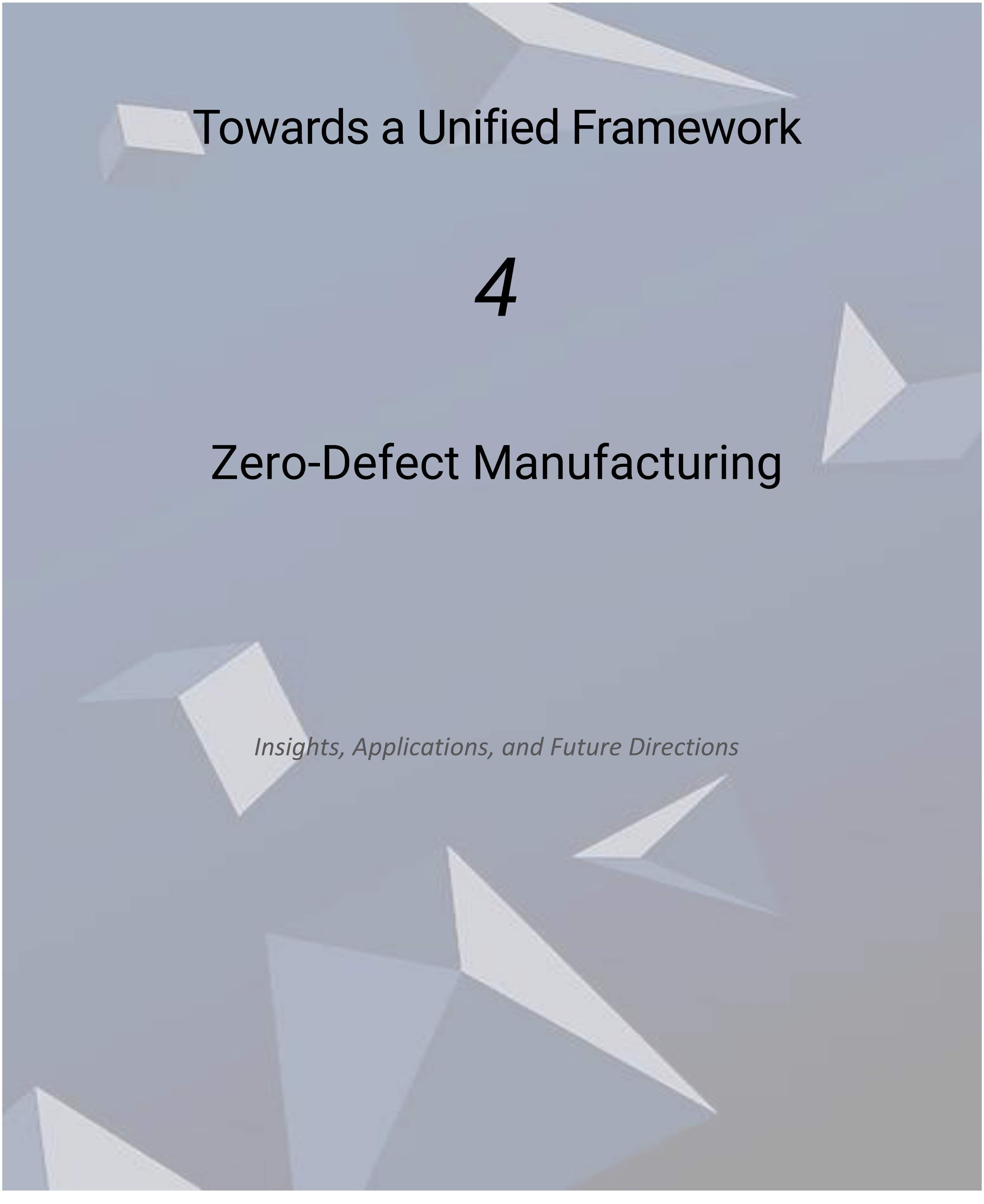

Towards a Unified Framework

4

Zero-Defect Manufacturing

Insights, Applications, and Future Directions

March 2025

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openZDM is an initiative that develops and demonstrates in five production lines an integrated open platform that combines advanced ICT solutions and non-destructive testing to realize Zero Defect Manufacturing

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ZDZW develops non-destructing inspection services as a set of strategic technologies to improve production efficiency, zero-defect and sustainable manufacturing of EU industries, covering the entire manufacturing process and product lifecycle

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TURBO aims to reduce defect formation through process simulation, monitoring and control as well as by improving defect identification with innovative methods of non-destructive testing of wind turbine blades manufacturing

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i4Q provides a holistic solution to improve the quality of manufactured products aiming at ZDM through the introduction of IoT-based reliable industrial data services and a complete set of intelligent software solutions

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Glossary

Term	Description
AAS	Asset Administration Shell
AI	Artificial Intelligence
COPQ	Cost of Poor Quality
DL	Deep Learning
EC	European Commission
EDIH	European Digital Innovation Hub
EPR	Extended Producer Responsibility
EPR	Enterprise resource planning
ERP	Enterprise Resource Planning
EU	European Union
EU AI Act	European Union Artificial Intelligence Act
GDPR	General Data Protection Regulation
IEC	International Electrotechnical Commission
IIoT	Industrial Internet of Things
ISO	International Organization for Standardization
LCA	Life Cycle Assessment
LCC	Life Cycle Costing
MES	Manufacturing Execution System
ML	Machine Learning
MQTT	Message Queuing Telemetry Transport
NDI	Non-Destructive Inspection
NDT	Non-Destructive Testing
OPC UA	Open Platform Communications Unified Architecture
RAMI4.0	Reference Architectural Model Industrie 4.0
SLCA	Social Life Cycle Assessment
SME	Small and Medium-sized Enterprise
XAI	Explainable Artificial Intelligence
ZDM	Zero-Defect Manufacturing

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Executive Summary

Zero-Defect Manufacturing (ZDM) has gained strategic importance across European industry as both a quality management paradigm and a framework for resilient, resource-efficient production systems. By shifting the focus from post-production defect detection to in-process defect prevention and real-time process optimization, ZDM supports the dual imperatives of quality assurance and sustainability in complex manufacturing environments.

The industrial relevance of ZDM stems from its capacity to combine advanced sensing, predictive analytics, and process control into continuous feedback loops that guide production decisions at every stage. This approach reduces scrap, minimizes rework, and optimizes resource efficiency, aligning directly with the European Green Deal and the broader policy goals of climate neutrality and responsible resource management.

Realizing ZDM at scale demands both technological integration and organizational adaptation. On the technological side, digital twins, cyber-physical systems, multi-sensor fusion, and AI-driven process monitoring provide the required infrastructure for predictive quality management. On the organizational side, ZDM requires cross-disciplinary collaboration between engineers, data scientists, quality managers, and system architects, as well as clear alignment with operational strategies and digital transformation plans.

This white paper draws on the combined outcomes of several EU-funded initiatives—including OPENZDM, I4Q, TURBO, and ZDZW, each addressing critical dimensions of zero-defect strategies, digital quality infrastructures, and intelligent process control frameworks. Together, these projects form the empirical and conceptual foundation for a unified ZDM framework, which integrates technological building blocks, deployment roadmaps, and real-world case evidence.

The case studies presented highlight ZDM implementations across various manufacturing sectors, offering quantified results in terms of defect reduction, process efficiency, and economic return, alongside the operational conditions required for success. By synthesizing these practical insights with the conceptual framework, this paper offers a clear reference for academic researchers, industrial practitioners, and technology providers seeking to advance the state of practice in high-precision, zero-defect production systems.

ZDM, as presented in this paper, is more than a static methodology. It is a dynamic, evolving paradigm that requires ongoing research, cross-sector learning, and technological innovation. Through this collaborative effort, European industry can establish globally competitive, defect-free manufacturing systems that are digitally enabled, environmentally responsible, and economically sustainable.

1 Introduction

Modern manufacturing systems increasingly rely on the coordinated integration of engineering expertise, data-driven methodologies, and sustainability-driven process design to transform raw materials into high-quality finished products. Within this evolving landscape, ZDM has emerged as a critical management philosophy and aim for ensuring product reliability, reducing waste, and enhancing process efficiency through proactive defect prevention rather than reactive quality control.

ZDM’s relevance has grown alongside intensifying global competition and the imposition of increasingly stringent environmental and resource-efficiency regulations. Manufacturing continues to account for a significant proportion of Europe’s Gross Domestic Product (GDP), making process efficiency, quality performance, and environmental sustainability central to broader industrial policy goals. Empirical studies estimate that defect rates and process inefficiencies contribute between 5% and 10% of production costs in several high-value sectors, illustrating the economic and operational importance of precision-driven process optimization. By integrating real-time monitoring, predictive process control, and closed-loop feedback systems, ZDM directly addresses these inefficiencies, delivering both economic and environmental benefits.

The societal and economic impacts of ZDM extend well beyond factory operations. As manufacturing processes embed advanced data analytics, predictive quality algorithms, and AI-supported defect prevention mechanisms, they generate demand for highly skilled professionals who combine expertise in process engineering, automation, and data science. This dynamic not only contributes to workforce development but also strengthens Europe’s technological leadership by advancing upskilling initiatives focused on industrial AI, real-time process optimization, and cyber-physical quality management. These outcomes align directly with European policy frameworks such as the European Green Deal, which promotes climate neutrality, resource efficiency, and digital skills development as part of a broader industrial transformation agenda.

The development of ZDM also complements Europe’s ongoing Industry 4.0 strategy, which emphasizes process transparency, digital connectivity, and cyber-physical system integration. While Industry 4.0 focuses on enabling data flows across interconnected production systems, ZDM adds a critical quality intelligence layer, allowing manufacturing systems to transition from reactive error correction to predictive and adaptive quality management. This integration of ZDM principles into digitally-enabled production systems positions Europe to advance sustainable, resilient, and defect-free manufacturing ecosystems that meet both economic performance goals and environmental responsibilities.

Despite the technological progress achieved in recent years, several challenges remain, particularly in areas related to system interoperability, cross-platform integration, and data governance. The growing complexity of manufacturing ecosystems, which often incorporate heterogeneous machinery, sensor networks, and legacy systems, complicates the seamless deployment of cross-domain ZDM solutions. Addressing these challenges requires closer collaboration between industry, academia, and policymakers to accelerate standardization efforts, align workforce development strategies, and facilitate the gradual diffusion of advanced quality management technologies across both large manufacturers and small-to-medium enterprises (SMEs).

This white paper examines ZDM from multiple perspectives, integrating technical insights, industry best practices, and results from EU-funded research initiatives, including OPENZDM, I4Q, TURBO, and

ZDZW. It provides a comprehensive framework that brings together technological enablers, practical implementation roadmaps, and validated case studies to guide researchers, engineers, and industrial leaders in designing and scaling ZDM strategies tailored to their specific production environments. By emphasizing ZDM's role in driving sustainable competitiveness, operational excellence, and workforce innovation, the paper highlights its importance as a strategic enabler of Europe's future industrial landscape.

2 Impact of Zero-Defect Manufacturing

The ZDM philosophy targets the continuous improvement and minimization of defects in manufacturing. The philosophy's core pillars include the real-time manufacturing process monitoring, the adoption of intelligent systems that can provide predictive maintenance and continuous proactive quality control as well as real-time analytics of production [1].

Early ZDM implementations were usually hampered by a lack of technological enablers such as limited data availability and processing power, a lack of modelling approaches and a non-standardised approach towards implementing autonomous systems for taking real-time correcting actions to avoid the generation of defective products [2]. In modern manufacturing however, the introduction of advanced technologies and Industry 4.0 concepts such as AI, Industrial Internet of Things (IIoT) and smart sensors, digital twins and automation and robotics has facilitated the adoption of ZDM [3].

The evolution of cyber-physical production systems has further enhanced manufacturers' ability to shift from reactive quality control to proactive defect prevention, supported by continuous process monitoring and adaptive feedback loops [4]. Getachew M. et. al. explored the different approaches of AI integration in manufacturing as an enabler of ZDM [5], concluding that AI can play a pivotal role in proactive defect detection, enabling a transition away from manual, time-consuming and costly inspections. These findings are supported by subsequent research demonstrating how AI, when integrated with IIoT infrastructures, supports real-time decision-making and predictive quality management, reducing reliance on manual inspections [6]. In addition to AI-enabled proactive quality control, the adoption of the Industrial Internet of Things (IIoT) and non-destructive inspection systems has further facilitated the adoption of ZDM [7]. IIoT sensors are able to collect a large amount of data from manufacturing processes enabling AI-driven approaches for predictive maintenance and root cause analysis [8], while the use of inline non-destructive testing examines in real-time the quality of products and identifies defects on the line, preventing further processing of already defective parts [9].

ZDM's impact extends beyond process efficiency and product quality, influencing both manufacturing performance metrics and wider societal and environmental objectives [10]. At the operational level, ZDM adoption is linked to reduced emissions, lower material waste, and enhanced resource efficiency, all of which contribute to more sustainable industrial practices [11, 12]. Table 1 summarizes the documented impacts of ZDM implementations across various sectors, highlighting the technologies used and measurable outcomes.

Table 1. Impact of ZDM adoption across different industrial domains.

Reference	Technology Used	Industrial Domain	Impact
[13]	AI-driven data analytics	Aerospace and Railway	Reduced scrap rates, minimized manual inspections, increased process efficiency and cost savings
[14]	IIoT sensors and data analytics	Steel parts manufacturing	Improved product quality and consistency; reduced defect rates
[15]	Digital twins	Bending machine manufacturer	Enhanced equipment performance, reduced defect generation, improved reliability
[16]	Non-Destructive Inspection Systems	Additive manufacturing	Improved process accuracy, lower defect rates
[17]	Data-driven analytics and feedback mechanisms	Medical supplies manufacturing	Enhanced process control and product quality
[18]	IIoT and ML-driven data analytics	Metal processing industry	Reduced defect rates, improved process efficiency, minimized downtime
[19]	AI-driven predictive analytics and IIoT sensors	Wood-based panels manufacturing	Optimized resource utilization, improved decision-making and production efficiency
[20]	AI-powered analytics	Olive oil production	Enhanced sustainability, production efficiency, and profitability
[21]	LCA	Steel and glass bottle production	Evaluated green manufacturing maturity and ZDM alignment

Despite the documented benefits and expanding technological enablers, several challenges continue to hinder broader adoption of ZDM, particularly in small and medium-sized enterprises (SMEs) [22]. Initial capital investment requirements for advanced sensor networks, digital twins, and predictive analytics platforms remain a substantial barrier for smaller manufacturers [23]. Beyond financial hurdles, the transition to AI-enabled ZDM environments necessitates workforce upskilling, ensuring personnel can effectively interpret data-driven insights and manage AI-supported decision-making workflows [24].

The absence of a comprehensive, interdisciplinary framework for ZDM implementation represents an even more systemic barrier. Although numerous technologies and methodologies have been developed independently, they are rarely integrated into cohesive deployment strategies that account for technical, operational, organizational, and regulatory considerations [24, 25].

This white paper directly addresses this gap by presenting a unified framework for ZDM, derived from extensive interdisciplinary research and validated through collaborative EU-funded projects. The proposed framework is accompanied by a practical implementation roadmap, providing manufacturers, technology providers, and policymakers with actionable guidance to facilitate the progressive adoption of ZDM principles across diverse industrial sectors.

3 Key enablers

3.1 Core Technologies

The advancement of Zero-Defect Manufacturing (ZDM) is inextricably linked to the proliferation of digital technologies introduced under the Industry4.0 paradigm. These technologies enable the digitalization of production systems, laying the groundwork for real-time defect prevention, predictive quality management, and resource-efficient manufacturing.

Among these technologies, Artificial Intelligence (AI), including Machine Learning (ML) and Deep Learning (DL), plays a central role. AI-driven analytics support predictive quality control by identifying deviations and defect patterns early in the production cycle. Such systems facilitate the removal of defective products from production lines before further value is added, reducing both material waste and energy consumption. In addition to defect identification, AI-powered recommendation systems dynamically adjust production parameters to avoid future defects. Furthermore, AI-driven predictive maintenance anticipates equipment failures, safeguarding process stability by preserving optimal machine performance and reducing defect risks linked to unplanned downtime.

Several large-scale industrial implementations illustrate the tangible value of AI-driven ZDM. Siemens' AI-based predictive maintenance platform detects early indicators of equipment degradation, enabling proactive interventions that prevent downstream quality deviations. Similarly, Intel's AI-enabled semiconductor defect detection system applies root cause analysis to defective chips, offering actionable insights into process configuration adjustments that mitigate defect recurrence.

ZDM's reliance on data-centric approaches underscores the importance of real-time data acquisition and sensor integration, facilitated by Industrial Internet of Things (IIoT) platforms. IIoT sensors continuously capture data on equipment performance, environmental conditions, and product quality, forming the real-time data streams essential for AI-powered defect prediction and continuous process monitoring.

Digital twins also serve as a foundational enabler of ZDM. By creating virtual representations of production processes, digital twins simulate real-time operations, predict potential defect scenarios, and optimize process configurations based on virtual experimentation. These models allow manufacturers to test alternative production parameters and assess their impact on defect rates without interrupting live operations.

In high-precision sectors, such as aerospace, Airbus' AI-enhanced digital twin system exemplifies ZDM in practice. This system simulates alternative process scenarios, identifies optimal process configurations, and mitigates high-cost defect generation, thereby improving first-pass yield rates in complex manufacturing environments.

Beyond AI, IIoT, and digital twins, robotics and automation systems enhance ZDM by automating precision workflows, ensuring repeatability and minimizing process variability. Cloud computing supports the seamless exchange of production data across geographically distributed facilities, fostering cross-site process benchmarking and centralized defect analysis. Meanwhile, Extended Reality (XR) technologies enrich operator training, enhancing the competence of frontline workers in quality-critical manufacturing environments.

Another core enabling methodology for ZDM is Life Cycle Analysis (LCA), alongside its extensions, Life Cycle Costing (LCC) and Social Life Cycle Analysis (SLCA). These methodologies provide a holistic evaluation of environmental, economic, and social impacts across the product lifecycle. Applied systematically, LCA and its variants allow manufacturers to identify energy-intensive processes, quantify the cost implications of defect generation, and assess social impacts, ensuring that ZDM strategies align with broader sustainability and social responsibility goals.

3.2 Advanced technologies in ZDM

Beyond the core technologies, advanced inspection, automation, and adaptive control techniques further enhance the capabilities of ZDM, particularly in high-value or high-complexity production environments.

Non-Destructive Inspection (NDI) and Non-Destructive Testing (NDT) provide essential capabilities for in-line defect detection without disrupting ongoing production processes. These techniques detect both surface and internal defects in real time, supporting early defect isolation and preventing further downstream processing of defective components. Prominent NDI/NDT techniques include:

- **Ultrasonic testing**: Uses high-frequency sound waves to detect internal flaws in metals, composites, and welds.
- **X-ray & computed tomography scanning**: Provides detailed internal imaging for defect detection in complex components (e.g., aerospace and automotive parts).
- **Thermography (infrared inspection)**: Identifies structural defects and heat anomalies in electronic circuits and composite materials.
- **Magnetic particle & eddy current testing**: Detects surface and near-surface defects in metals using electromagnetic fields.
- **Machine vision & AI-augmented optical inspection**: High-resolution cameras and AI analyze microscopic defects in real time.

Advanced automation systems, enabled by AI, IIoT, and digital twins, further support ZDM by reducing reliance on human intervention while maintaining adaptive quality control. Automation platforms increasingly feature autonomous control loops, where real-time defect predictions trigger preemptive corrective actions, such as automated adjustment of process parameters to maintain optimal process stability.

In the context of Industry 4.0, the Asset Administration Shell (AAS) concept provides a framework for event-driven manufacturing system control. In particular, Type 3 AAS (Proactive AAS) abstracts control mechanisms, enabling seamless integration of autonomous corrective actions across heterogeneous production systems. By decoupling control logic from individual machines, AAS simplifies cross-platform defect mitigation, enabling manufacturers to adapt production parameters in real time without custom programming at each node. This level of adaptability is essential for scalable ZDM deployment across modern manufacturing ecosystems.

4 Unified framework

4.1 Overview

The extent of ZDM adoption across manufacturing environments can be directly measured through the degree of implementation of core enabling technologies, including AI-driven analytics, IIoT-based data collection, non-destructive testing and inspection (NDT/NDI), digital twins, automation, and data interoperability frameworks. Quantifying this degree of adoption provides manufacturers with a structured assessment tool, enabling them to identify technology gaps and prioritize investments. To operationalize this assessment, a technology adoption scoring system is proposed, assigning numerical scores from 1 to 10 for each enabling technology. These scores represent the level of maturity and deployment of the technology within a given manufacturing system. The following levels define the ZDM adoption scale:

- *Minimal – Scores ~1-3*: Technology is present in a minimal form.
- *Initial – Score ~3-4*: Technologies are being gradually adopted and minimally used.
- *Moderate – Score ~5-6*: Broader use of technology in some areas of the manufacturing system.
- *High – Score ~7-9*: Technology is being integrated into most areas of the manufacturing system, enabling proactive defect prevention.
- *Complete – Score ~9-10*: The technology is highly embedded in day-to-day manufacturing operations, decision-making is highly automated and systems are characterized by a high degree of automation.

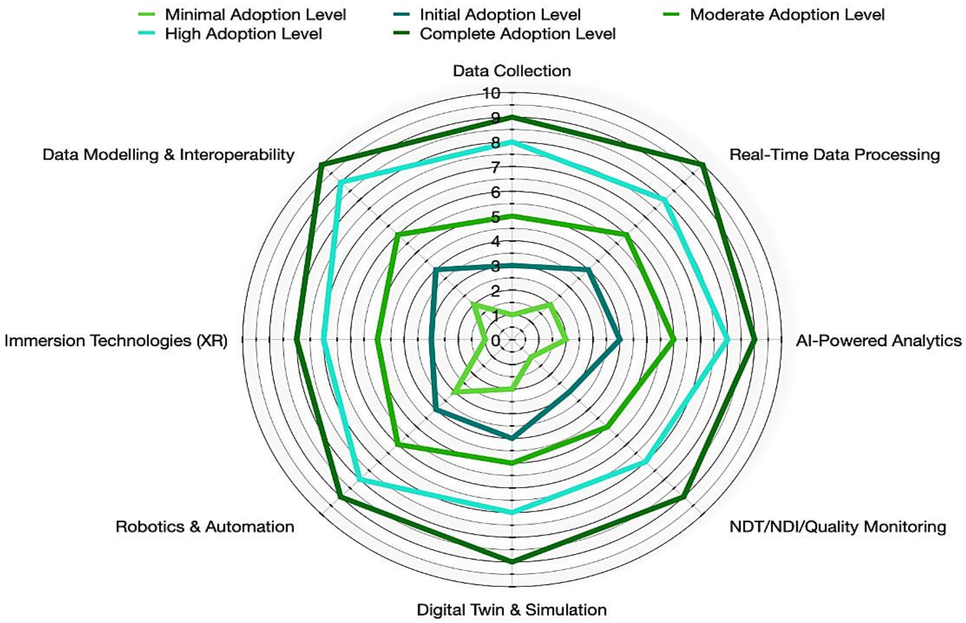

Figure 1. Quantification of the degree of ZDM adoption based on the degree of key ZDM-enabling technologies implementation.

Based on this, the level of ZDM adoption is quantified based on the degree of implementation of each key ZDM-enabling technology. This quantification is observed in Figure 1. Achieving full ZDM adoption does not require every enabling technology to be implemented at the highest level. Instead, each technology is weighted according to its criticality to the ZDM strategy. For instance, data collection, real-time processing, data modeling, interoperability, and AI-powered analytics are considered critical enablers; NDT/NDI and digital twins hold high importance, while robotics and automation have moderate importance, and immersive technologies, while valuable for training, have lower relative importance. This weighted scoring approach allows manufacturers to evaluate their current ZDM maturity and strategically plan their technological evolution.

4.2 Framework

To fully capitalize on these enabling technologies, a unified ZDM framework is essential. This white paper presents a modular, interoperable framework that synthesizes building blocks, methodologies, and best practices derived from multiple EU-funded projects, including OPENZDM, I4Q, TURBO, and ZDZW. These projects emphasize the need for a common, open platform capable of seamless integration across diverse technologies and manufacturing domains, underpinned by a standardized data model.

The foundation of the framework is an open platform built upon the RAMI4.0 reference architecture [27] and extended to accommodate integration with Manufacturing Information Systems (MIS). The open platform is coupled with an interoperability layer provided by the reactive Asset Administration Shell (AAS) concept (AAS Type 2). This layer of interoperability provides a common data modelling approach, where the technical and operational data of assets in manufacturing systems.

The unified ZDM framework architecture is composed of a total of seven layers. A graphical representation of the unified framework architecture can be seen in Figure 2.

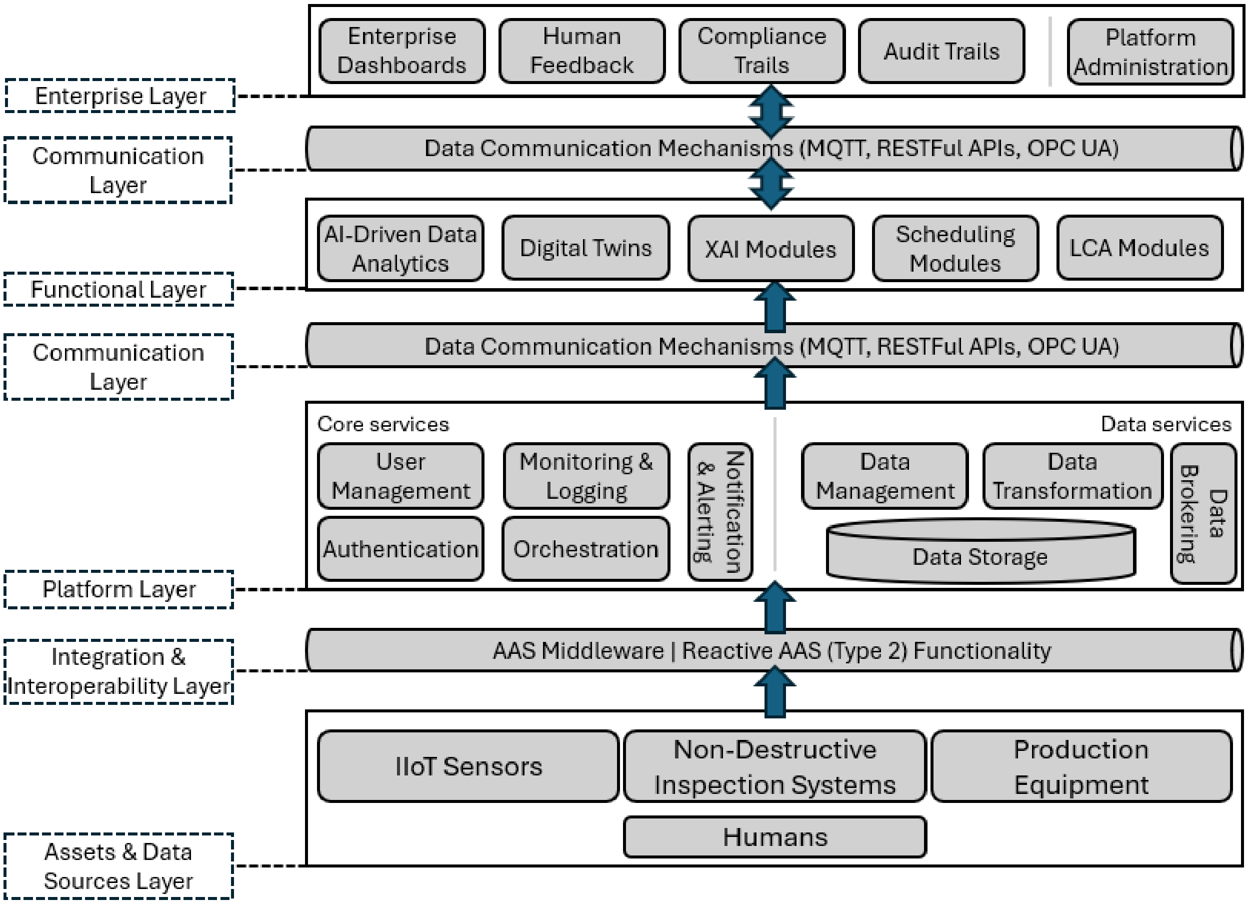

Figure 2. The unified framework architecture.

A description of each layer and the components residing inside each layer of the ZDM framework is presented hereafter.

- ***Assets & Data Sources Layer***: The data sources are assets and equipment of manufacturing systems who can provide data or interact with an intelligent system. Data sources may include existing production systems and available IIoT sensors, non-destructive inspection systems capable of checking critical quality metrics of products directly on the line, as well as humans who can interact with intelligent systems and provide feedback for the system's continuous improvement.
- ***Integration & Interoperability Layer***: This layer is built upon an AAS middleware. It is responsible for providing an interoperable and standardized data model that represents the data sources based on the AAS data model. The middleware exposes a RESTful Open API that enables the functionality of populating the assets' AASs with their real-time operational data, thus, exposing them to the platform and the rest of the ZDM framework.
- ***Platform Layer***: The platform sits at the core of the ZDM architecture. It is responsible for collecting data provided by the data sources and can communicate such data to the components residing in the functional layer of the framework. The platform also provides the necessary services for monitoring the functionality of all components connected to it, it acts as the data storage provider of the ZDM framework and provides the necessary authentication and authorization protocols for secure user login and data communication.
- ***Communication Layer***: This layer exposes the data found in the data storage section of the platform layer to the services residing in the functional layer of the framework. Supporting scalability and adaptability, the layer provides support for various communication protocols such as MQTT, RESTful APIs and OPC UA.
- ***Functional Layer***: The functional layer is where the intelligent applications enabling ZDM reside. These include a combination of technologies and methodologies created in the different projects and include:
    - Digital Twins: Digital twins provide a real-time representation of the manufacturing system. Through digital twin models real-time and feedforward simulation is provided enabling the authoring and evaluation of alternative what-if scenarios.
    - AI-Driven Data Analytics: AI-based analytics reside on top of the digital twins, calculating in real-time critical KPIs that evaluate the performance of manufacturing systems and provide predictive and forecasting capabilities to predict the occurrence of future defects or maintenance needs.
    - Explainable (XAI) Modules: These modules interact with both digital twin models and AI-based analytics providing explanations on the outputs of such models. These are then provided to the enterprise layer for operators and managers to better understand the intelligent decisions made by the framework.
    - Scheduling Modules: These modules are responsible for performing intelligent scheduling of manufacturing systems operations. They work in tandem with digital twins and AI-driven analytics to make informed and intelligent decisions that are then presented to managers in the enterprise layer.
    - LCA Modules: LCA modules perform real-time assessment of the environmental performance of manufacturing systems. These modules get real-time data from the digital twin and the manufacturing assets themselves and through life cycle impact assessment methodologies assess

the environmental sustainability of systems. These outputs are communicated to managers via the enterprise layer.

- ***Enterprise Layer***: The enterprise layer is where users directly interact with the ZDM framework. Enterprise dashboards present the outputs of the AI-driven analytics and the explanations generated by the XAI modules. The layer also provides a space where humans can audit the performance of the entire ZDM framework and provide feedback to the intelligent applications closing the loop for continuous improvement.

5 Selected Industrial Case studies

In the following subsections, four case studies demonstrate the practical benefits and sectoral adaptability of the unified ZDM framework across high-precision manufacturing, renewable energy, food and beverage production, and battery assembly. They also illustrate how advanced digital technologies, including AI, digital twins, IIoT, NDI, and XAI, contribute to quality-driven sustainability improvements, aligned with both industrial efficiency goals and environmental objectives.

5.1 Illy caffe pilot case

The first case study, conducted under the ZDZW project, focuses on the manufacturing processes at Illy Caffe, covering capsule assembly, filling and welding, and packaging. A graphical representation of the production line is provided in Figure 3.

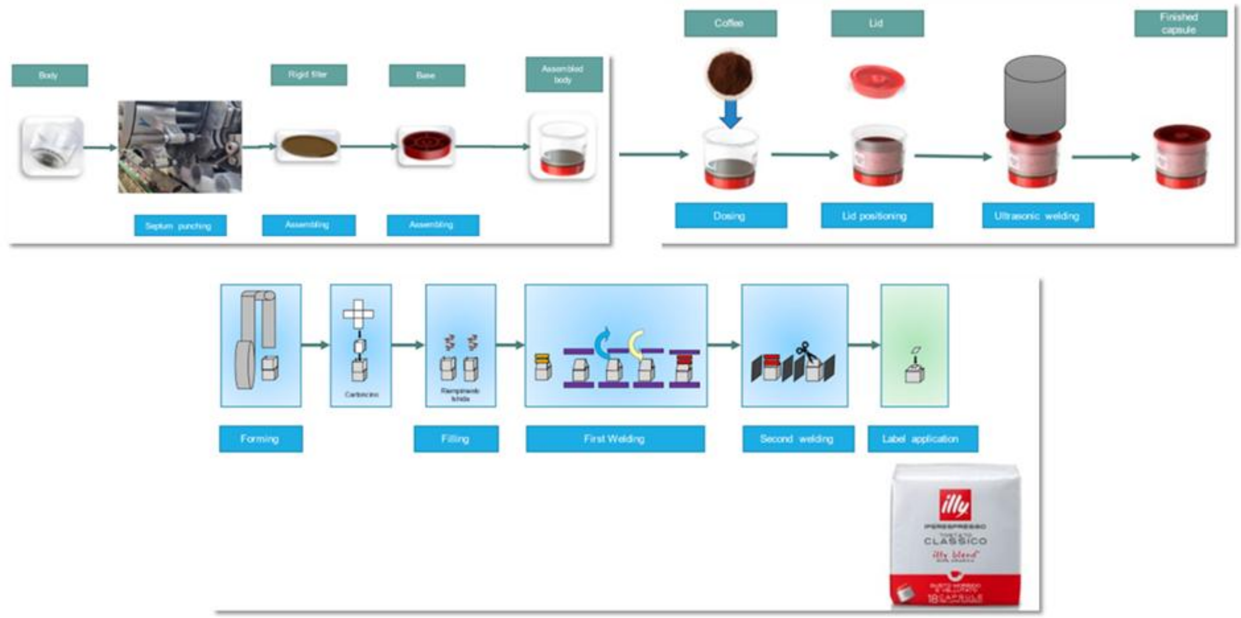

Figure 3. Graphical representation of the Illy Caffe pilot case.

The total climate change (kg CO_2 eq.) has been quantified using Environmental Footprint 3.1 impact assessment methodology for all the processes and estimated to be 1.5 Mio CO_2 eq. per year. This includes the impacts from all the inputs such as capsules (plastic), filling and welding (energy), coffee powder (green beans and energy for milling), and packaging (paper, aluminium, packaging film). Throughout the production process, Illy ensured to use the renewable source of energy to keep a check on their environmental emissions.

Within the ZDZW project, the aim is to implement a Non-destructive inspection (NDI) solution which could be integrated within the existing production line of Illy Caffe and help to reduce the defects in their process. This also ensures a reduction in scrap and ultimately increases the process efficiency and decreases the price per product. The expected reduction is 50%, which would eventually mean 750K CO_2 eq. emission per year.

Since the analysis represents only one production line, Illy Caffe could potentially reduce their emissions significantly after implanting the NDI solution. The system is developed by Video System and could be offered on a subscription basis to other manufacturers as well.

5.2 FACTOR production system

The second case study is part of the i4Q project and focuses on the manufacturer FACTOR. FACTOR is a company that produces metallic high-precision parts, manufactured with CNC Lathes. FACTOR has 26 CNC Lathes to support the highly required precision and low delivery times requested by FACTOR's customers. An overview of the FACTOR production system can be seen in Figure 4.

Figure 4. Overview of the FACTOR production system.

Before implementing parts of the ZDM framework, FACTOR faced several operational challenges in its pursuit of defect-free production. The company struggled with efficiency failures caused by improper management of cutting lubricants, leading to tool breakages and the blockage of cooling channels. This hindered the ability to diagnose and evaluate breakage incidents effectively and made it difficult to ensure that tools operated within their optimal range. FACTOR lacked the capability to predict equipment damage and had no efficient system for inspecting all manufactured parts, particularly complex ones. Additionally, there was no continuous process validation in place to qualify manufacturing lines and certify the quality of production. As a result, FACTOR could not guarantee the inalterability of product and process data, limiting its ability to consistently meet high-quality standards. Nevertheless, the adoption of several parts of the ZDM framework in FACTOR's manufacturing system has led to significant advancements in its defect reduction strategy. Key parts of the ZDM framework adopted in the FACTOR pilot include:

- **Data repository**: Centralized and scaled data storage, streamlining data management and enabling advanced analytics for improved CNC performance.
- **Data analytics dashboard**: Offered real-time visualization of machine performance, production quality, and resource allocation, enabling informed decision-making and improved efficiency.

- **Data integration and transformation**: Cleaned and unified sensor data, optimizing CNC processes, predicting maintenance needs, and ensuring consistent product quality.
- **Data analytics services**: Simplified the development of data analytics workflows, improving collaboration, predictive maintenance, and quality control through fast, accurate insights.
- **Big data analytics suite**: Eased deployment of analytics solutions across infrastructures, providing scalable insights to drive data-driven decision-making.
- **AI model distribution**: Automated and scaled AI model deployment across multiple sites, improving efficiency in CNC processes and supporting Factor's growth.
- **Infrastructure monitoring**: Enabled the prediction and prevention of machine failures, reducing downtime, optimizing machine performance, and ensuring high-precision production.
- **Edge workloads placement**: Efficiently deployed AI workloads at the edge, optimizing CNC machine processes, quality control, and predictive maintenance in a scalable manner.
- **Digital twin**: Simulated and optimized CNC production processes virtually, reducing the risks and costs of physical testing while improving productivity.
- **Line reconfiguration toolkit**: Optimized machine parameters, improving quality, increasing productivity, and reducing setup time and costs through real-time reconfiguration.
- **Continuous process qualification tool**: Enabled the prediction of real-time quality outcomes, reducing waste, improving process efficiency, and enabling proactive adjustments for better decision-making.

The adoption of these technologies has resulted in significant improvements in the FACTOR pilot. These improvements include:

- **Creation of a dedicated process quality team**: A dedicated team was established to manage infrastructure, data analytics, and organizational needs, ensuring smooth deployment and operation of Industry 4.0 technologies.
- **Improved efficiency and quality**: Enhanced Overall Equipment Effectiveness by optimizing tool life, reducing downtime, and improving real-time data collection for continuous process qualification.
- **Data centralization and value**: A unified data repository now integrates data from Enterprise Resource Planning (ERP), Manufacturing Execution System (MES), and other sources, ensuring long-term data quality and availability for analysis and decision-making.
- **Enhanced communication infrastructure**: FACTOR has improved its IIoT infrastructure, industrial data communication (including exploration of 5G), and data storage/cleansing practices. Alternative open-source technologies are also adopted given the introduction of Open APIs.
- **Increased industry 4.0 maturity**: Through the partial adoption of the ZDM framework, FACTOR gained expertise in data acquisition, storage, analysis, and presentation, fostering data-driven decision-making, enhanced production efficiency, and future scalability.

The improvements from the adoption of ZDM in the FACTOR pilot have been quantified and are presented in Table 2.

Table 2. Improvements recorded in the FACTOR pilot through the adoption of ZDM.

KPI	Description	Base Value	Target Value	Achieved Value
1	Quality Ratio	96,1%	100%	98,5 %
2	Machine stops due to quality issues	4,9 h/month	N/A	1,39 h/month

KPI	Description	Base Value	Target Value	Achieved Value
3	Overall Equipment Effectiveness (OEE)	42,9%	75%	79,85 %
4	Availability	46%	75%	82,65 %
5	Effectiveness	97%	100%	> 100 %
6	Machine stops due to corrective maintenance operations	43,21 h/month	N/A	6,18 h/month
7	Machine stops due to tool breakage issues	N/A	N/A	13,26 h/month

5.3 Manufacturing of wind turbines

The third case study focuses on blade manufacturing for wind turbines and incorporates the SIEMENS pilot from the TURBO project. Since the 1970s, blade manufacturing methods have remained largely unchanged, with minimal implementation of NDT or in-line quality control. As a result, high defect rates, frequent repairs, and excessive material waste persist. TURBO aims to address these challenges by reducing defects and optimizing repair strategies for wind turbine blade (WTB) composites and coatings.

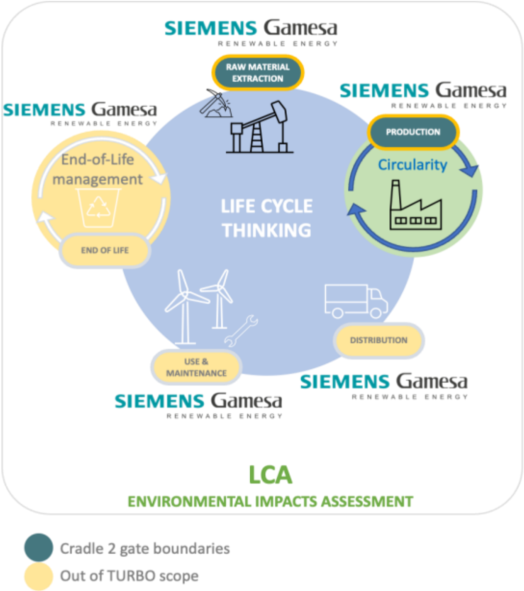

Figure 5. Graphical representation of the TURBO pilot case study.

A key objective of TURBO's case study is to demonstrate the environmental benefits of the adoption of ZDM's enabling technologies integrated into the current wind turbine blade manufacturing process. These technologies include:

- Digital twins that simulate the production system aiming at process reconfiguration which will reduce the generation of defects
- NDT for composite manufacturing
- NDT for coating inspection
- In-line ML-based systems for production control
- Digital twins for data collection and data management
- LCA for the evaluation of the degree of greening of the manufacturing system after the adoption of ZDM.

A study has been formed in the pilot to evaluate the impact of ZDM adoption. The study included a baseline scenario and a "TURBO" scenario, as presented hereafter:

- ***Baseline scenario****:* Evaluates the environmental impact of manufacturing a 97m blade using SGRE's existing processes, with data collected in collaboration with SGRE.
- ***TURBO's scenario****:* Assesses the environmental impact of a 15m section demonstrator and extrapolates findings to a full 97m blade.

TURBO through the application of ZDM aims at a reduction of 80% in defects generated during the blade infusion process, a 90% decrease in post-casting repairs and a reduction in waste repair materials and overall production time. The scope of the study is depicted in Figure 5. Nonetheless, apart from the aforementioned benefits, the pilot included in the TURBO project is expected to also benefit from the adoption of ZDM by significantly reducing the generation of defects arising in the casting process in order to prevent reworks (challenge 1 of the TURBO project). These benefits are presented in Table 3.

Table 3. Expected benefits for TURBO challenge 1.

Driving factor of benefit	Operations where the benefit is realized	Benefits/Savings		
		Process Time / Person Time	**Material**	**Energy**
Reduced defect sum (per blade)	Defect removal	Time to remove defects	Material removed as part of defect removal	Rework equipment energy
		Number of operators performing defect removal		Facility energy
	Defect repair	Time to add repair materials	Material added	Re-cure energy
		Number of operators performing repairs	Extra consumables used for repair	Facility energy

In addition, the pilot is expected to benefit in terms of optimizing casting time, without compromising on defect generation prevention (challenge 2), minimizing the consumption of excess resin during the blade infusion process (challenge 3), in optimizing laminate repair processes (challenge 4), and in optimizing blade coating repair strategies (challenge 5). These are presented in Table 4, Table 5, Table 6 and Table 7 Respectively.

Table 4. Expected benefits for TURBO challenge 2.

The driving factor of benefit	Operations where the benefit is realized	Benefits/Savings		
		Process Time / Person Time	**Material**	**Energy**
Duration of the casting process	Infusion	Time of infusion	N/A	Machine energy consumption
	Curing	Time of cure	N/A	Cure equipment energy consumption

Table 5. Expected benefits for TURBO challenge 3.

The driving factor of benefit	Operations where the benefit is realized	Benefits/Savings		
		Process Time / Person Time	**Material**	**Energy**
Amount of resin in excess of nominal	Infusion process	N/A	Resin	N/A

Table 6. Expected benefits for TURBO challenge 4.

The driving factor of benefit	Operations where the benefit is realized	Benefits/Savings		
		Process Time / Person Time	**Material**	**Energy**
Number of laminate repairs	Inspection	Time of inspection	N/A	Energy consumption of inspection equipment
		Number of operators inspecting		
	Sentencing	Time to formulate a repair	N/A	N/A
		Number of operators		
	Repair	Time to repair defects	Material quantities removed	Energy consumption of rework tools
		Number of operators performing repairs		

Table 7. Expected benefits for TURBO challenge 5.

The driving factor of benefit	Operations where the benefit is realized	Benefits/Savings		
		Process Time / Person Time	**Material**	**Energy**
Number of coating repairs post-coating and during the blade's lifetime	In-use maintenance	Time of inspection	Material removed or replaced	Equipment energy required for inspection
		Number of operators		
	Post coating inspection	Time of inspection	N/A	Energy consumption of inspection equipment
		Number of operators		
	Post coating repair	Time to repair defects	N/A	Energy consumption of re-cure equipment
		Number of operators performing repairs		

5.4 EV battery manufacturing

The fourth case study focuses on a battery manufacturer, APTIV. The APTIV pilot is focused on an automated welding process that utilizes a hybrid arc and laser welding technique (Figure 6). The handling of the components is mainly automated with little intervention from the operators. A significant challenge with battery module welding is the length of the bead (~1m), making it very difficult to achieve a consistent, high-quality weld in its whole length. An in-line quality assessment system for the welding process, feeding the early defect identification in real-time

Figure 6. Overview of the process under examination in the APTIV pilot.

is of utmost importance to ensure the weld consistency. Another challenge is related to the gap control between the individual components. Moreover, considering the optimization of the production of the battery trays, as well as the need for digitalization of the production, a solution is needed to collect production data in a non-destructive approach, incorporate data analytics to enhance the reconfigurability as a result of quality assessment of the process, aid decision-making and contribute to the goal of zero-defect.

To address such requirements, parts of the proposed ZDM framework have been applied to the APTIV pilot. These parts along with some customised components of the openZDM project aim to facilitate proactive quality control in the pilot by identifying defects in early production steps and mitigating further processing of defective products. This early defect identification will ensure by the end of the openZDM project, substantial cost savings for the manufacturer and will increase its environmental sustainability by eliminating the wasting of resources that would be needed to process defective products. Parts of the framework that have been applied to the APTIV pilot include:

- Asset Administration Shell modeling: Assets of the pilot, including the welding process itself, the products of APTIV and installed equipment such as non-destructive inspection systems are modelled using the AAS concept. This provides an interoperable data model where information on the assets and real-time operational data is collected and made available to the rest of the components of the framework.
- An infrared vision-based non-destructive inspection system: The system is installed inside the laser welding process and is coupled with an AI-based Deep Learning solution that processes acquired image data to check in real-time for electrical defects on the welds.
- A vision-based non-destructive inspection system capturing images in the visible range: The system is installed outside the laser welding process. Images are acquired before and after the execution of the welding process. This two-fold acquisition ensures that aesthetical defects on the cells are identified before the battery modules are welded, while missing weld defects are identified after the process has concluded. These capabilities are offered by an AI-based Deep Learning solution that uses the images acquired by the vision-based system.
- Explainability modules: XAI modules operate on top of the Deep Learning models of the non-destructive inspection systems. These provide visual explanations on the defect detections made by the inspection systems, increasing the trustworthiness of the solution since operators and quality managers are better equipped to understand the outcomes of such models.
- Digital Twin: The digital twin is responsible for visualising the production system in real-time. It receives data from the non-destructive inspection systems as well as production data and offers a holistic view of the process.
- Data-driven analytics: These are different software modules that have been customized for the needs of the pilot. These modules calculate essential KPIs, and descriptive statistics based on production data coming from the digital twin.
- The openZDM platform: The platform is responsible for storing the Asset Administration Shells of the APTIV pilot. The platform through its interoperability middleware exposes an Open API that enables the population of the AASs of the APTIV assets with their real-time operational data, which can then be accessed by the digital twin and the data-driven analytics. In addition, the platform provides the

necessary user interfaces through which the operators and managers of the pilot interact with the system and consume the information provided by it.

Through the application of the ZDM philosophy via the proposed ZDM framework, the APTIV pilot at its current state has demonstrated improvements in terms of KPIs that evaluate both its economic and environmental performance. These KPIs are presented in Table 8.

Table 8. Improvements recorded in the APTIV pilot through the adoption of ZDM.

KPI	Description	Base Value	Target Value	Achieved Value
1	Defects related to electrical defects and missing weld defects on the battery modules	2.0%	0.8%	1.7%
2	Cost of poor quality on the revenue of APTIV	2%	0.9%	1.9%

As seen in Table 8, the adoption of the ZDM philosophy in the APTIV pilot case using parts of the unified ZDM framework has demonstrated an improvement in terms of KPIs related to the number of defects and the cost of poor quality. The gains in revenue for the manufacturer can be seen in Table 9.

Table 9. Gains in revenue were demonstrated in the APTIV pilot through the adoption of ZDM principles.

#	Description	Gain [€]
1	Gains as a direct result of early defect identification in the laser welding process per battery containing multiple modules	5,500
2	Gains as a direct result of early defect identification in the laser welding process yearly	45,000

As demonstrated in Table 8 and Table 9, the current level of adoption of the ZDM framework in APTIV has already resulted in significant gains in terms of yearly revenue for the manufacturer, which can be directly translated to environmental impact. It is projected that by the end of the openZDM project the yearly revenue gains for APTIV will be approximately 300,000€ if the KPI targets are met. To achieve this, the current customized solution made available to APTIV is continuously refined to meet the initial requirements set by the manufacturer.

6 Roadmap

The successful implementation of Zero-Defect Manufacturing (ZDM) depends on the availability of enabling technologies, but also on the structured alignment of these technologies with the specific operational, regulatory, and strategic context of each manufacturer. This requires a flexible roadmap that can adapt to company size, sector-specific requirements, product complexity, production volumes, and external regulatory or supply chain obligations. To address this need, the following four-phase roadmap is proposed, providing a structured yet adaptable approach for manufacturers to adopt ZDM in a way that maximizes both operational performance and long-term competitiveness.

1. The first phase focuses on establishing a baseline assessment of the manufacturing system's current capabilities, sustainability performance, and quality control practices. This initial assessment identifies

defect-prone processes, waste streams, and gaps in process visibility and data availability. Beyond internal processes, the assessment must also account for external factors, such as sector-specific quality expectations, regulatory requirements, and the traceability obligations that apply to highly regulated industries like pharmaceuticals, aerospace, and food production. In parallel, the assessment should address product complexity, recognizing that highly customized, precision components demand more sophisticated prevention strategies than standard, high-volume products. The combination of process analysis, product requirements, and external obligations ensures that ZDM adoption is technically feasible, operationally relevant, and strategically aligned.

2. The second phase focuses on conducting a feasibility study and cost-benefit analysis, with the aim of identifying the most suitable technological enablers and establishing the business case for ZDM adoption. For SMEs, feasibility analysis should prioritize scalable, modular solutions with minimal integration effort and predictable costs, including options for subscription-based analytics and quality monitoring services. For larger enterprises, feasibility must extend to evaluating cross-plant deployment potential, the integration of ZDM capabilities into existing MES and ERP platforms and ensuring compatibility with legacy equipment and automation systems. In all cases, the feasibility analysis must address not only technology readiness but also the regulatory and compliance dimensions, particularly where ZDM data must support external audits, product certifications, or industry-specific quality standards. In sectors characterized by multi-tier supply chains, feasibility must also consider the potential need for real-time quality data exchange with upstream suppliers and downstream customers, ensuring that defect prevention capabilities extend beyond the factory floor.
3. The third phase focuses on piloting the selected ZDM-enabling technologies within a controlled production environment, enabling real-world validation of both technical performance and operational benefits. For SMEs, pilot projects should target specific processes with high defect rates, tracking KPIs such as defect reduction, process efficiency, and cost of poor quality (COPQ). For larger enterprises, the pilot must also serve as an integration testbed, ensuring that ZDM technologies can effectively interoperate with existing digital infrastructure, including process monitoring systems, digital twins, and data governance frameworks. In both cases, the pilot phase should also confirm the regulatory readiness of the ZDM solution, particularly for sectors where quality assurance processes require full traceability and auditable documentation of defect prevention measures.
4. The final phase focuses on the scaling and continuous optimization of ZDM capabilities across the entire manufacturing system. For SMEs, scaling strategies should emphasize cost-effective, incremental deployments, supported by open-standard data communication protocols (e.g., MQTT, OPC UA) to ensure compatibility between new and legacy equipment. For larger enterprises, scaling requires enterprise-wide standardization of data models, quality reporting formats, and AI model governance frameworks, ensuring that ZDM insights can be compared across plants and product lines, regardless of local process variations. Additionally, for manufacturers operating in complex supply chains, scaling should also explore opportunities for cross-enterprise data sharing, enabling defect prevention strategies to extend across key suppliers and strategic customers.

Regardless of organizational size or sector, workforce development is essential to the successful scaling of ZDM. Operators, engineers, and quality managers must develop the skills needed to interpret AI-driven quality insights, respond to real-time defect alerts, and provide continuous feedback to data scientists and system architects to refine predictive models over time. This human-in-the-loop approach, where technology augments rather than replaces human expertise, is particularly important in high-mix, low-volume manufacturing environments and in sectors where regulatory oversight requires human validation of automated decisions.

Finally, as ZDM becomes embedded into daily operations, manufacturers should establish long-term performance monitoring systems that track defect rates, process efficiency, and sustainability impacts over time. Establishing these ZDM dashboards provides manufacturers with the ability to benchmark internal performance trends, compare quality performance across sites, and align internal defect reduction goals with external sustainability and circular economy targets. By linking defect prevention with material efficiency and emissions reduction, manufacturers can ensure that ZDM contributes directly to both operational excellence and broader environmental objectives, fully aligning with the European Green Deal and Industry 5.0 policy goals.

This four-phase roadmap aims to serve as an adaptable approach, ensuring that ZDM adoption is aligned with the specific characteristics of each manufacturer’s sector, products, processes, and regulatory context. Following this approach, manufacturers can systematically improve product quality, enhance process efficiency, reduce environmental impact, and strengthen long-term competitiveness, positioning themselves at the forefront of Europe’s transition to sustainable, resilient, and defect-free manufacturing ecosystems.

7 ZDM, the EU green transition and future directions

7.1 Contribution to the EU green transition

Zero-Defect Manufacturing (ZDM) directly supports the objectives of the European Green Deal by enhancing both the environmental sustainability and resource efficiency of manufacturing systems. By preventing defect generation at the earliest possible stage, ZDM ensures that materials, energy, and labor resources are applied exclusively to products that meet required quality standards. This directly reduces waste, energy consumption, and the carbon footprint of manufacturing operations, aligning with the EU’s broader net-zero emissions targets for 2050.

ZDM facilitates resource and energy efficiency by eliminating the unnecessary processing of defective products, thereby conserving raw materials, energy inputs, and auxiliary process resources such as cooling fluids, lubricants, and consumables. This systemic reduction in resource use lowers both direct production emissions and the indirect emissions embedded in material and energy supply chains, amplifying the positive environmental impact across product life cycles.

Additionally, ZDM plays a critical role in promoting circular economy strategies. By identifying defects early and pinpointing root causes, manufacturers can reconfigure processes in real time to minimize scrap. In cases where defective components are generated, recovery pathways can be developed, enabling products to be reworked or remanufactured rather than discarded. This tightens material loops within production environments, reducing primary material demand and associated environmental impacts.

ZDM also enhances manufacturing resilience and competitiveness by increasing process reliability and predictability. Through advanced monitoring, predictive quality control, and self-adaptive processes, ZDM reduces unexpected downtime, stabilizes output quality, and increases first-pass yield rates. This contributes to lower production costs, improved supply chain performance, and enhanced customer satisfaction, enabling European manufacturers to compete more effectively on global markets while aligning with sustainability expectations.

Beyond direct environmental and economic benefits, ZDM also supports social sustainability by creating demand for digitally skilled workforces. As intelligent systems for predictive quality, data analytics, and real-time process optimization become pervasive, the workforce must acquire new competences in data interpretation, model supervision, and digital twin interaction. This upskilling process contributes to the creation of a highly competent, adaptable workforce, aligned with Europe's broader goals for digital transformation and industrial leadership.

Overall, ZDM serves as a strategic enabler of climate-neutral, resource-efficient, and innovation-driven manufacturing ecosystems, reinforcing the dual goals of economic competitiveness and environmental stewardship underpinning the European Green Deal.

7.2 Technological evolution and adoption across industries

The long-term impact of ZDM will depend not only on the adoption of current enabling technologies, such as AI-driven predictive analytics, digital twins, and non-destructive inspection systems, but also on the ongoing evolution of these technologies to address emerging industrial challenges. Several critical technological and operational challenges will need to be addressed to ensure ZDM can scale across all sectors and manufacturing contexts.

One pressing challenge is data quality and interoperability. Many manufacturing environments, particularly legacy production systems, suffer from fragmented data infrastructures and incompatible data formats, which inhibit real-time data sharing across machines, lines, and plants. ZDM requires seamless, standardized data exchange, ensuring that quality-related data can flow across entire production ecosystems, from sensor level to enterprise analytics platforms. Efforts to standardize data models and harmonize data interfaces, particularly through the AAS model, must accelerate to enable cross-platform ZDM deployment.

Real-time decision-making is another technological imperative. Although edge computing and industrial cloud platforms have made significant strides, achieving ultra-low latency defect prediction and autonomous process adaptation in complex, multi-step production processes remains challenging, especially in sectors with high-speed, continuous processes. Ongoing advances in edge AI, combined with dynamic process modeling and simulation, will be essential to achieving real-time defect prevention at scale.

The increasing interconnectivity between production systems and external data ecosystems also heightens cybersecurity risks. As manufacturers deploy ZDM-enabling technologies, they must also adopt comprehensive cybersecurity strategies that include continuous vulnerability assessments, end-to-end encryption, and real-time threat detection systems. These capabilities are especially critical for manufacturers operating in highly regulated sectors or those participating in distributed supply chains, where data breaches could compromise both product quality and intellectual property.

Workforce development and skills transformation represent another critical dimension. The successful implementation of ZDM depends, besides advanced technologies, on the workforce's ability to interpret data, validate AI outputs, and collaborate effectively with digital systems. Comprehensive training programs will be needed to upskill the workforce in data-driven decision-making, digital twin interaction, and AI model supervision, ensuring that human expertise complements automated defect prevention processes.

Finally, ZDM adoption needs to extend beyond discrete manufacturing processes, encompassing the broader industrial landscape, including energy systems, material suppliers, and logistics providers. Each industrial domain presents unique defect prevention challenges, requiring sector-specific adaptation of ZDM technologies and methodologies. Collaborative innovation ecosystems, linking manufacturers, technology providers, and research institutions, will be critical to tailoring ZDM frameworks to the specific requirements of different industrial sectors.

7.3 Recommendations for stakeholders

In order to unlock the full potential of ZDM and ensure its widespread adoption across European industry, coordinated action is required from manufacturers, technology providers, research institutions, policymakers, and standardization bodies.

First, awareness-raising campaigns targeting manufacturers, particularly SMEs, should be prioritized, highlighting both the economic benefits and the environmental advantages of ZDM adoption. The recently established European Digital Innovation Hubs (EDIHs) network can play a central role, offering test-before-invest opportunities, allowing companies to evaluate ZDM-enabling technologies in low-risk demonstration environments.

Second, manufacturers should be encouraged to establish collaborative partnerships with technology providers, research centers, and industry associations to co-create and validate ZDM solutions that align with their specific processes, products, and regulatory obligations. These partnerships should also focus on developing training programs to ensure the workforce can actively engage with AI-based quality systems and digital twins, bridging the digital skills gap that inhibits technology adoption.

Policymakers must also ensure that legislative frameworks evolve in parallel with technological advancements. Clear regulatory guidelines should be established to facilitate the integration of AI, digital twins, and real-time NDI/NDT systems into existing quality management and regulatory compliance processes. Collaborative forums, bringing together policymakers, industrial stakeholders, and standardization bodies, should focus on reducing regulatory complexity, particularly for SMEs, to accelerate the adoption of intelligent quality systems.

The development of standardized, open data-sharing protocols is particularly critical to prevent vendor lock-in and ensure that ZDM data can flow freely across heterogeneous industrial environments. Parallel investments in explainability and trustworthiness of AI models will be needed to foster operator trust and ensure that ZDM solutions remain transparent, auditable, and aligned with evolving regulatory requirements, including the EU AI Act.

Finally, coordinated action is needed to develop international standards for ZDM, encompassing both enabling technologies (e.g., digital twins, AI-driven quality control, NDI/NDT) and process-level best practices for implementing ZDM principles across different manufacturing sectors. European stakeholders, including industry leaders, policymakers, and research institutions, should actively participate in global standardization efforts led by ISO, IEC, and CEN, ensuring that ZDM frameworks reflect both European leadership and global applicability.

8 Outlook for the future

8.1 Future innovations

The future of ZDM will be defined by the continuous evolution of digital technologies, advanced simulation environments, and AI-driven intelligence systems, all converging to create increasingly autonomous, self-optimizing production ecosystems.

In the domain of AI and machine learning (ML)-driven quality control, future advances will center on the deployment of more complex predictive models, including deep learning architectures and explainable AI (XAI) frameworks. As computational capacity at the edge level improves, these models will transition from cloud-centric deployments to real-time, on-machine applications, delivering highly accurate, ultra-low latency defect predictions directly at the source of production. This shift will enhance the responsiveness of defect prevention mechanisms, enabling seamless parameter reconfiguration to avoid recurring defect patterns and continuously optimize process conditions.

The evolution of digital twins will further strengthen ZDM capabilities. Beyond acting as real-time process representations, future digital twins will become fully autonomous process optimization agents, capable of simulating the downstream consequences of every process deviation and recommending immediate corrective actions. Enabled by 5G and next-generation industrial communication technologies, these digital twins will achieve near-zero latency synchronization with physical systems, even in high-speed production environments, ensuring that defect prevention measures are applied in real-time.

The role of robotics and collaborative automation will also evolve to reinforce ZDM principles. While industrial robots already automate defect-prone tasks with high precision, the next generation of collaborative robots (cobots) will be increasingly equipped with integrated sensors and embedded AI capabilities, allowing them to self-correct their actions based on real-time quality data. This will enable adaptive task execution, where cobots dynamically adjust grip force, path trajectory, or processing speed to prevent defect formation in high-precision assembly or machining tasks.

As data becomes the cornerstone of all ZDM-enabling technologies, the importance of secure, transparent data exchange across the entire manufacturing ecosystem will grow. Emerging industrial data spaces, based on sovereign data-sharing models and distributed ledger technologies (e.g., blockchain), will ensure that quality and defect-related data can be shared across organizational boundaries with full traceability and ownership protection. This is particularly relevant in multi-tier supply chains, where seamless defect data exchange between suppliers, manufacturers, and customers will enable collaborative defect prevention strategies.

Finally, the human dimension of ZDM will also require ongoing innovation. As intelligent quality systems increasingly inform and, in some cases, autonomously control manufacturing processes, ensuring human oversight, trust, and understanding becomes critical. The integration of explainability techniques within AI-driven ZDM platforms will provide operators, quality managers, and auditors with transparent justifications for automated decisions, reinforcing trust in AI-powered defect prevention. These capabilities will also support regulatory compliance, particularly in sectors where human validation remains a legal requirement.

8.2 Legislative landscape and industry regulation

The regulatory landscape shaping ZDM reflects the intersection of quality management standards, digital transformation policies, sustainability regulations, and workforce development initiatives. As smart manufacturing ecosystems emerge, policy frameworks must evolve to safeguard product quality, ensure ethical AI deployment, protect data, and drive sustainability performance.

The foundation for ZDM in Europe is already partially embedded in existing quality management standards, including ISO 9001 (quality management), ISO 14001 (environmental management), and ISO 45001 (occupational health and safety). These frameworks emphasize process optimization, waste reduction, and continuous improvement, all of which align closely with ZDM objectives. However, none of these standards fully capture the proactive, AI-enabled defect prevention strategies at the heart of modern ZDM systems. The introduction of new, dedicated standards for proactive quality management in AI-driven production environments will also be essential.

In parallel, the EU AI Act introduces regulatory guardrails for AI systems, including those deployed in manufacturing quality control. ZDM systems that incorporate autonomous defect detection and process adjustment capabilities may be subject to classification as high-risk AI systems, requiring demonstrable safety, transparency, and bias mitigation measures. Ensuring that ZDM platforms comply with the AI Act—through explainability mechanisms, robust validation processes, and clear governance frameworks—will be crucial for their legal acceptance across Europe.

Data governance also plays a pivotal role in ZDM deployment, particularly in cross-organizational quality assurance processes. The General Data Protection Regulation (GDPR) already governs the handling of personal data, but ZDM systems increasingly generate product, process, and machine data that also require clear ownership, access rights, and data-sharing frameworks. Emerging data space initiatives, such as GAIA-X, could serve as templates for ensuring secure, interoperable data sharing across ecosystems.

On the sustainability front, the EU Green Deal and Circular Economy Action Plan are progressively aligning environmental, economic, and social sustainability requirements into the regulatory obligations of manufacturers. This includes extended producer responsibility (EPR) schemes, where manufacturers must account for the lifecycle impacts of their products, including defect-related material waste. ZDM, by reducing scrap and enabling remanufacturing pathways, aligns directly with circular economy strategies, making it a key enabler of regulatory compliance in sustainable manufacturing.

8.3 Policy and industry alignment

The successful industrialization of Zero-Defect Manufacturing depends on a balanced and coordinated alignment between technological innovation, industrial standards, and supportive policy frameworks. As manufacturing transitions toward intelligent, data-driven, and highly adaptive production systems, policymakers have a pivotal role in creating the conditions for widespread ZDM adoption.

First, standardization bodies, working alongside industry leaders and research institutions, should develop dedicated ZDM standards, covering both technological enablers and process-level methodologies for defect prevention and continuous quality assurance. These standards should support sector-specific adaptations, ensuring applicability across automotive, aerospace, medical devices, food production, and other key sectors.

Simultaneously, regulatory frameworks should be modernized to reward and certify ZDM adoption. This could include voluntary certification schemes, where manufacturers adopting ZDM-compliant processes could be recognized as leaders in environmentally responsible production, qualifying for green labeling schemes, tax incentives, or preferential public procurement access.

To accelerate adoption, particularly among SMEs, policymakers should expand funding programs, combining R&D grants, tax credits, and access to innovation vouchers to support pilot implementations of ZDM-enabling technologies. EDIH networks can play a crucial role by offering test-before-invest environments, where SMEs can evaluate ZDM platforms without assuming excessive financial or operational risks.

Finally, education and workforce development policies must be aligned with ZDM requirements. Academic curricula, vocational training programs, and lifelong learning initiatives should explicitly incorporate ZDM principles, ensuring that future workforces are equipped to operate, maintain, and continuously improve intelligent quality systems. Collaboration between industry, academia, and government should drive the development of competence frameworks and certification programs focused on data-driven quality management, digital twin operation, and AI-assisted defect prevention.

In conclusion, the convergence of technological innovation, regulatory modernization, and industry-wide standardization will determine whether ZDM becomes a cornerstone of European industrial competitiveness. By embedding proactive quality strategies into Europe's digital and green transitions, ZDM can advance economic resilience, environmental responsibility, and technological sovereignty, positioning Europe as a global leader in intelligent, defect-free, and sustainable manufacturing.

9 Conclusion

In conclusion, ZDM has evolved from a forward-looking quality concept into a strategic pillar for Europe's sustainable and resilient industrial future. By proactively preventing defects through the integration of advanced digital technologies, real-time monitoring, predictive analytics, and autonomous process optimization, ZDM not only enhances product quality and operational efficiency, but also directly supports Europe's green and digital transitions.

The insights gathered from EU-funded projects and practical case studies illustrate the tangible environmental, economic, and technological benefits that ZDM adoption can deliver across sectors and company sizes. However, achieving widespread ZDM adoption requires addressing technological, organizational, and regulatory challenges, ensuring that solutions are accessible, scalable, and aligned with evolving policy frameworks.

With the right combination of technological innovation, workforce upskilling, supply chain collaboration, and regulatory support, ZDM can redefine European manufacturing competitiveness, demonstrating that high-quality, defect-free production is fully compatible with resource efficiency, climate neutrality, and digital transformation goals.

In this context, ZDM is no longer a future aspiration, but it is turning out to be an essential enabler for the next era of resilient, sustainable, and globally competitive European manufacturing.

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