or structure, defines the ontological framework and conceptual relationships within the semantic models, essential for knowledge synchronization; The A-box corresponds to the data or instance, populating the digital twin models critical for the data flow. The dual arrows indicate bidirectional interactions where the T-box and A-box define and validate each other to maintain a coherent system state.

3.7. Data flow and knowledge synchronization

Our proposed industrial metaverse architecture features data flow and knowledge synchronization across the physical and metaverse spaces. As illustrated in Fig. 3, central to the orchestration between data and knowledge lie two fundamental ontological components, known as the Terminology box (T-box) and the Assertion box (A-box) that govern the structure and instantiation of information within the system.

The T-box refers to the schema or structure of data, defining the ontological framework for abstract entities such as "Machine", "Material", "Personnel", and their conceptual interrelations. In the knowledge synchronization process, the T-box informs the semantic models that shape the interaction between these entities within the metaverse. In contrast, the A-box populates the ontology with individual, concrete instances of the data, which are specific details like the actual sensor readings, machine states, personnel activities, and environmental conditions. The A-box reflects digital twin models guiding the data flow process. Through the interconnected operation of the T-box and A-box in guiding both the data flow and the knowledge synchronization, the industrial metaverse is able to maintain coherent and synchronized semantic models and digital twins of the physical space, facilitating an intelligent and responsive environment.

3.7.1. Data flow

The proposed industrial metaverse architecture relies on a finely-tuned data flow mechanism that ensures seamless interaction between

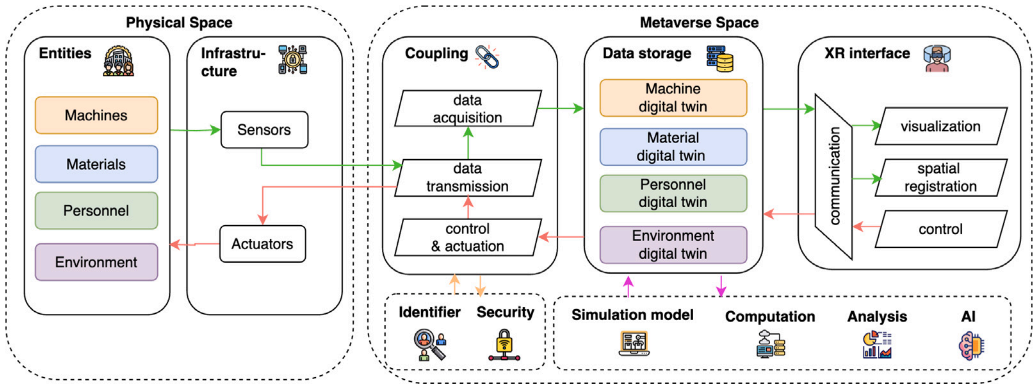

Fig. 4. Diagram of the bi-directional data flow process interlinking the physical space with the metaverse space across various modules and components: Starting from the primary entities in the physical space, data is collected by sensors and forwarded to the coupling module. This data undergoes transmission augmented by the identity and security modules and is stored in the data storage module, which continually refines digital twins of machines, materials, personnel, and the environment by harnessing outputs from the connected modules of simulation model, computation, analysis, and AI. Simultaneously, control commands are dispatched from the data storage module, passing through the coupling module to influence actuators in the physical space. The XR module fetches data with its communication function to aid visualization and spatial registration while ensuring instantaneous updates and efficient control via feedback to the data storage module.

the physical and the metaverse spaces. As illustrated in Fig. 4, this involves the bi-directional data exchange across several crucial modules. The data flow process is primarily facilitated by the A-box, which contains concrete data instances, essential for updating digital twins.

Commencing with physical entities of machines, materials, personnel, and the environment, the system employs an array of sensors and actuators to collect data and execute control commands respectively. The data captured by sensors from various sources is then funneled to a central coupling module, which acts as a gateway to the metaverse space. Within the coupling module, the data transmission function, facilitated by communication protocols, ensures that data flow remains synchronized between the two spaces. Following this, data is organized by the data acquisition function and stored within the data storage module. Data security and identity verification are paramount in this process: The coupling module works in tandem with the security module that maintains data integrity, and the identity module that manages authentication and authorizes data exchange. The stored data manifesting as digital twin models are continually updated and refined through inputs from the simulation model, computation, analysis, and AI modules. Concurrently, control commands issued from the metaverse space traverse through the same route in reverse. These commands are retrieved from the data storage module and dispatched to the physical space's actuators via the coupling module, allowing for precise manipulation of the physical components based on the digital twin models. The XR interface module further presents the data visually and interactively: Its communication function retrieves data from the data storage module, allowing the visualization and spatial registration functions to render an immersive and coherent XR environment, which users can engage with; Meanwhile, control inputs generated by users via the control function are fed back to the communication function, and subsequently to the data storage module, which further manipulate the physical space.

3.7.2. Knowledge synchronization

The knowledge synchronization process within the industrial metaverse is depicted in Fig. 5, which elucidates the translation of real-world data into a structured ontology that guides interactions between the physical and metaverse spaces. Knowledge synchronization is dominated by the T-box, which defines the ontological framework and conceptual relationships within the semantic models.

Starting with the ontology modeling of entities in the physical space, including machines, materials, personnel, and the environment, the process encapsulates the comprehensive knowledge structure into the semantic models in the semantic link module in the metaverse space. The knowledge from the semantic link module progresses towards the XR interface through ontology-based querying within the customization function. This query process distills data into actionable insights and targeted information relevant to the tasks at hand, such as machine and material statuses, personnel profiles, and conditions of the operational environment. The XR interface module, now informed by this curated knowledge, customizes the overall XR interface to align with the operational landscape. Inside the XR interface module, the visualization function uses the structured knowledge to render intricate details of the metaverse, ensuring that users are presented with accurate and relevant visual cues. The control function references the fetched knowledge to understand the potential actions and commands applicable to different machines and processes, thus enabling precise and effective control within the virtual environment. Spatial registration accuracy is achieved by applying the knowledge to map the physical entities within the virtual space. The communication function benefits from this knowledge to prioritize and channel information in alignment with user requirements and system needs.

4. Case study: in-plant material flow tracking

To demonstrate the applicability of our industrial metaverse architecture, we conducted a focused case study centering on in-plant material flow tracking. This study showcases the multifaceted capabilities of the architecture in enhancing industrial workflows.

4.1. Physical space of the case study

The physical space investigated in the material flow tracking case study consists of materials, transport mechanisms, tracking systems, human oversight, and the environment. This case unfolds at the Aalto Industrial Internet Campus (AIIC) at Aalto University, as illustrated in Fig. 6.

The setup involves an overhead crane system serving as the transportation machine, and materials represented by wooden pallets to be transported. A human operator is tasked with monitoring and managing the flow of materials. A UWB-based indoor positioning system with beacon devices facilitates the materials tracking. The AIIC environment is equipped with the crane's wireless network, complemented by a campus-wide private 5G network to ensure seamless connectivity.

4.2. Metaverse space of the case study

This section explores the metaverse modules implemented in our case study: the coupling module for data flow, the semantic link for

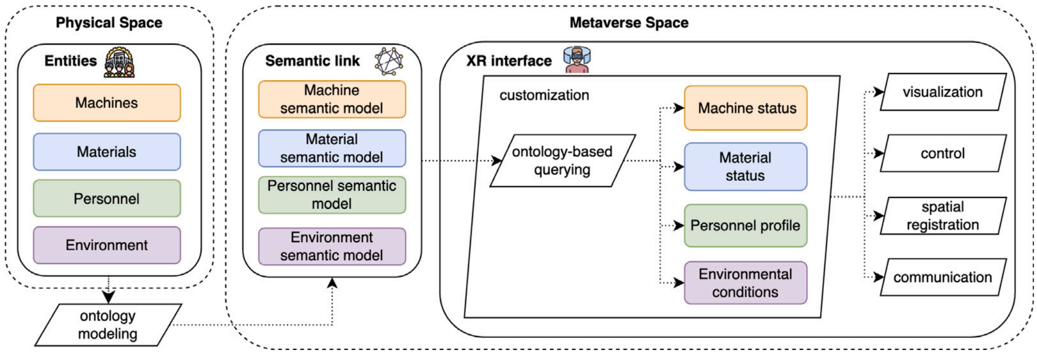

Fig. 5. Diagram of the knowledge synchronization process bridging the physical space and the metaverse space across various modules and components: Starting from ontology modeling of entities in the physical space, the knowledge traverses through the semantic link module to form semantic models. This structured representation feeds into the XR interface via ontology-based querying within the customization function. The XR module utilizes this knowledge to tailor the application across its visualization, control, spatial registration, and communication functions.

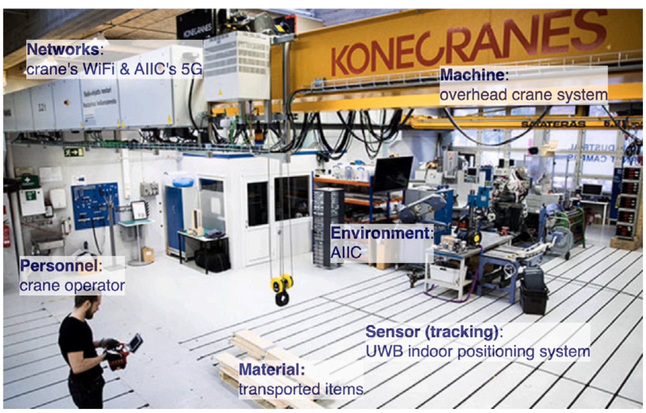

Fig. 6. Overview of the physical space for the case study of in-plant material flow tracking: The physical space at the AIIC involves transported materials, an overhead crane system, a UWB indoor positioning system, and a human operator managing the process within AIIC's network environment.

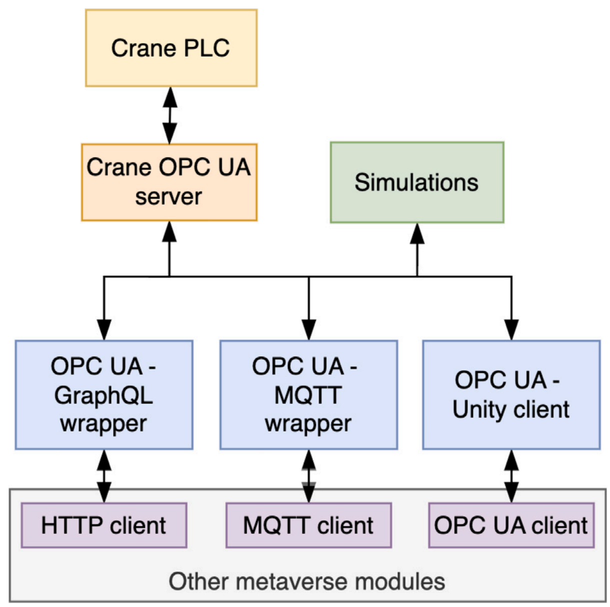

Fig. 7. The bi-directional data flow structure of the crane coupling module: The crane's PLC directly processes crane sensor and actuator data, subsequently interfacing with an OPC UA server. Through three distinct communication middleware systems, the OPC UA server or the crane simulation is coupled to various communication clients inherent to other metaverse modules.

knowledge synchronization, the XR interface module for user interaction, and the simulation module as a support function. Detailed architectural decisions and implementation are elaborated on for each module, providing concrete examples to elucidate their functions within the metaverse infrastructure.

4.2.1. Data flow: coupling module implementation

The coupling implementation covers three key functions: data acquisition, data transmission, as well as control and actuation. Fig. 7 illustrates the data flow for the crane example enabled by the coupling module.

Data acquisition is executed by a Programmable Logic Controller (PLC) that manages the crane sensor and actuator data. This data is subsequently exposed via an OPC UA server that functions as the primary external interface. Data transmission employs three distinct types of communication middleware, the OPC UA-GraphQL wrapper, the OPC UA-MQTT wrapper, and the OPC UA-Unity client, as articulated in our prior work [21]. These middleware solutions connect OPC UA server and diverse client types, namely, HTTP, MQTT, and OPC UA clients. These clients are integral parts of other metaverse modules like the XR interface. Furthermore, simulation models of crane operation also directly interfaces with the communication middleware, allowing simulated interactions with the system. Incorporating bi-directional data flow, the control and actuation component of the coupling module operates in a manner reciprocally parallel to the process described for data acquisition and transmission. Commands originating from other modules like the XR interface, traverse through the communication middleware and execute control operations on the physical crane or its simulation counterpart.

Furthermore, the coupling module incorporates real-time positional data from the UWB indoor positioning system in the physical space. This ensures the materials' precise locations, trajectories, and statuses within the physical space are accurately mirrored in the metaverse, facilitating real-time tracking in both spaces.

4.2.2. Knowledge synchronization: semantic link module implementation

In the case study, the semantic link module utilizes the InPro ontologies introduced in our previous work [22]. The InPro is capable of formalizing and integrating production process information, especially for use cases like material flow tracking, as illustrated in Fig. 8.

The InPro assimilates both structured and unstructured data from heterogeneous sources. These sources span from real-time feeds such as the OPC UA server, to integral information systems like Enterprise Resource Planning (ERP), Manufacturing Execution System (MES), Human Resource Management System (HRMS), Warehouse Management System (WMS), and Product Lifecycle Management (PLM). Zooming

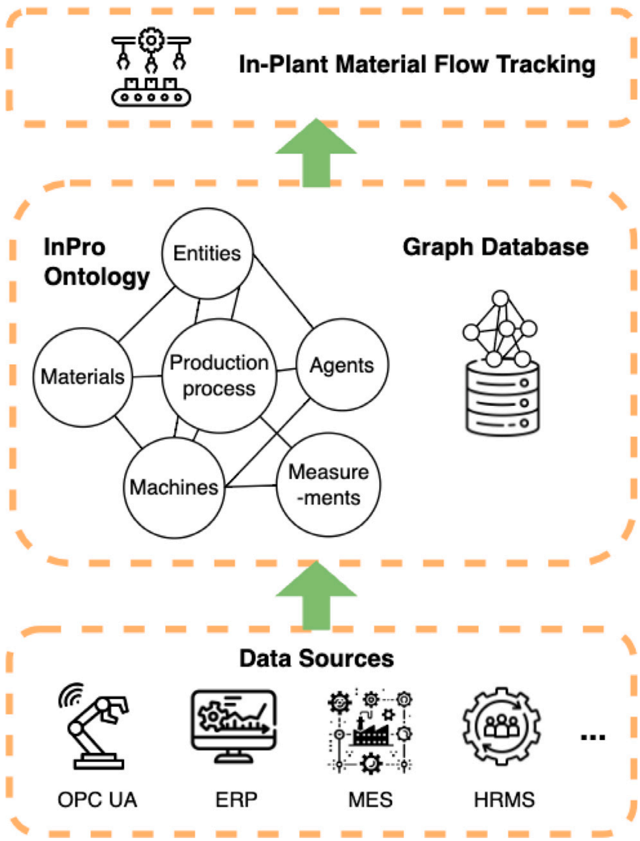

Fig. 8. Using InPro in the semantic link module for in-plant material flow tracking: InPro model incorporates data sources spanning OPC UA systems and various industrial systems (like ERP, MES, and HRMS) to its seven ontology modules, namely, *Entities*, *Agents*, *Machines*, *Materials*, *Methods*, *Measurements*, and *Production Process*. The ontologies further converge into a graph database for streamlined information retrieval.

in to the in-plant material flow tracking scenario: ERP provides business activities like production orders; MES disseminates production process information from raw material to the final product; HRMS supplies personnel's schedules and tasks for production activities; WMS sheds light on material inventory and delivery information; and PLM furnishes process plans and operation details. Delving deep into the InPro, the ontologies comprise seven main domain modules: *Entities*, *Agents*, *Machines*, *Materials*, *Methods*, *Measurements*, and *Production Processes*. The *Agents* module includes a specialized *Personnel* subclass, with properties that enable knowledge representation of organizational relations, capabilities, and task schedules of each personnel. Parallelly, the *Machine* module encapsulates robotics-related knowledge in alignment with the OPC UA Companion Specification, thereby facilitating direct and interoperable integration between the OPC UA server and a host of industrial ecosystems. The *Material* module describes materials used in the production process. The InPro is instantiated and converted to RDF format for subsequent storage within a dedicated semantic graph database - GraphDB. The database offers an interface for information retrieval through SPARQL query language.

4.2.3. User interaction: XR interface module implementation

The XR interface module enables user interaction within the material flow tracking paradigm in the industrial metaverse. Built on the game engine Unity's XR framework, this module comprises both VR and AR/MR interfaces, each fine-tuned to specific scenarios associated with the surveillance and management of material flow, as illustrated in Figs. 9 and 10.

The VR interface offers an immersive virtual representation of the physical environment for remote operation. It enables operators to oversee material flows from a distance, facilitating timely interventions when necessary. Fig. 9 showcases the scenario where users are submerged in a virtual landscape tailored for remote crane material flow operation. Utilizing VR headsets like Varjo XR or Meta Quest, personnel can remotely monitor factory situations and maneuver cranes to transport materials. This is conducted within an immersive setting that closely mirrors the actual crane operating space. The AR/MR interface, in contrast, is engineered for on-site scenarios, where personnel, equipped with smart glasses or handheld devices, are presented with an augmented overlay of vital information directly onto the physical environment. As showcased in Fig. 10, the user, wearing a Microsoft HoloLens headset running our MR application, can perceive real-time conditions of the crane, materials, and the overall operating environment on the virtual dashboard, while operating the crane via a holographic controller interface. In both remote VR and on-site AR/MR interfaces, materials being transported by the crane are visualized with real-time data and synchronized information overlays. These overlays, sourced from UWB tracking systems and other industrial systems, integrated by the InPro and communicated via coupling processes, provide

Fig. 9. A scene captured from our VR application for remote crane operation and material flow tracking: Users can remotely monitor material flows and control the crane through a virtual representation of the physical crane operating space with VR headsets.

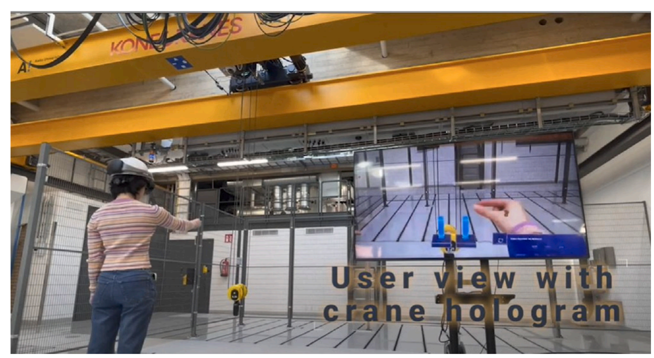

Fig. 10. MR application for on-site crane operation and material flow tracking: The user leverages the MR application running on the Microsoft HoloLens headset to perceive real-time information about the crane, materials, and the factory environment, and to intervene the process through holograms overlaying on the physical world.

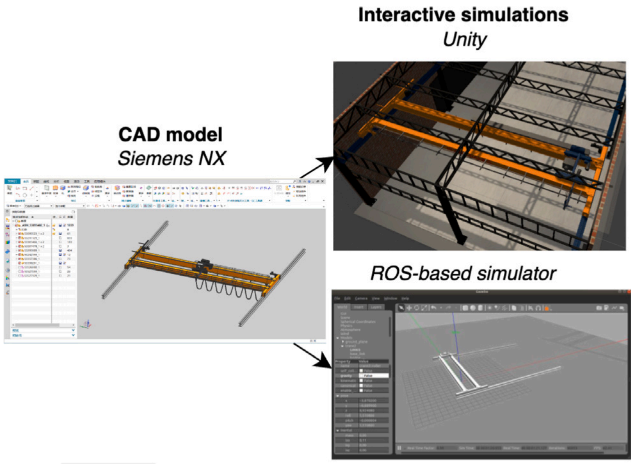

Fig. 11. Overview of crane simulation models: The crane CAD model is first developed in Siemens NX, and then converted into interactive simulations in the Unity game engine and in the ROS-based Gazebo simulator [21].

users with instant insights into the material's specifications, current status, and location.

Building on the TwinXR method delineated in our prior study [19], XR applications are able to interchange based on the knowledge encapsulated within the semantic models. Within XR applications, the customization component makes SPARQL queries to the GraphDB database, sourcing requisite information about the crane, materials, personnel, and the environment. The acquired knowledge then enables the adaptation of XR interfaces across their visualization, control, spatial registration, and communication functions. For instance, based on production stages, users proficiency, and their role specifications, the visualization and control functions exhibit varying data depths and operational alternatives. The spatial registration function employs fetched environment information to render accurate replicas of physical entities in the XR space. This ensures immediate mirroring of any real-world structural modifications within the virtual space, maintaining coherence. With knowledge about the current requirements from other functions of the XR interface, the communication function determines the granularity and frequency of data transfer between the XR interface and the crane, mediated via the aforementioned coupling module.

4.2.4. Support function: simulation module implementation

In the case study, simulation model module employs CAD models of the crane, materials, and their operating environment. These models are subsequently transformed into simulations that seamlessly integrate the crane, materials, and their dynamic flow within the operating environment.

As depicted in Fig. 11, the process initiates with the creation of CAD models using the Siemens PLM software NX. This is followed by progressing to interactive simulations using the Unity game engine and the Robot Operating System (ROS) -based Gazebo simulator. The Unity-based simulation serves as the foundational blocks of the XR scene, facilitating immersive VR experiences as in [21] or spatial registration for AR/MR development as in [20]. Concurrently, ROS-based Gazebo simulations are augmented with virtual sensors like inertial measurement units (IMUs), allowing for realistic system behaviors and facilitating virtual commissioning, when further coupled with other support functions of metaverse space like computation, analysis, and AI modules.

5. Discussion

This section explores the extensive implications of our research, focusing on the multifaceted contributions and the emerging challenges. Drawing upon our work, we aim to elucidate the broader impact and delineate future research trajectories within the industrial metaverse domain.

5.1. Contributions of this work compared with existing literature

Our research unfolds in three intertwined contributions, each addressing specific gaps in current academic literature and industrial practice. These contributions are expounded below, along with their attendant benefits.

5.1.1. Novel architecture for industrial applications

At the forefront of our contributions is the introduction of a novel industrial metaverse architecture that bridges the divide between physical factories and their metaverse counterparts. While existing architectures often target consumer applications [6,10–12] and provide only conceptual frameworks for industrial contexts [7,8], our architecture addresses the specific demands of smart factory environments. Our design meticulously articulates the components of the physical space including machines, materials, personnel, and the environment, alongside the requisite infrastructure like sensors, actuators, network, and support systems essential for smart factories. The metaverse space within our architecture is structured around ten pivotal modules, including coupling and data storage for seamless data flow, semantic links for knowledge synchronization, and the XR interface module for immersive user interaction. These are supported by additional modules of identifier, security, simulation model, computation, analysis, and AI, each meticulously defined to facilitate their roles and interactions within the industrial metaverse.

By providing a comprehensive, actionable blueprint for implementation, our architecture addresses a notable gap in existing research, transitioning from theoretical constructs to practical applicability in industrial settings. Moreover, the architecture's scalability and interoperability are emphasized, reflecting the needs of both the academic community and industry practitioners for a broad-based industrial metaverse infrastructure. This work synthesizes and extends our prior research in digital twins and XR integration [16–22], significantly broadening the scope to encompass critical elements of the industrial metaverse, expanding from machines to include also personnel, materials, and the environment, presenting a unified, holistic framework.

5.1.2. Orchestrated data flow and knowledge synchronization

A pivotal attribute of our architecture is the orchestrated data flow and knowledge synchronization, achieved through the incorporation of digital twins and semantic models. This integration enables concurrent updating of physical and digital components, enhancing the relevance and utility of data. The orchestration of data flow and knowledge synchronization is delineated by a robust interplay between the T-box and A-box within our architecture: The T-box represents the ontological schema that informs the semantic models, ensuring knowledge synchronization aligns with a consistent ontological framework. Conversely, the A-box comprises live, operational data populating the digital twins, reflecting the dynamic data flow. The bidirectional interplay of T-box and A-box defines and validates each other, thus preserving a coherent and up-to-date representation of both the physical and virtual domains. Together, they ensure that the metaverse is both semantically informed and practically responsive, capable of not just reflecting but also acting upon the physical world it parallels.

This orchestrated approach not only facilitates a seamless integration with existing industrial systems through semantic models but also addresses the challenges of interoperability by enabling the architecture to adapt without requiring comprehensive system modifications. As the physical environment changes, the architecture's knowledge base is dynamically updated to provide an accurate semantic mirror of both the structural and operational aspects of the industrial setting, ensuring the metaverse's relevance and responsiveness.

5.1.3. Validation through a case study

The efficacy of our architecture is corroborated through a detailed case study focused on in-plant material flow tracking. The physical setup of the case study involves materials in transit, an overhead crane system for transportation, a UWB indoor positioning system for tracking, and a human operator managing the workflow within AIIC's interconnected network environment. The case study selectively implements four critical modules of the metaverse space: the coupling module enabling bi-directional data flow for the overhead crane and integrating real-time positional data from the UWB system for accurate material tracking; the semantic link module employing the InPro model to assimilate heterogeneous data sources into a cohesive and synchronized knowledge base across seven ontology domains; the XR interface module providing VR and AR/MR interfaces for user interaction for both remote and on-site scenarios of crane material flow operation, adapting dynamically based on insights derived from the semantic models. The simulation model module blending CAD models of the crane, materials, and the operating environment into interactive simulations within Unity and Gazebo, serving as foundational elements for XR interfaces and further integration with the metaverse's supportive functions.

This empirical exploration not only demonstrates the architecture's practical applicability but also extends beyond the scope of previous studies that focused solely on XR [8,13–15] by offering a comprehensive view of a digital–physical integrated ecosystem. The case study underscores the architecture's real-world utility, highlighting often-overlooked elements like data integration and semantic modeling, thus providing a robust empirical foundation for our theoretical framework.

In summary, our contributions tackle the research gaps and practical limitations of existing works. The architecture we propose serves as an extensible, and actionable guide for industrial metaverse advancement. This research marks a significant stride towards actualizing the comprehensive potential of the industrial metaverse.

5.2. Limitations and future work

While this study marks a significant step towards realizing an industrial metaverse, it acknowledges certain limitations and identifies key areas for future research. The key aspects are outlined below:

Comprehensive validation: Our case study provides an preliminary proof-of-concept demonstration, but a broader range of application scenarios and operational complexities need to be addressed to affirm the architecture's robustness and versatility. The future trajectory of research must involve extensive validation of the architecture in diverse industrial settings. The impact of the architecture on actual industrial processes, such as manufacturing efficiency, error reduction, and cost implications, should be quantitatively analyzed.

Customization and personalization: Our architecture's modularity and scalability are key strengths, designed to cater flexibly to a broad range of industry-specific requirements. This adaptability is crucial as different sectors have unique operational needs and technological landscapes. Future research will delve deeper into developing tailored modules and functionalities that align with the specific characteristics and challenges of these diverse sectors. This will involve engaging with sector experts and stakeholders to identify critical requirements and integrate sector-specific best practices and standards into the architecture. Additionally, personalization capabilities will be enhanced to allow for user-specific configurations that adjust to individual or organizational preferences and workflows, thereby improving user engagement and operational efficiency. For each sector, the adaptability of the proposed architecture will be rigorously tested not only for functionality but also for its integration with existing legacy systems and the latest technological advancements.

Multi-user interaction: The current implementation of the XR Interface in the case study is primarily designed for individual users, while future work should broaden its functionality to support multi-user virtual collaborations. This expansion is critical to advancing the Industry 5.0 vision, which emphasizes collaborative industrial environments where interdisciplinary teams and clients can engage both physically and virtually. Enhancing the XR Interface to support avatars and collective virtual experiences will facilitate interactive activities such as joint training programs and cooperative operations. Additionally, the upcoming enhancements will focus on incorporating a sophisticated representation of personnel digital twins and detailed personnel profiles into multi-user scenarios. This improvement will not only manage digital identities more effectively but also boost active participation across multiple users in the metaverse, enriching the digital workspace with a dynamic and inclusive user interaction framework.

Real-world data challenges: While our architecture offers foundational data management capabilities, and our case study demonstrates effectiveness in a controlled lab setting, real-world factory environments present unique challenges such as data integrity, instantaneous communication, and robust cybersecurity. Notably, the integration of a 5G network within the AIIC's infrastructure in our case study is crucial for supporting high-speed data transmission and low latency, essential for the operations of the industrial metaverse. Although 5G promises key advantages for real-time data processing and interaction in digital twins, actual data speeds often vary and may not consistently reflect these advanced capabilities. Empirical measurements are therefore critical to verify real data speeds and accurately evaluate system latency. Future research endeavors must validate the network's effectiveness, data integrity and cybersecurity across diverse industrial environments. Comprehensive efforts to confirm the true capabilities of 5G will help address practical obstacles effectively, ensuring the robust application of the architecture in the dynamic and complex landscape of actual industrial settings.

Human factors and human-centric design: The architecture's emphasis on XR for HMI necessitates rigorous study on its ergonomic and psychological implications. The design of XR interfaces needs to consider factors such as usability, accessibility, and adaptability, prioritizing human-centric design principles that address ergonomic comfort and psychological well-being. In the context of Industry 5.0, understanding the expected level of operator autonomy is crucial, especially as it varies with cultural backgrounds and educational levels. These factors significantly influence how operators interact with advanced technologies. Future work must explore human-centered designs that enhance productivity while mitigating potential health risks and must ensure that XR interfaces are adaptable to support a diverse workforce. This will ensure inclusivity and effectiveness in a digital work environment that harmonizes human and machine collaboration.

Environmental impact:The sustainable deployment of the industrial metaverse poses significant challenges due to the resource-intensive nature of technologies such as data centers and XR devices. To mitigate these impacts, future work will focus on enhancing energy efficiency and integrating sustainability practices. Efforts will include optimizing data center energy consumption through advanced virtualization technologies that reduce physical hardware needs and improve server efficiency. Additionally, transitioning to energy-efficient hardware and smarter algorithms will lower power requirements and cut energy use. A key strategy will be the adoption of renewable energy sources to power metaverse infrastructures, thereby reducing dependence on fossil fuels. Implementing innovative cooling techniques, such as liquid immersion cooling, will further decrease energy consumption used for heat management. The lifecycle impacts of metaverse hardware will also be addressed, incorporating sustainable manufacturing, promoting component recyclability, and supporting a circular economy to manage electronic waste effectively.

Ethical and regulatory considerations: Rapid advancements in industrial metaverse technologies, particularly the use of digital twins for personnel, could outpace existing regulations, leading to ethical challenges like data privacy, workers' rights, and the potential implications of human tracking within the metaverse. The use of sensitive data from health records, employee monitoring systems, or wearable devices necessitates stringent privacy protections and transparency. Moreover, ethical concerns surrounding data privacy and surveillance of individuals in the Metaverse are amplified with the integration of blockchain technology, which, while enhancing the security and auditability of transactions, must also safeguard privacy and autonomy. Future research must develop robust policies and ethical standards to guide responsible technology deployment. This effort should focus on securing personal data, clearly communicating data usage to all stakeholders, and updating regulatory frameworks to address new challenges posed by these advanced technologies. It is essential to ensure that these innovations protect individual well-being and privacy rights, maintaining a respectful balance between technological innovation and human dignity.

Overall, the future research trajectory is committed to comprehensive validation and real-world implementation, aligning with the foundational premise of this article. As the architecture continues to evolve, interdisciplinary research collaborations and partnerships with industry stakeholders will be essential in addressing these challenges and achieving the pragmatic application of the industrial metaverse.

6. Conclusion

The advent of the metaverse paradigm within the realm of Industry 5.0 underscores the need for a transformative architecture that unifies the digital and physical elements of industrial environments. This work proactively responds to this need, proposing a data-centric and semantic-enhanced industrial metaverse architecture that interlinks the operation of physical factories with the digital expanse of the metaverse.

The proposed architecture comprises interconnected physical and metaverse spaces: The physical space encompasses tangible entities of machines, materials, personnel, and the environment, as well as the infrastructure elements of sensors, actuators, networks, and support systems; The metaverse space is constructed around ten modules, including the coupling and data storage modules for data flow, the semantic link module for knowledge synchronization, the XR interface module for user interactions, and the dedicated support functions of identifier, security, simulation, computation, analysis, and AI modules.

Central to our architecture is the orchestration of the data flow and the knowledge synchronization, facilitated by the integration of digital twins and semantic models. This integration ensures practical and operational relevance, enabling precise reflections of physical entities within the metaverse and facilitating seamless interactions. The semantic modeling approach also allows for integration with existing industrial systems, offering a pragmatic path to industrial metaverse adoption.

The case study on in-plant material flow tracking serves as a practical demonstration of the proposed architecture in a real-world setting, incorporating an overhead crane, materials in transit, UWB tracking, and human oversight within an interconnected network. It showcases the proof-of-concept implementation of four key architectural modules: the coupling module for crane data flow and material localization, the semantic link module for integrating data into a unified knowledge base using the InPro ontology, the XR interface module for immersive remote and on-site crane operation, and the simulation model module for creating interactive simulations. This practical application highlights the architecture's ability to facilitate comprehensive data flow, knowledge synchronization, and immersive user interactions.

This work advances the industrial metaverse concept but recognizes the need for broader validation across varied industrial applications to confirm the architecture's efficacy and flexibility. Future research will address customization for specific industry needs, tackle real-world data challenges in factory settings, and explore the human factors associated with XR interface use. Environmental sustainability and ethical considerations related to the deployment of industrial metaverse also present areas for further investigation. Addressing these points is essential for achieving our long-term vision for a fully integrated, human-centric industrial metaverse, highlighting a path for interdisciplinary research and industry collaboration.

CRediT authorship contribution statement

Xinyi Tu: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Riku Ala-Laurinaho:** Conceptualization, Funding acquisition, Methodology, Project administration, Resources, Supervision, Writing – review & editing. **Chao Yang:** Funding acquisition, Project administration, Software, Visualization. **Juuso Autiosalo:** Conceptualization, Resources, Supervision. **Kari Tammi:** Conceptualization, Funding acquisition, Project administration, Supervision, Writing – review & editing, Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

This work was supported by the Business Finland under Grant 10768/31/2022 Project "NECOVERSE".

References

[1] Jiang Y, Kaynak O, Luo H, Liu M, Yin S. Industrial metaverse: Solutions from a higher-dimensional world. 2022, TechRxiv.
[2] Yao X, Ma N, Zhang J, Wang K, Yang E, Faccio M. Enhancing wisdom manufacturing as industrial metaverse for industry and society 5.0. J Intell Manuf 2022;1–21.
[3] Leng J, Sha W, Wang B, Zheng P, Zhuang C, Liu Q, et al. Industry 5.0: Prospect and retrospect. J Manuf Syst 2022;65:279–95.
[4] Jagatheesaperumal SK, Rahouti M. Building digital twins of cyber physical systems with metaverse for industry 5.0 and beyond. IT Prof 2022;24(6):34–40.
[5] Mystakidis S. Metaverse. Encyclopedia 2022;2(1):486–97.
[6] Mourtzis D, Panopoulos N, Angelopoulos J, Wang B, Wang L. Human centric platforms for personalized value creation in metaverse. J Manuf Syst 2022;65:653–9.
[7] Zheng Z, Li T, Li B, Chai X, Song W, Chen N, et al. Industrial metaverse: Connotation, features, technologies, applications and challenges. In: Methods and applications for modeling and simulation of complex systems: 21st Asia simulation conference, Asiasim 2022, changsha, China, December 9-11, 2022, proceedings, part i. Springer; 2022, p. 239–63.
[8] Lee J, Kundu P. Integrated cyber-physical systems and industrial metaverse for remote manufacturing. Manuf Lett 2022;34:12–5.
[9] Cai Y, Llorca J, Tulino AM, Molisch AF. Compute-and data-intensive networks: The key to the metaverse. In: 2022 1st international conference on 6G networking. IEEE; 2022, p. 1–8.
[10] Ludlow P, Wallace M. The Second Life Herald: The virtual tabloid that witnessed the dawn of the metaverse. MIT Press; 2007.
[11] Duan H, Li J, Fan S, Lin Z, Wu X, Cai W. Metaverse for social good: A university campus prototype. In: Proceedings of the 29th ACM international conference on multimedia. 2021, p. 153–61.
[12] Lee L-H, Braud T, Zhou P, Wang L, Xu D, Lin Z, et al. All one needs to know about metaverse: A complete survey on technological singularity, virtual ecosystem, and research agenda. 2021, arXiv preprint arXiv:2110.05352.
[13] Yang B, Yang S, Lv Z, Wang F, Olofsson T. Application of digital twins and metaverse in the field of fluid machinery pumps and fans: A review. Sensors 2022;22(23):9294.

[14] Njoku JN, Nwakanma CI, Amaizu GC, Kim D-S. Prospects and challenges of metaverse application in data-driven intelligent transportation systems. IET Intell Transp Syst 2023;17(1):1–21.
[15] Alpala LO, Quiroga-Parra DJ, Torres JC, Peluffo-Ordóñez DH. Smart factory using virtual reality and online multi-user: Towards a metaverse for experimental frameworks. Appl Sci 2022;12(12):6258.
[16] Autiosalo J, Vepsäläinen J, Viitala R, Tammi K. A feature-based framework for structuring industrial digital twins. IEEE Access 2019;8:1193–208.
[17] Ala-Laurinaho R, Autiosalo J, Nikander A, Mattila J, Tammi K. Data link for the creation of digital twins. IEEE Access 2020;8:228675–84.
[18] Autiosalo J, Siegel J, Tammi K. Twinbase: Open-source server software for the digital twin web. IEEE Access 2021;9:140779–98.
[19] Tu X, Autiosalo J, Ala-Laurinaho R, Yang C, Salminen P, Tammi K. TwinXR: Method for using digital twin descriptions in industrial extended reality applications. Front Virtual Real 2023;4. http://dx.doi.org/10.3389/frvir.2023.1019080.
[20] Tu X, Autiosalo J, Jadid A, Tammi K, Klinker G. A mixed reality interface for a digital twin based crane. Appl Sci 2021;11(20):9480.
[21] Yang C, Tu X, Autiosalo J, Ala-Laurinaho R, Mattila J, Salminen P, et al. Extended reality application framework for a digital-twin-based smart crane. Appl Sci 2022;12(12):6030.
[22] Yang C, Zheng Y, Tu X, Ala-Laurinaho R, Autiosalo J, Seppänen O, et al. Ontology-based knowledge representation of industrial production workflow. Adv Eng Inform 2023;58:102185.
[23] Silva D, Carvalho LI, Soares J, Sofia RC. A performance analysis of internet of things networking protocols: Evaluating MQTT, CoAP, OPC UA. Appl Sci 2021;11(11):4879.
[24] Jaloudi S. Communication protocols of an industrial internet of things environment: A comparative study. Future Internet 2019;11(3):66.
[25] Purimetla B, Sivasankaran RM, Ramamritham K, Stankovic JA. Real-time databases: Issues and applications. Adv Real-Time Syst 1995;487–507.
[26] Reis DG, Gasparoni FS, Holanda M, Victorino M, Ladeira M, Ribeiro EO. An evaluation of data model for NoSQL document-based databases. In: Trends and advances in information systems and technologies: volume 1 6. Springer; 2018, p. 616–25.
[27] Özsu MT, Valduriez P, et al. Principles of distributed database systems, vol. 2, Springer; 1999.
[28] Pokornỳ J. Graph databases: their power and limitations. In: Computer information systems and industrial management: 14th iFIP TC 8 international conference, CISIM 2015, warsaw, Poland, September 24-26, 2015, proceedings 14. Springer; 2015, p. 58–69.
[29] Hu L, Nguyen N-T, Tao W, Leu MC, Liu XF, Shahriar MR, et al. Modeling of cloud-based digital twins for smart manufacturing with MT connect. Procedia Manuf 2018;26:1193–203.
[30] Microsoft. Digital Twin Definition Language. 2020, [Online]. Available: https://github.com/Azure/opendigitaltwins-dtdl. [Accessed 5 Septemper 2023].
[31] Kaebisch T, McCool M, Charpenay V, Kovatsch M. Web of Things (WoT) Thing Description. 2020, [Online]. Available: https://www.w3.org/TR/wot-thing-description. [Accessed 5 Septemper 2023].
[32] Plattform Industrie 40. Details of the asset administration shell. 2020, [Online]. Available: https://www.plattform-i40.de/IP/Redaktion/EN/Downloads/Publikation. [Accessed 5 Septemper 2023].
[33] Sporny M, Longley D, Kellogg G, Lanthaler M, Lindström N. JSON-LD 1.1. 2020, W3C Recommendation, Jul.
[34] Jagatheesaperumal SK, Yang Z, Yang Q, Huang C, Xu W, Shikh-Bahaei M, et al. Semantic-aware digital twin for metaverse: A comprehensive review. 2023, arXiv preprint arXiv:2305.18304.
[35] Schemaorg. [Online]. Available: https://schema.org/. [Accessed 5 September 2023].
[36] SAREF. [Online]. Available: https://saref.etsi.org/. [Accessed 5 September 2023].
[37] GS1 Web Vocabulary. [Online]. Available: https://www.gs1.org/voc/. [Accessed 5 September 2023].
[38] Choi S, Jung K, Noh SD. Virtual reality applications in manufacturing industries: Past research, present findings, and future directions. Concurrent Eng 2015;23(1):40–63.
[39] Stone R. Virtual reality for interactive training: an industrial practitioner's viewpoint. Int J Hum-Comput Stud 2001;55(4):699–711.
[40] Berg LP, Vance JM. Industry use of virtual reality in product design and manufacturing: a survey. Virtual Realit 2017;21:1–17.
[41] Palmarini R, Erkoyuncu JA, Roy R, Torabmostaedi H. A systematic review of augmented reality applications in maintenance. Robot Comput-Integr Manuf 2018;49:215–28.
[42] Makris S, Pintzos G, Rentzos L, Chryssolouris G. Assembly support using AR technology based on automatic sequence generation. CIRP Ann 2013;62(1):9–12.
[43] Marino E, Barbieri L, Colacino B, Fleri AK, Bruno F. An Augmented Reality inspection tool to support workers in Industry 4.0 environments. Comput Ind 2021;127:103412.
[44] Berners-Lee T, Fielding R, Masinter L. Uniform resource identifier (URI): Generic syntax. Tech. rep, 2005.
[45] Gadekallu TR, Huynh-The T, Wang W, Yenduri G, Ranaweera P, Pham Q-V, et al. Blockchain for the metaverse: A review. 2022, arXiv preprint arXiv:2203.09738.
[46] Reed D, Sporny M, Longley D, Allen C, Grant R, Sabadello M, et al. Decentralized identifiers (dids) v1. 0. 2020, Draft Community Group Report.
[47] Heron S. Advanced encryption standard (AES). Netw Secur 2009;2009(12):8–12.
[48] Rescorla E. The transport layer security (TLS) protocol version 1.3. Tech.rep, 2018.
[49] Kürtünlüoğlu P, Akdik B, Karaarslan E. Security of virtual reality authentication methods in metaverse: An overview. 2022, arXiv preprint arXiv:2209.06447.
[50] Ferraiolo D, Cugini J, Kuhn DR, et al. Role-based access control (RBAC): Features and motivations. In: Proceedings of 11th annual computer security application conference. 1995, p. 241–8.
[51] Hu VC, Kuhn DR, Ferraiolo DF, Voas J. Attribute-based access control. Computer 2015;48(2):85–8.
[52] Ghosh A, Senthilrajan A. Research on packet inspection techniques. Int J Scient Technol Res 2019;8:2068–73.
[53] Rehman RU. Intrusion detection systems with Snort: advanced IDS techniques using Snort, Apache, MySQL, PHP, and ACID. Prentice Hall Professional; 2003.
[54] Cid D, Hay A, Bray R. OSSEC host-based intrusion detection guide. Syngress; 2008.
[55] Boot AW, Thakor AV. Security design. J Finance 1993;48(4):1349–78.
[56] Wang Y, Su Z, Zhang N, Xing R, Liu D, Luan TH, et al. A survey on metaverse: Fundamentals, security, and privacy. IEEE Commun Surv Tutor 2022.
[57] Moser A, Appl C, Brüning S, Hass VC. Mechanistic mathematical models as a basis for digital twins. In: Digital Twins: Tools and Concepts for Smart Biomanufacturing. Springer; 2021, p. 133–80.
[58] Wagg D, Worden K, Barthorpe R, Gardner P. Digital twins: state-of-the-art and future directions for modeling and simulation in engineering dynamics applications. ASCE-ASME J Risk Uncertain Eng Syst B Mech Eng 2020;6(3):030901.
[59] Hinchy E, Carcagno C, O'Dowd N, McCarthy C. Using finite element analysis to develop a digital twin of a manufacturing bending operation. Procedia CIRP 2020;93:568–74.
[60] Schluse M, Priggemeyer M, Atorf L, Rossmann J. Experimentable digital twins—Streamlining simulation-based systems engineering for industry 4.0. IEEE Trans Ind Inform 2018;14(4):1722–31.
[61] Kousi N, Gkournelos C, Aivaliotis S, Giannoulis C, Michalos G, Makris S. Digital twin for adaptation of robots' behavior in flexible robotic assembly lines. Procedia Manuf 2019;28:121–6.
[62] Mourtzis D, Papakostas N, Mavrikios D, Makris S, Alexopoulos K. The role of simulation in digital manufacturing: applications and outlook. Int J Comput Integ Manuf 2015;28(1):3–24.
[63] Valaskova K, Horak J, Bratu S. Simulation modeling and image recognition tools, spatial computing technology, and behavioral predictive analytics in the metaverse economy. Rev Contemp Philos 2022;21:239–55.
[64] Pangilinan E, Lukas S, Mohan V. Creating augmented and virtual realities: theory and practice for next-generation spatial computing. " O'Reilly Media, Inc."; 2019.
[65] Vaupel T, Seitz J, Kiefer F, Haimerl S, Thielecke J. Wi-fi positioning: System considerations and device calibration. In: 2010 international conference on indoor positioning and indoor navigation. IEEE; 2010, p. 1–7.
[66] Feldmann S, Kyamakya K, Zapater A, Lue Z. An indoor bluetooth-based positioning system: Concept, implementation and experimental evaluation. In: International conference on wireless networks, vol. 272. 2003.
[67] Sahinoglu Z, Gezici S, Güvenc I. Ultra-wideband positioning systems: theoretical limits, ranging algorithms, and protocols. Cambridge University Press; 2008.
[68] Hartmann B, Link N, Trommer GF. Indoor 3D position estimation using low-cost inertial sensors and marker-based video-tracking. In: IEEE/ION position, location and navigation symposium. IEEE; 2010, p. 319–26.
[69] Tsai T-H, Chang C-H, Chen S-W. Vision based indoor positioning for intelligent buildings. In: 2016 2nd international conference on intelligent green building and smart grid. IEEE; 2016, p. 1–4.
[70] He W, Xi M, Gardner H, Swift B, Adcock M. Spatial anchor based indoor asset tracking. In: 2021 IEEE virtual reality and 3D user interfaces. IEEE; 2021, p. 255–9.
[71] Milojicic D. The edge-to-cloud continuum. Computer 2020;53(11):16–25.
[72] Dhelim S, Kechadi T, Chen L, Aung N, Ning H, Atzori L. Edge-enabled metaverse: The convergence of metaverse and mobile edge computing. 2022, arXiv preprint arXiv:2205.02764.
[73] Stojanovic N, Milenovic D. Data-driven digital twin approach for process optimization: An industry use case. In: 2018 IEEE international conference on big data. IEEE; 2018, p. 4202–11.
[74] Mehdiyev N, Lahann J, Emrich A, Enke D, Fettke P, Loos P. Time series classification using deep learning for process planning: A case from the process industry. Procedia Comput Sci 2017;114:242–9.
[75] Benabdellah AC, Benghabrit A, Bouhaddou I. A survey of clustering algorithms for an industrial context. Procedia Comput Sci 2019;148:291–302.
[76] Stojanovic L, Dinic M, Stojanovic N, Stojadinovic A. Big-data-driven anomaly detection in industry (4.0): An approach and a case study. In: 2016 IEEE international conference on big data. IEEE; 2016, p. 1647–52.

[77] Xu J, Huang E, Hsieh L, Lee LH, Jia Q-S, Chen C-H. Simulation optimization in the era of Industrial 4.0 and the Industrial internet. J Simul 2016;10(4):310–20.
[78] Lu J, Wang X, Cheng X, Yang J, Kwan O, Wang X. Parallel factories for smart industrial operations: From big AI models to field foundational models and scenarios engineering. IEEE/CAA J Autom Sin 2022;9(12):2079–86.
[79] Wang Y, Wang C, Zhang H. Industrial robotic intelligence simulation in metaverse scenes. In: 2022 China automation congress. IEEE; 2022, p. 1196–201.
[80] Watson R, et al. The virtual economy of the metaverse: Computer vision and deep learning algorithms, customer engagement tools, and behavioral predictive analytics. Linguist Philos Investig 2022;(21):41–56.
[81] Lv Z. Generative artificial intelligence in the metaverse era. Cogn Robotics 2023.
[82] Zanzotto FM. Human-in-the-loop artificial intelligence. J Artificial Intelligence Res 2019;64:243–52.