Journal of Intelligent Manufacturing (2026) 37:1875–1890
https://doi.org/10.1007/s10845-025-02625-1

COGNIMAN Digital Twin Architecture for Flexible Manufacturing

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Received: 15 February 2024 / Accepted: 10 May 2025 / Published online: 12 June 2025

Abstract
Despite recent progresses in smart manufacturing, existing architectures often fail to meet the comprehensive demands of modern manufacturing environments, such as flexibility, scalability, and seamless human-machine interaction. The COGNitive Industries for smart MANufacturing (COGNIMAN) architecture addresses these gaps by integrating advanced technologies with a focus on human-centric design. This article introduces COGNIMAN architecture as an essential pillar for Industry 5.0, enhancing operational efficiency through continuous monitoring, real-time data analysis, and predictive insights powered by machine learning. Its modular design optimizes resource utilization, reduces waste, and improves energy efficiency, aligning with eco-conscious manufacturing trends. By integrating sensors, robotics, digital twins, simulation, and AI, COGNIMAN offers a flexible, resilient, and sustainable platform adaptable to various manufacturing processes. The novelty of COGNIMAN architecture lies in its comprehensive approach, addressing key requirements such as flexibility, interoperability, maintainability, and adaptability. It fosters inclusive and safer working environments while supporting sustainable manufacturing practices. A case study in glass fiber manufacturing demonstrates COGNIMAN's architecture applicability across different fields, enhancing the global competitiveness of European technology and manufacturing sectors.

Keywords Flexible manufacturing · Digital twin · Sensors · Data storage · Artificial intelligence · Security · Ethics

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Introduction

Context

Recently, there has been a growing interest in the concept of Industry 5.0 (Breque et al., 2021), which emphasizes human-centricity, sustainability, and resilience. While Industry 4.0 primarily focused on technical advancements and economic viability, Industry 5.0 promotes inclusive and safer working environments, empathy, and respect for human rights (Xu et al., 2021). It encourages sustainable solutions by developing circular processes where natural resources are reused, repurposed, and recycled, leading to less waste and reduced harmful emissions. The resilience component of Industry 5.0 emphasizes emergency preparedness through robust, adaptable, and flexible production processes and resilient value/supply chains (Breque et al., 2021).

The evolution from Industry 4.0 to Industry 5.0 highlights the need for human-centric values such as sustainability, resilience, and workers well-being (Xu et al., 2021; Wang et al., 2024). While automation has advanced, humans remain crucial for decision-making, troubleshooting, and adaptive responses. However, current frameworks often underemphasize these roles.

Human operators provide contextual experience, make complex decisions, and ensure safe operations (Lou et al., 2024). Yet, many existing system lack features that integrate human input effectively (Mylonas et al., 2021). Automated systems struggle with contextual nuances, limiting adaptability, and fragmented interfaces hinder collaboration, while privacy and ethical concerns remain under-addressed (Zheng et al., 2018).

The COGNIMAN (COGNItive Industries for smart MANufacturing) solution advances towards a human-centric Industry 5.0 vision by embedding human roles into its design, enabling real-time decision-making, system customization, and continuous improvement.

Digital Twin (DT) technology has been a key enabler for Industry 4.0, driving advancements in automation, data analytics, and connectivity (Waszak et al., 2022). It remains equally important for Industry 5.0, particularly in enhancing human-machine interaction. A typical DT model consists of three core components: the Physical Space (real entities), the Virtual Space (digital replicas), and data connections linking both (Rajratnakharat et al., 2018). Recent advancements have integrated AI/ML, image analysis, and graph-based algorithms into DTs to introduce optimization, simulation, reasoning, and learning capabilities. Initiatives like the COGNITWIN project (COGNITWIN, xxx) have introduced concepts such as Hybrid Twin and Cognitive Twin to enhance cognitive services within DTs (Abburu et al., 2020). A significant advancement within Industry 5.0 is the development of Human Digital Twins (HDTs) (Wang et al., 2024), which are digital representations of human workers capturing physiological, psychological, and cognitive data. This technology can monitor worker health, optimize work conditions, and enhance training through personalized simulations.

Rationale, Focus, and Challenges

Smart manufacturing uses advanced technologies and data-driven processes to enhance efficiency, productivity, and flexibility in manufacturing operations (Zheng et al., 2018). Key requirements for smart manufacturing include technological, organizational, and strategic elements.

The deployment of sensors and data capture mechanisms is crucial. These sensors, strategically placed throughout the production environment, provide real-time data on machine performance, product quality, and environmental conditions. High-quality, accurate sensors are essential to ensure data reliability. Robust connectivity is another fundamental requirement. A well-structured network infrastructure, encompassing both wired and wireless connections, facilitates seamless communication among sensors, machines, and systems, forming the backbone of smart manufacturing.

Data analytics and artificial intelligence (AI) are critical to smart manufacturing. Advanced analytics and AI tools process the vast amount of data generated by sensors. Machine learning algorithms can uncover patterns, predict equipment failures, optimize processes, and improve product quality, enabling proactive decision-making. The integration of automation, robotics, and control systems drives autonomous operation, process optimization, and real-time adjustments, enhancing efficiency and productivity. Human-Machine Interfaces (HMIs) allow operators to visualize data, monitor the manufacturing process, and intervene when necessary, ensuring harmonious and safe human-robot interactions.

Addressing the integration of the human-cyber-physical (Lou et al., 2024; Zhou et al., 2019) system poses significant challenges for smart manufacturing. These complex interactions require advanced solutions to ensure seamless collaboration, security, safety, and efficiency across all elements of the manufacturing process.

Smart manufacturing leverages advanced technologies and data-driven processes to enhance efficiency, productivity, and flexibility in manufacturing operations. However, the implementation of such systems presents a series of challenges (Phuyal et al., 2020; Sahoo & Lo, 2022; O'Connell et al., 2023) that are addressed in this study: (i) data reliability and sensor integration: noisy sensor readings, environmental variability, or hardware limitations need to be considered to ensure accurate, real-time data collection while maintaining system reliability; (ii) complex system interactions, that need to be seamlessly managed as a result of the integration of diverse components such as sensors, robots, actuators, and human-machine interfaces among others, to enable real-time communications and adaptive responses; (iii) human-machine collaboration, supporting dynamic human-machine interactions and decision-making, especially in critical scenarios; and (iv) data privacy, security, and ethical considerations to comply with applicable regulations such as GDPR, and ensuring secure data exchange, access control, and ethical AI usage.

Despite these advancements, existing architectures do not fully meet the comprehensive demands of modern manufacturing environments, especially for difficult-to-automate processes such as glass fiber production. Glass fiber manufacturing is unpredictable and difficult to trace, requiring specific sensors and lifelong learning for anomaly detection. There is also a cost vs. waste reduction challenge, balancing the cost of equipment for controlling the process against allowing waste.

The COGNIMAN architecture addresses these challenges by leveraging DT technology, that facilitates the creation of virtual representations of the physical manufacturing environment, enabling real-time monitoring, analysis, and predictive maintenance. It also provides: (i) enhanced data accuracy through the integration of diverse data sources, ensuring continuous data validation and improving overall system reliability; (ii) seamless system integration, thanks to its modular design that supports flexible and scalable systems and seamless integration of sensors, robotics, and AI-driven analytics; (iii) process optimization, by continuously analyzing process data, detecting anomalies, minimizing downtime, and reducing waste; (iv) human-in-the-loop interaction, which incorporates operator feedback into the decision-making processes, thus enhancing system adaptability; and (v) ethical and secure operations, by embedding privacy and security protocols on every layer, ensuring compliance with relevant regulations, and fostering user trust.

Contribution

The unique contributions of the COGNIMAN architecture presented in this study are as follows: (i) human-centric design, explicitly integrating human roles, including operators, developers, and administrators, ensuring collaborative decision-making and adaptive responses; (ii) real-time human-machine collaboration, supporting human-in-the-loop interactions, where humans can adjust system parameters, validate machine learning results, and intervene during critical events; (iii) advanced DT integration, incorporating predictive maintenance capabilities, context-aware anomaly detection, and AI-driven recommendations, enabling a proactive and adaptive manufacturing environment; (iv) ethical and secure framework, embedding data privacy, security mechanisms, and ethical compliance as core design principles, ensuring transparency and responsible AI use; and (v) modular and scalable design, supporting seamless integration of new technologies, and enabling scalability across various manufacturing domains. Aiming at addressing the challenges detailed in the previous section, the COGNIMAN architecture provides the following capabilities:

- *Flexibility*: Allowing smooth integration of diverse components such as simulations, digital twins, sensors, and cognitive robotics tailored to specific manufacturing needs.
- *Scalability*: Supporting the addition or removal of modules without disrupting the whole system, and enabling gradual enhancement of capabilities.
- *Interoperability*: Ensuring compatibility across different technologies and systems.
- *Maintainability*: Allowing individual modules to be independently developed and interconnected.
- *Resilience*: Enhancing issue/failure management, and ensuring continuous operation and easier troubleshooting.
- *Adaptability*: Facilitating rapid adaptation to changes, ease of integration, customizable workflows, and scalability to handle varying production volumes and complexities in smart manufacturing environments.

This architecture comprises seven layers:

1. Physical Twin: Represents real-world entities and processes, such as sensors, machinery, and equipment.
2. Data Layer: Manages raw data collected from sensors and other sources.
3. Digital Twin: Creates a virtual replica of the physical twin using real-time data.
4. Service Layer: Provides functionalities and services, including analytics and simulations.
5. User Interface: Enables human interaction and monitoring of the digital twin.
6. Connectivity and Integration: Facilitates data exchange between system components and external systems.
7. Ethics: Ensures responsible and ethical use of data, addressing privacy and security concerns.

These layers work together to create an intelligent, adaptable, and human-inclusive manufacturing environment. Functional requirements for smart manufacturing include sensor definition, real-time data collection, data accuracy, data storage, data pre-processing, simulation and modeling, predictive analysis, performance optimization, autonomous behavior, failure detection, behavior visualization, remote monitoring, sensor integration, API integration, cloud integration, data privacy, consent management, transparency, regulatory compliance, and security.

The COGNIMAN architecture offers substantial benefits to smart manufacturing through its modular design, providing unmatched flexibility, scalability, and adaptability. By facilitating the integration of advanced technologies such as sensors, digital twins, machine learning, and cognitive robotics, it ensures seamless interoperability and customization. This approach allows manufacturers to rapidly adapt to new processes and technologies, efficiently scale operations, and maintain cost-effectiveness. Additionally, the modularity enhances maintainability and resilience, ensuring continuous operation and fostering innovation within the manufacturing sector.

Article structure

The remainder of this article is structured as follows: Section 2 provides an overview of smart manufacturing solutions utilizing digital twins and explores existing architectures. In Section 3, we explain the designed architecture: COGNIMAN. Section 4 illustrates the practical application of this architecture through a real case study. Section 5 discusses the obtained results. Finally, Section 6 presents the conclusions and future work.

Digital Twins and Existing Architectures

While the notion of the Digital Twin is not particularly new, it has experienced in recent years a remarkable surge of interest, primarily centered around its applications in smart manufacturing and Industry 4.0. Notably, the first actual DT can be traced back to NASA's Apollo 13 mission in 1970, three decades before the term appeared in the literature (Mylonas et al., 2021). Accordingly, one of the earliest definitions of the term "Digital Twin" was proposed by Grieves in 2013 within the context of product life management (Rajratnakharat et al., 2018), followed by a more widely accepted definition of NASA in 2014 (Shafto et al., 2012). Subsequently, smart manufacturing began to dominate the DT domain, resulting in the emergence of various definitions. The ISO 30173 standard - "Digital Twin - Concepts and terminology" - defines a DT as *"a digital representation of a target entity with data connections that enable convergence between the physical and digital states at an appropriate rate of synchronization"* (ISO, xxx). According to the Digital Twin Consortium (DTC), *"a digital twin is a virtual representation of real-world entities and processes, synchronized at a specified frequency and fidelity"* (DTC, xxx). Early definitions of DT models comprise three main components: (i) the *Physical Space*, consisting of real entities (e.g. assets, processes, products, plants), (ii) the *Virtual Space* containing the digital replicas, and (iii) the connections of data and information that link the Virtual and Physical spaces together (Rajratnakharat et al., 2018). In recent years, the initial concept of DT has seen significant evolution through the integration of advanced technologies, including AI/ML, large language models, image analysis, and graph-based algorithms, aiming to introduce optimization, simulation, reasoning, and learning capabilities into the virtual space (Waszak et al., 2022; Alvarez et al., 2023). For example, Gurcan et al. propose an LLM-powered Social Digital Twinning Platform that embeds conversational and collaborative AI services directly into the DT framework, enabling more natural human-machine interaction and community-driven use cases (Gürcan et al., 2025).

For instance, Tao et al. introduced a *Service* dimension within their five-dimensional DT model, to provide real-time monitoring, control, optimization, and simulation (Tao et al., 2019). In the context of the COGNITWIN project (COGNITWIN, xxx), one of the European initiatives dedicated to realizing cognitive production plants, the concepts of Hybrid Twin and Cognitive Twin have emerged to streamline the conceptualization of cognition services, enabling human-like cognition on top of DTs (Abburu et al., 2020; Johansen et al., 2023). Additionally, various initiatives have focused on the dynamicity and self-adaptation aspects of DTs, leading to the proposal of different architectural DT frameworks in the literature to support the development of DT systems capable of delivering intelligent services (Mylonas et al., 2021). While Industry 4.0 focuses on process automation and optimization, Industry 5.0 provides solutions to environmental and social metrics, where the core values are sustainability, human-centricity, and resilience (Xu et al., 2021). Still, DTs are essential technologies to enable this new vision, especially for human-machine cooperation. The concept of DTs has been evolved into HDTs to represent not only physical assets but also the humans, "aiming to supplement the humans' strengths, amplify humans' productivity, dig out humans' potential, and prioritize physical and mental well-being in smart manufacturing systems" (Wang et al., 2024)

Table 1 provides an analysis of such initiatives within the smart manufacturing domain. It highlights key architectural dimensions-such as human interaction, cognition, and data modeling-across a representative set of European projects, standards, and commercial frameworks, thereby offering a comparative view of the current landscape. The table includes architectural frameworks developed in European research and innovation projects, ongoing standardization activities, as well as research and commercial products. Regarding the architectural pattern (*Arch. pattern*), most of the investigated solutions are Reference Architectures (Ref.) that employ a layered pattern to provide a structured framework for developing and organizing DT systems. Some of these architectures also adopt the microservices (SOA) paradigm, which models communication as standardized services to enhance interoperability and flexibility of system components (Lam & Haugen, 2019). Our proposed COGNIMAN Architecture also employs this SOA (Service Oriented Architecture) paradigm for the same reasons. An important observation is the limited emphasis on human interaction (*Human Interact.*) in the analyzed DT architectures, with the majority not explicitly addressing this aspect (ND).

As discussed earlier, human involvement is a central focus of Industry 5.0. Therefore, the COGNIMAN architecture will prioritize Human-Machine interactions, as well as address Social Sciences and Humanities (SSH) and ethical implications associated with these aspects. Furthermore, *Security, Safety, and Privacy* (SSP) are critical considerations in DT implementations, particularly in industries like manufacturing. The majority of the architectures acknowl-

Table 1 Digital Twin Architectures for Smart Manufacturing

		Arch. pattern	Human Interact.	SSP	Cog.	Services	Data model	Tools
EU Projects	COGNIMAN	Ref., Layered	Y	Y	Y	AI/ML, 2D/3D Viz.	KG, Ontologies	Toolbox
	COGNITWIN (Johansen et al., 2023)	Ref., Layered	ND	Y	Y	AI/ML, 2D/3D Viz., Data Space	AAS, KG, Ontologies	Toolkit
	CAPRI (CAPRI, xxx; Vega et al., 2022)	Ref., Layered	ND	Y	Y	AI/ML, Data Space	Ontologies	Data platform
	FACTLOG (FACTLOG, xxx; Rozanec et al., 2021)	Layered	ND	Y	Y	AI/ML	KG, Ontologies	Toolset
	MIDIH (MIDIH, xxx; Jakab et al., 2019)	Ref., Layered	ND	Y	ND	AI/ML, Big Data	FIWARE	Data platform
	CircularTwAIn (CircularTwAIn, xxx; Volz et al., 2023)	Ref., Layered	Y	Y	ND	AI/ML, Data Space	AAS, Ontologies, Standards	Toolkit
Standard	RAMI4.0 (Hankel & Rexroth, 2015)	Ref., Layered+SOA	Limited	Y	ND	ND	AAS, OPC-UA	AAS Impl.
	DTC RA (DTC, xxx)	Ref., Layered+SOA	ND	Y	ND	ND	FIWARE, Ontologies,	ND
	ISO 23247 (ISO, xxx)	Ref., Layered	ND	Y	ND	ND	ND	ND

Table 1 continued

		Arch. pattern	Human Interact.	SSP	Cog.	Services	Data model	Tools
Res. & Com.	BDV RM (BDV, xxx)	Ref., Layered	Y	Y	ND	Big Data, Data Space	Standards	Data platform
	FIWARE (FIWARE, xxx)	Layered	ND	Y	ND	AI/ML, CEP, Big Data, Data Space	Smart data models	Data platform
	IBM DT RA (IBM, xxx)	Ref., Layered+SOA	ND	Y	ND	AI/ML	ND	Cloud stack
	Azure DT (Microsoft, xxx)	SOA	ND	ND	ND	AI/ML, 2D/3D Viz., workflow mngmt.	DTDL	Cloud stack
	AWS TwinMaker (Amazon, xxx)	SOA	ND	Y	ND	2D/3D Viz.	ND	Cloud stack
	DIGITbrain (Talasila et al., 2021)	SOA	Y	ND	ND	2D/3D Viz.	ND	Cloud platform
	HDTs (Wang et al., 2024)	Ref., Layered	Y	Y	Y	ND	ND	ND

edge these concerns and incorporate measures to address them. The COGNIMAN architecture will also integrate these considerations in the form of **SSP rules**. *Cognition (Cog.)* capabilities play a pivotal role in enhancing DT functionality and facilitating seamless human-machine collaboration. Cognition features enable the integration of human knowledge and experience into the DTs, allowing these systems to leverage both AI and human insights. Several projects such as COGNITWIN and CAPRI explicitly mentioned the integration of cognition features. Additionally, cognition can be enabled within HDTs which are digital representation of humans, transforming human-system interaction by directly incorporating human characteristics into system design and performance, thus enhancing system efficiency and user experience (Wang et al., 2024). This indicates a trend within European initiatives toward making DTs more intelligent and capable of autonomous decision-making. Although the others did not define cognition explicitly within their architectures, many exhibit similar features in their provided *Services* by leveraging AI/ML or Big Data analytics. For simplicity, the COGNIMAN architecture will adopt a similar approach by introducing a dedicated Services layer atop the DT models to enable cognition and provide further data-driven support. The selection of *Data model* varies across architectures. Notably, the use of Knowledge Graphs (KG), Ontologies, and standards like Asset Administration Shells (AAS) is prevalent. These choices reflect the importance of structured data representation in DTs for effective communication and seamless interoperability. As interoperability stands as a key point in COGNIMAN, existing standardized solutions for graph-based model and AI-based model will be considered for DT data representation within our proposed architecture. Finally, most analyzed approaches have incorporated specific *Tools* into a toolkit, data platform or cloud stack to realize their proposed conceptual frameworks. The proposed solution employs a modular approach, comprising various tools and modules, thereby facilitating adaptable instantiation and broad applicability of the architecture across diverse use cases. In alignment with this prevailing approach, a **COGNIMAN toolbox** will be also provided. Accordingly, relevant software tools for data management and data-driven model development will be investigated and integrated to enable functions such as real-time monitoring, optimization, and simulation. This modular solution ensures that the COGNIMAN architecture remains versatile and adaptable, allowing users to select and integrate tools based on their specific needs and use cases. By leveraging modularity, the COGNIMAN toolbox maximizes flexibility and scalability, empowering users to customize their digital twin implementations effectively. An example of COGNIMAN architecture instance realized by the COGNIMAN toolbox will be presented in detail in Section 4.

COGNIMAN Architecture

The manufacturing industry faces numerous challenges impacting efficiency, productivity, sustainability, and adaptability. Addressing global competition, rapid technological advancements, and stringent quality control, the COGNIMAN Architecture is designed to deal with manufacturing processes by developing a collaborative framework among humans, technologies, and machines. This architecture aims to, autonomously or cooperatively, improve processes, reduce costs, and drive innovation to maintain a competitive edge.

The COGNIMAN Architecture takes into account both functional and non-functional requirements. Functional requirements define the system or its components, while non-functional requirements concern the quality attributes of system services. This architecture, not only improves manufacturing processes, but also establishes a suitable framework for human-centric interactions. In this section, we define the functional requirements of the architecture, the detailed architecture description and the human roles in the architecture.

Functional requirements for the Architecture

In the context of smart manufacturing, several crucial functionalities are outlined, emphasizing the unique human-centric approach:

Firstly, it is important to *define sensors* capable of capturing the necessary data, guaranteeing if necessary, real-time data collection constrains. Data accuracy and calibration are important to ensure that the data collected from sensors are precise and reliable. Including human feedback in sensor placement and calibration can enhance data relevance and accuracy.

Secondly, effective *data management* is important. This involves storing raw data in structured formats for future exploitation and conducting data pre-processing to eliminate noise and inconsistencies. Human operators play a critical role in validating data quality and relevance during pre-processing, ensuring that the system adapts to real-world conditions while respecting data confidentiality.

Next, the development of *simulation and modeling* tools that replicate the behavior of physical twins to facilitate the future analysis and prediction of sensor behavior. Data fusion from various sensors is also necessary to create a comprehensive view of the physical twin. Incorporating human expertise in the simulation models allows for more accurate and practical predictions, leveraging experiential knowledge that might not be fully captured by automated systems.

Furthermore, smart manufacturing requires *predictive analysis* capabilities to forecast equipment failures and optimize performance. Autonomous behavior and failure detection models should be defined to prevent *system failures*. Including the humans in the loop while making decisions is important to exploit human experience and enrich system knowledge. Some tasks need to interact with the human to be finalized, while others do not need human validation. This human-in-the-loop approach ensures that critical decisions benefit from human intuition and experience, enhancing overall system reliability and performance.

For effective *human-machine interaction*, designing interactive systems or user interfaces to monitor the system's behavior is essential. These interfaces should be intuitive and provide clear insights to operators, enabling effective decision-making. Additionally, remote monitoring capabilities should be in place to access the digital twin and make informed decisions remotely. Ensuring that the user interface supports different levels of expertise and provides the necessary training and support is crucial for maximizing human-machine collaboration.

In terms of *connectivity and integration*, establishing communication protocols for seamless data transmission from sensors to the data layer is crucial. Developing APIs for data exchange among the digital twin, services, and external systems is also important. Furthermore, integration with cloud platforms for scalable storage, processing, and analysis, especially for big data, is necessary. Ensuring that these integrations are user-friendly and provide real-time feedback to human operators enhances the effectiveness of the digital twin system.

Ethical considerations play an important role in smart manufacturing, including the implementation of mechanisms for data privacy to restrict access to sensitive manufacturing data to authorized personnel, managing user consent for data collection and usage, and maintaining transparency in how data is used, processed, and stored. Addressing ethical issues ensures that human-centric systems respect user rights and foster trust among operators and stakeholders.

Finally, compliance with relevant *regulations* and ensuring robust *security* measures are indispensable components for smart manufacturing. Human-centric approaches should include continuous training and awareness programs for operators to understand and adhere to these regulations and security protocols, ensuring a secure and compliant manufacturing environment.

The definition of the architecture

From the functional requirements previously detailed, we encapsulate the functionalities into a human-centric architecture and defined the seven layers of the COGNIMAN architecture as follows (See Fig. 1):

Physical Twin The physical twin represents the actual physical object, process, or system within the real world. This layer includes physical machinery, equipment, devices, and any other tangible components that are part of the manufacturing environment. Sensors and actuators embedded in these physical assets collect real-time data, which serves as the basis for creating and updating the digital twin.

Data Layer The data layer serves as the foundation for the entire digital twin ecosystem. It encompasses the collection, storage, and management of raw data generated by sensors and other data sources associated with the physical twin. This data can include measurements, sensor readings, operational parameters, environmental conditions, and more. Proper data processing and storage are crucial to ensure accurate and reliable digital twin representations. This layer aligns with cyber-physical-human systems, where human data, such as ergonomic parameters, are integrated to optimize data exploitation while respecting confidentiality (personal information) for a better robot and human information extraction.

Digital Twin Representation The heart of the architecture is the digital twin itself. This layer is a virtual representation of the physical twin, constructed using the real-time data collected from sensors and combined with relevant contextual information. The digital twin accurately mirrors the behavior, characteristics, and conditions of its physical counterpart through modeling, such as Artificial Intelligence (AI), Graph based modeling, etc. It enables simulations, analysis, and monitoring, allowing for predictive insights and informed decision-making. In this layer, the human-centric digital twin takes into account feedback from human operators, making them central to human-cyber-physical systems and allowing the possible interaction between the humans and the system digitization.

Service Layer The service layer encapsulates the functionalities and services that leverage the capabilities of the digital twin. This layer includes various algorithms, models, simulations, and analytics that use the data from the digital twin to generate insights, predictions, and optimization strategies. It is responsible for translating raw data into actionable information and facilitating interactions among different layers of the architecture. This layer takes into account the principles of social cyber-physical systems by integrating social factors and human needs into services, ensuring that the outputs are not only technical but also profiled depending on the user needs.

User Interface The user interface layer is a critical enabler of human interaction with the digital twin ecosystem, offering a suite of tools and interfaces such as graphical user interfaces (GUIs), dashboards, augmented reality (AR) or virtual reality (VR) applications, and other visualization and interaction mechanisms. A unique contribution of this layer lies in its incorporation of human-centric design principles, ensuring that interfaces are intuitive, accessible, and adapted to diverse human roles within the system. These roles, including operators, engineers, and managers, are detailed further in Subsection 3.3. By prioritizing human-in-the-loop

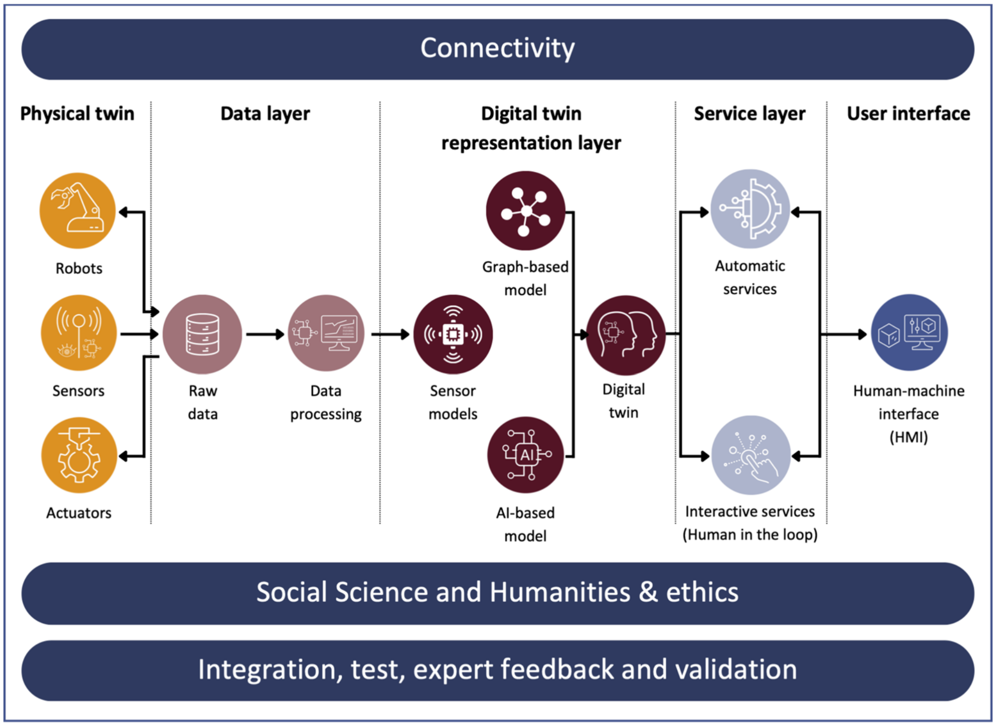


Fig. 1 Illustration of the defined COGNIMAN architecture with its seven layers

interactions, the user interface facilitates the communication between users and the digital twin, enabling effective monitoring, insight generation, and decision-making within human-cyber-physical systems. This approach reflects a commitment to social cyber-physical systems that integrate human agency as a fundamental component of the ecosystem.

Connectivity and Integration The connectivity and integration layer ensures seamless communication among the various components of the architecture. This layer facilitates data exchange between the physical twin, data layer, digital twin, service layer, user interface, and external systems. It might involve technologies such as Internet of Things (IoT) protocols, APIs (Application Programming Interfaces), middleware, and networking solutions to enable smooth and reliable data flow.

Social Science & Humanities (SSH), and Ethics The Social Science & Humanities and ethics layer focuses on the responsible and ethical use of digital twin technology including social aspects. As digital twins gather extensive data, including potentially sensitive information, ethical considerations around data privacy, security, consent, and transparency become paramount. This layer addresses ethical concerns and ensures that the implementation of digital twins respects legal and societal norms, and safeguards data and privacy. Thus, the COGNIMAN architecture integrates the concept of “human in the loop" to consider not only technical aspects, but also how the integration between human operators and machines can achieve successful collaboration. In line with the applicable regulation, on-site analysis and interviews are used to define the needs for effective cooperation between humans and machines, respecting ethical issues and considering social aspects.

Security, Safety and Privacy (SSP) The CCOGNIMAN architecture for digital twins in smart manufacturing prioritizes Security, Safety, and Privacy through a multi-layered approach to cybersecurity. At the data layer, the architecture employs robust access control mechanisms to ensure that only authorized personnel can access sensitive information. This is complemented by the use of dataspaces, which segment data into secure domains, thereby enhancing data protection and privacy. Importantly, all data are meticulously cleaned to remove Personally Identifiable Information (PII), ensuring compliance with General Data Protection Regulation (GDPR) standards. Network connectivity is fortified through Virtual Private Network (VPN) connections and secure protocols, ensuring that data transmission remains confidential and tamper-proof. The architecture also incorporates resilient software and hardware components designed to withstand cyber attacks, further bolstering system security. Trustworthy AI algorithms are integrated, ensuring that AI-driven decisions within the digital twin are reliable and transparent. Moreover, the digital twin itself undergoes rigorous testing for security vulnerabilities, ensuring a high level of protection against potential threats. This comprehensive security framework within the COGNIMAN architecture not only safeguards operational integrity, but also fosters trust in the deployment of digital twins in smart manufacturing environments.

Human roles - human in the loop

The COGNIMAN Architecture integrates diverse human roles to ensure effective collaboration between human operators and automated systems, enhancing overall manufacturing processes. The key human roles involved are:

- **Human Operator**: The operator is the primary user of the COGNIMAN architecture within industrial settings, focused on process optimization and automation. Although not an expert in machine operation or Information and Communication Technology, the operator actively engages with the platform to optimize workflows, improve efficiency, and automate tasks within their operational domain.
- **Human Technical Developer**: This role encompasses individuals with expertise in Information and Communication Technology or machining. These users support the platform to create, enhance, and test functionalities or solutions for industrial applications. This role includes two key actors:
  - **Toolbox Component Developer**: Focuses on developing and refining individual components within the system.
  - **Machining Engineer**: Works on integrating these components to deal with machining constraints.
- **Human Administrator**: The administrator supervises the platform's management, responsible for managing user accounts, setting permissions, and handling basic configuration tasks to ensure smooth operation and security.

Application of the COGNIMAN architecture solution to glass fiber manufacturing case study

In this section, we instantiate the overarching COGNIMAN architecture for manufacturing to the glass fiber production domain. By instantiating this architecture to a specific context, we can get a real-world view of the challenges and difficulties in a specific industry.

For this case study, it is necessary to determine what services and functionality are desired in order to fully understand how to instantiate a tailored solution. A clear and detailed definition of the Physical Twin Layer is critical for each application domain. Knowing which devices and sensors are used for certain activities helps to better understand what interactions are taking place between them and what kind of data are being exchanged. Similar architectural approach has also been used in the context of some other industrial processes such as in COGNITWIN project, with excellent results (Johansen et al., 2023). This shows that this solution has the scalability, interoperability, and customisability properties to cover the entire manufacturing context.

Definition of the Case Study

The company 3B-Fibreglass[1] is a global manufacturer of a range of glass fiber products for reinforcement of thermoplastic and thermoset polymers.

The core activity in glass fiber production is the melting of raw materials (silica, calcium oxide, aluminum oxide, and magnesium oxide). During the melting process, numerous complex chemical reactions take place. Stability in the melting process is key to achieve a homogeneous glass with stable temperature, chemical, and physical properties. A key factor among these properties is the temperature distribution during fiber formation. This property is also highly correlated with the diameter distribution of the fiber, which in turn correlates with the stress inherent to the fiber. An instability can lead to defects in the fiber forming process, an event that leads to a general deterioration of production performance.

The main objective is therefore to be able to create a Digital Twin system that can detect defects as soon as possible, so that immediate action can be taken on the process to minimize waste and downtime. In order to achieve this, computer vision systems using cameras were taken into consideration.

Architecture deployment for the Case Study

The customization and configuration of the architectural solution included an initial discussion with the 3B-Fibreglass company, in order to better understand what the functional and nonfunctional requirements were and how they related to the distinct layers of the architecture. Subsequently, a specific instance of the architecture was developed, showing all the specifics of the case, such as the services, the sensors, and the models used to describe the behavior of the devices under analysis. A figure expressing the connections between the high-level requirements drawn up together with the company involved and the different architectural layers is shown below.

As shown in Fig. 2, the main objectives concern the possibility of creating a service capable of detecting when there is a defect in the formation of the glass fibers and, consequently, how to characterize the type of defect in order to be able to understand the causes of it. The digital twin to be implemented will relate to "*bushings*", which are alloy

[1] https://www.3b-fibreglass.com/

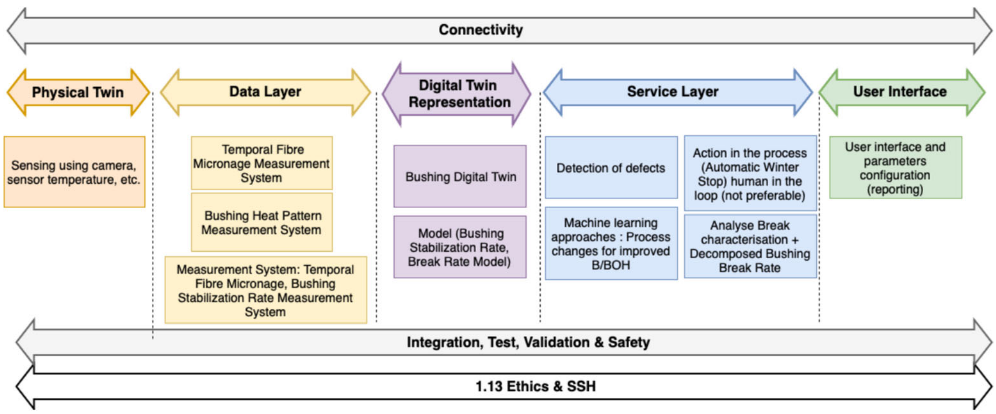


Fig. 2 Bindings between case study requirements and the architecture layers

boxes where glass flows in from an opening the top and out through small eyelets with a precisely sized orifice called tips, one for each fiber. Models will have to be built on this component that can effectively describe the temperature distribution, defect rate, and stabilization rate after production has been interrupted. However, the design and configuration of the architecture will be driven by the choice of devices and sensors to be used and the data collected from them. The sensors under consideration are cameras that can be placed in the proximity of the bushings to gather information on temperature distribution.

Enabling Tools & Technologies

It is essential to identify and clarify the technologies and tools currently available, as well as their potential integration within the architecture. For Digital Twin applications in manufacturing, this includes various communication protocols, dedicated data formats, information metamodels, and specialized tools. To gain a comprehensive understanding, these elements should be analyzed based on their relevance to specific architectural layers. An exception applies to the Ethics layer, which is handled internally through appropriate documentation.

Fig. 3 summarizes some of the most widely used technologies for each layer of the architecture. Some of these products, such as the FIWARE tools[2] (IoT Agent, Orion, etc.), are designed to interact seamlessly and are therefore often adopted together in certain solutions. Similar to collections of products in the same family, toolboxes such as COGNITWIN[3] including its SINDIT Digital Twin Framework (Waszak et al., 2022; Lam et al., 2024) are also a benchmark when it comes to developing a solution by integrating different technologies.

[2] https://www.fiware.org/catalogue/

[3] https://cognitwin.github.io/toolbox/

The Toolbox is structured in a pipeline, consisting of tools for data acquisition, for DT representation, for DT analysis services, and for DT visualization and control. While only a subset of these technologies is currently utilized in the COGNIMAN project (e.g., MQTT, OPC UA, Keras and Panda python libraries and React JS for the HMI), specifically across its four digital twins corresponding to four pilot implementations, the solution is designed with extensibility in mind. This ensures that additional technologies can be integrated into the framework as needed, enhancing its adaptability to future requirements and advancements.

The COGNIMAN toolbox via its advanced user interface supports a human-in-the-loop approach by allowing users to configure its functionalities and parameters to align with specific needs and objectives, ensuring tailored operation and flexibility. Additionally, the DT provides detailed analysis results along with interpretative insights, empowering users to make informed and effective decisions based on the system's outputs.

Another branch of technology to consider are cloud services. Relying on a cloud technology such as Azure DT and AWS TwinMaker makes it possible to build a Digital Twin solution that is scalable and easy to instantiate.

Architecture instance

The COGNIMAN architecture, specifically designed for the detection of production defects in glass fiber manufacturing, is instantiated in the following manner to highlight its human-centric approach and its alignment with Industry 5.0 principles. This section outlines how each layer of the architecture is configured for this case study, emphasizing the unique benefits and advantages of the proposed system to 3B-Fibreglass for defect detection.

The method combines data from the Physical Twin (machinery and equipment), Data Layer, Digital Twin, and

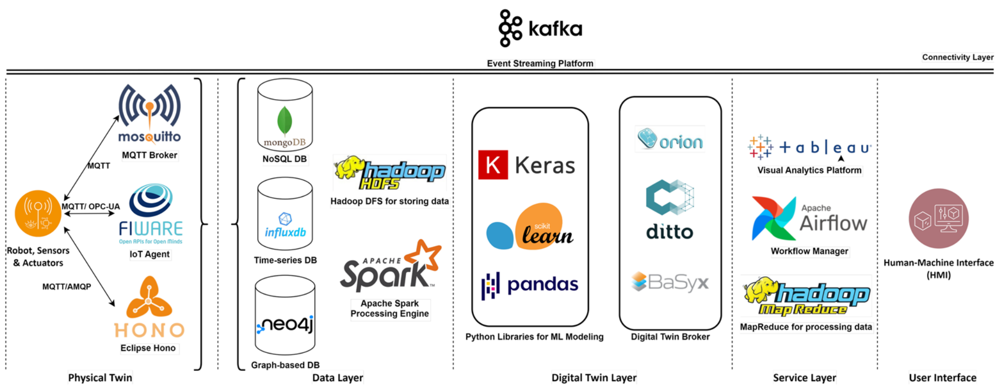


Fig. 3 Illustration of some examples of technologies linked to the architecture

Service Layer to detect defects in real-time. The architecture layers functionality is instantiated as follow:

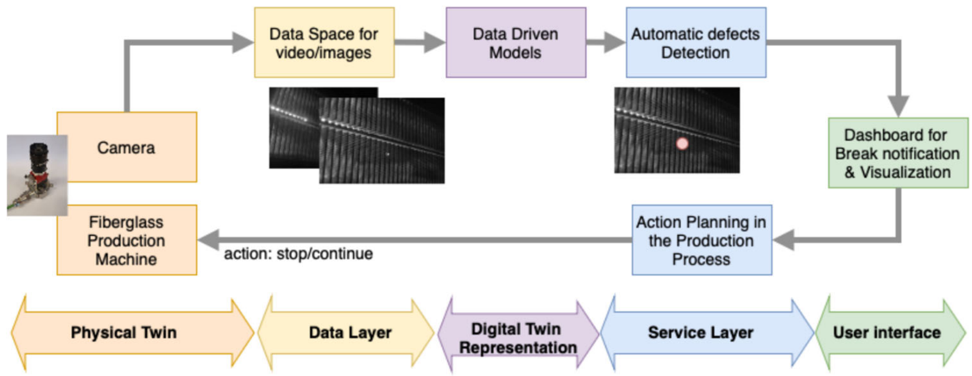
- Physical Twin: The physical twin integrates gray-scale cameras into the manufacturing equipment to capture real-time video data streams of the glass fiber production process. These cameras continuously monitor the process, providing essential visual data that forms the foundation for the digital twin. This setup ensures that the physical environment is accurately represented in the digital environment, facilitating precise monitoring and control.
- Data Layer: Raw data from the gray-scale cameras is collected and transmitted to the data layer for processing. This layer handles the storage, management, and initial processing of the data to ensure it is ready to be used by the digital twin. In this case study, data processing includes filtering and transforming the visual data into a format suitable for further analysis and modeling.
- Digital Twin Representation: The digital twin is generated using the real-time data from the physical twin, generating a virtual replica of the physical production environment. This digital representation includes models trained to detect and characterize production defects, enabling predictive maintenance and real-time decision-making. The digital twin allows for simulations and analyses that can preemptively address potential issues, thereby improving overall process efficiency.
- Service Layer: The service layer implements the automatic defect detection service, which uses advanced algorithms to analyze data from the digital twin. When a defect is detected, the system sends relevant images and data to the operator interface. Additionally, this layer includes services that execute the operator's decisions, such as stopping the fiberglass production machines to limit production losses. By translating raw data into actionable insights, the service layer enhances the responsiveness and effectiveness of the system.
- Human in the loop: Human-centricity is a key aspect of the COGNIMAN architecture, particularly in the context of Industry 5.0, which emphasizes the collaboration between humans and machines. In this instance, the system provides actionable insights to human operators, who then inspect the bushing with identified defects and decide on appropriate actions. This interaction ensures that human expertise and intuition are integrated into the decision-making process, thereby enhancing the system's overall safety and efficiency. The novelty of this human-centric architecture lies in its ability to increase the safety and well-being of operators by significantly reducing accidents linked to glass fiber manipulation. By providing real-time data and predictive insights, the system helps to prevent potential hazards and improve operational safety.

3B-Fibreglass defined several Key Performance Indicators (KPIs) to evaluate the COGNIMAN architecture impact on safety and operational efficiency. These KPIs include:

- Safety Level: A 50% reduction in accidents related to glass fiber manipulation at the bushing, thereby improving operator safety.
- Well-Being: Enhanced well-being of operators by minimizing their exposure to hazardous conditions and reducing the physical and mental stress associated with manual inspection tasks.
- Operational Efficiency: Improved detection and response times for production defects, leading to reduced losses and increased productivity.

By focusing on these KPIs, the COGNIMAN architecture demonstrates its advantages and the critical role of human-centric design in modern manufacturing environments.

Fig. 4 Illustration of an instance of COGNIMAN Digital Twin Architecture for 3B-Fibreglass



Discussion

The COGNIMAN architecture adheres to existing digital twin standards, ensuring compliance with established frameworks such as ISO 23247 for Digital Twins in manufacturing and the Digital Twin Consortium's specifications. By aligning with these standards, we ensure interoperability, data integrity, and consistency across various manufacturing environments. Furthermore, our approach emphasizes a human-centric design, incorporating the requirements and feedback of end users throughout the design process and facilitating interaction with the digital twin solution at various phases of its implementation. This user-focused methodology ensures that the technology not only meets technical specifications but also aligns with the practical needs and preferences of its operators.

Implementing such an architecture presents significant challenges, particularly in maintaining the delicate balance between advanced technological integration and user accessibility. The COGNIMAN project is actively progressing in this area, demonstrating its applicability and effectiveness across four distinct sectors. These efforts underscore our commitment to developing a versatile and robust digital twin solution that enhances flexibility, resilience, safety, and sustainability in smart manufacturing. Through continuous development and sector-specific adaptations, COGNIMAN aims to lead the way in creating adaptable and efficient manufacturing systems that can respond to the dynamic demands of the market.

Innovation

The COGNIMAN architecture encompasses a comprehensive set of features and principles to drive innovation and improvement in manufacturing processes, addressing the unique challenges and requirements of diverse industries while emphasizing security, ethics, and human collaboration. In the following, we present the various innovations of this architecture.

- Cognitive Manufacturing: COGNIMAN architecture introduces cognitive manufacturing, which implies the integration of advanced cognitive technologies into the manufacturing processes. This includes the use of artificial intelligence (AI), machine learning (ML), and data analytics to enable machines and systems to learn, adapt, and optimize manufacturing operations. Cognitive manufacturing improves efficiency, reduces errors, and enhances decision-making within the manufacturing environment by leveraging real-time data and intelligent algorithms.
- Generic Architecture for All Manufacturing Fields: COGNIMAN offers a generic architecture that is designed to be applicable across diverse manufacturing sectors. This means that the core framework can be adapted and customized to meet the specific needs and requirements of various industries, such as additive manufacturing, robotics, metallurgy, and more. This generic approach promotes scalability and versatility, allowing manufacturers from different domains to adopt and implement the COGNIMAN architecture without major overhauls or modifications.
- Following the Standards of Digital Twins: Digital twins are virtual representations of physical objects or systems. COGNIMAN adheres to the applicable standards, in particular, ISO/TC 184 for industrial data in the smart factory field, ISO/IEEE for the digital health data, IEC TC65 for the interoperability in the smart factory, and oneM2M for service function for digital twin services, meaning it employs a digital representation of the manufacturing process, enabling real-time monitoring, analysis, and optimization. This standardization ensures interoperability, compatibility, and consistency in implementing digital twin technologies, fostering a seamless integration of COGNIMAN into existing manufacturing systems.
- Respects Security and Ethics: COGNIMAN places a strong emphasis on security and ethical considerations in its design and implementation. This involves incorporating robust security measures to protect sensitive manufacturing data and ensuring ethical practices in

data collection, usage, and decision-making processes. Enhanced security safeguards against potential cyber threats, ensuring the integrity and confidentiality of manufacturing data. Ethical considerations contribute to responsible and transparent use of AI within manufacturing processes.

- Modular and Instantiable by Different Technologies: COGNIMAN adopts a modular architecture, allowing for flexibility and adaptability. It can be instantiated using various technologies, providing manufacturers with the freedom to choose and integrate the most suitable tools, hardware, and software components for their specific needs. This modularity facilitates easy integration with existing systems, and accommodates future technological advancements. Manufacturers can tailor the implementation to their preferences, optimizing resource utilization and overall performance.
- Human-Centric: Human-centric innovation is a key principle of the COGNIMAN architecture, aligning with the core values of Industry 5.0. This approach emphasizes the active involvement of human operators in the manufacturing process, fostering collaboration between humans, machines, and digital systems. COGNIMAN integrates Human-in-the-Loop (HITL) principles, allowing human operators to oversee, validate, and provide feedback during key processes such as anomaly detection, predictive maintenance, and decision-making. The architecture defines distinct human roles, including Operators, Technical Developers, and Administrators, each with specific responsibilities and interactions within the system. Operators focus on process optimization, while Technical Developers contribute to component development and system configuration. Administrators manage access control, permissions, and the overall system environment. By embedding human-centric design at its core, COGNIMAN prioritizes human safety, well-being, and job satisfaction, while also enhancing operational efficiency and system adaptability.

We applied the COGNIMAN Architecture to a case study in glass fiber manufacturing, we focus on detecting fiber defects to optimize the production process. This involves computer vision using grayscale cameras.

Conclusion and future work

The COGNIMAN architecture, as presented in this work, addresses the challenges of smart manufacturing by integrating digital twins with advanced sensor technologies, data spaces, and machine learning. The primary contribution of the COGNIMAN architecture lies in its comprehensive approach to smart manufacturing. Unlike some existing architectures that lack emphasis on human interaction, COGNIMAN prioritizes human-machine cooperation including social science & humanities, and ethical considerations. This emphasis aligns with the principles of Industry 5.0, making COGNIMAN a forward-looking solution.

The modular and service-based nature of COGNIMAN allows for adaptability in various manufacturing sectors. The case study on glass fiber manufacturing demonstrates the genericity of the COGNIMAN architecture. By focusing on detecting process defects through computer vision, COGNIMAN showcases its flexibility and applicability across different manufacturing processes.

Future work for COGNIMAN involves continuous refinement and validation of the architecture through additional industry-specific case studies. Additionally, further exploration of emerging technologies and continuous updates to the COGNIMAN solution will ensure that the architecture remains at the forefront of smart manufacturing advancements. The idea is to present an architectural solution with a predefined set of applicable technologies, which can be customized according to the needs of the specific manufacturing context into which it is to be introduced.

Acknowledgements This work has been co-funded by the European Commission through the Horizon Europe COGNIMAN Project (grant agreement No. 101058477).

Funding Open access funding provided by NORCE Norwegian Research Centre AS.

Data Availability Not applicable.

Declarations

Conflicts of Interest Not applicable.

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