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A global survey on the current state of practice in Zero Defect Manufacturing and its impact on production performance

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ABSTRACT

To be competitive in dynamic and global markets, manufacturing companies are continuously seeking to apply innovative production strategies and methods combined with advanced digital technologies to improve their flexibility, productivity, quality, environmental impact, and cost performance. Zero Defect Manufacturing is a disruptive concept providing production strategies and methods with underlying advanced digital technologies to fill the gap. While scientific knowledge within this area has increased exponentially, the current practices and impact of Zero Defect Manufacturing on companies over time are still unknown. Therefore, this survey aims to map the current state of practice in Zero Defect Manufacturing and identify its impact on production performance. The results show that although Zero Defect Manufacturing strategies and methods are widely applied and can have a strong positive impact on production performance, this has not always been the case. The findings also indicate that digital technologies are increasingly used, however, the potential of artificial intelligence and extended reality is still less exploited. We contribute to theory by detailing the research needs of Zero Defect Manufacturing from the practitioner's perspective and suggesting actions to enhance Zero Defect Manufacturing strategies and methods. Further, we provide practical and managerial suggestions to improve production performances and move towards sustainable development and zero waste.

1. Introduction

In order to remain competitive in today's dynamic and global markets, manufacturing companies must continuously explore innovative production strategies and methods, and leverage advanced digital technologies to improve their flexibility, productivity, quality, environmental impact, and cost performance. The emergence of Industry 4.0 has greatly facilitated the rapid development of digital technologies to handle production complexity and improve data management for decision-making (Dalenogare et al., 2018; Fragapane et al., 2022). However, while the maturity of digital technologies increases, providing the basis for better decision-making, such technologies are often developed and introduced in isolation from other advanced production strategies and methods. Modern production concepts must cultivate production strategies and methods that integrate complementary advanced technologies and cover the manufacturing decision-making areas (Caccamo et al., 2021; Powell et al., 2022).

Zero Defect Manufacturing (ZDM) is a disruptive concept that focuses on advancing production strategies and methods with advanced digital technologies in quality management, production management, and maintenance management (Psarommatis et al., 2020a). The strategies of detection, prevention, prediction, and repair (including defect mitigation and compensation) are the cornerstones of the ZDM concept. They include data-driven decision-making methods to improve product quality, increase process flexibility, and boost productivity, while also reducing costs and resource usage within entire industrial ecosystems.

The idea of zero defects is not new, with the initial concept first introduced in 1965 with the US Army Pershing Missile System at the Martin Company, which implemented it as a quality and reliability program (Eleftheriadis and Myklebust, 2016). From the beginning, it aimed for the complete elimination of defects, errors, and waste in single manufacturing processes up to multi-stage manufacturing systems and so increase the production performance throughout the supply chain. ZDM builds on the same quality management philosophy that underpins both Lean Production, Six Sigma, Theory of Constraints and Total Quality Management, but it differentiates in systematically applying

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strategies, methods and technologies to move from reactive to predictive and preventive quality management - achieving a "first-time-right" level of quality (Powell et al., 2022). Moreover, the strong focus on reliability supports the development of strategies and methods to predict maintenance and prevent errors and failures (Psarommatis et al., 2020a).

Looking back at the last two decades, practical interest in companies and the number of published articles on ZDM have increased significantly. Driven by companies' needs, ZDM strategies, approaches, methods, technologies, and tools have been developed and introduced. As the ZDM literature has matured, the ZDM knowledge has been mapped and frameworks introduced. While "much of the extant ZDM literature is based on applied research and presents practical examples of ZDM concepts" (such as single or multiple case studies, etc.) (Powell et al., 2022; p5), these studies only represent a small part of the overall ZDM picture. Despite the exponential growth in scientific knowledge in this field, the current practices of ZDM and their impact on companies remain largely unknown.

We believe, therefore, that the time is right to conduct a global ZDM survey and compare the current state of the art of research knowledge with ZDM practice in companies. The latest literature reviews provide a solid basis to design the survey instrument for conducting a global survey – the aim of which is to bring new insights of status and needs of ZDM in practice to light. Furthermore, the results and analysis will be distributed to respondents to increase their awareness of ZDM, advance their current level of maturity in ZDM, and identify potential improvement areas.

In this paper, we aim to answer the following research questions:

1) What is the current state of practice of ZDM in manufacturing companies?
2) What are the limitations and barriers in implementing and applying ZDM?
3) How does ZDM impact the production performance of manufacturing companies?

The rest of the paper is organized as follows: Section 2 presents the current ZDM literature and research gaps. In Section 3, we describe the research method and detail the important parts of the survey. Section 3 presents the survey results and compares them with the current academic ZDM landscape. In Section 4, we indicate the practical and managerial implications. Section 5 presents further ZDM research needs based on the survey findings. We conclude in Section 7.

2. Theoretical background

The following section provides a synthesis and summary of recent literature reviews that structure ZDM research areas and map the academic developments. The section defines and explains ZDM strategies, approaches, methods, technologies and tools, and limitations and provides the basis for the survey questionnaire and for the survey result analysis.

2.1. ZDM strategies

A ZDM strategy is a set of methods, tools, resources, and rules with the aim of avoiding defects and increasing the sustainable performance of complex manufacturing systems (Powell et al., 2022). Five distinctive strategies have been identified (Caiazzo et al., 2022; Powell et al., 2022; Psarommatis et al., 2020a): (I) Detection, (II) Prediction, (III) Prevention, (IV) Repair, and (V) Defect mitigation or compensation. Conducting a meta-analysis of recent literature reviews on ZDM (Caiazzo et al., 2022; Powell et al., 2022; Psarommatis et al., 2020a) shows that the detection of defects is the most popular research interest (as shown in Table 1).

Table 1
ZDM strategies published articles distribution.

ZDM strategies	Published articles distribution*
Detection	60%
Prediction	24%
Prevention	9%
Repair	4%
Defect mitigation or compensation	3%

* Note: average distribution result of the ZDM literature reviews (Caiazzo et al., 2022; Powell et al., 2022; Psarommatis et al., 2020a)

Detection strategies refer to the recognition of defects, anomalies and faults by analyzing, classifying and identifying them on the basis of the parameters that resulted in the undesirable effect (Caiazzo et al., 2022). The detection actions focus both on the generation of the detected defect and its propagation to the next production levels and supply chain steps (May and Kiritsis, 2019). The major research streams still focus on physical detection. However, virtual detection is increasingly receiving more attention due to greater data availability and lower operational costs (Kang and Kang, 2017; Kurz et al., 2014; Susto et al., 2015). Here, the most relevant and most cited work focuses on introducing digital twins and artificial intelligence (AI) for detection. For example, Park et al. (2019) proposes an approach combining an autoencoder to detect a rare fault event and a long short-term memory network for fault detection in chemical processes. Tabernik et al. (2020) present a segmentation-based deep-learning architecture that is designed for the detection and segmentation of surface anomalies in the electric commutators production. Yuan et al. (2019) introduce stacked quality-driven autoencoder to exploit the quality data in industrial debutanizer column processes. Xu et al. (2019) present a two-phase digital-twin-assisted fault diagnosis method using deep transfer learning for fault diagnosis in the development and maintenance phases of car body production. Zhou et al. (2019) propose the design and implementation of a novel automatic inspection system for automobile surface defects and apply forward multi-scale defect binarization based on a Hessian matrix algorithm for fault detection. Wang et al. (2020) introduce an extended deep belief network model for fault diagnosis in chemical processes.

Prediction strategies consider defect-, anomaly-, and fault prediction, which aims at forecasting the quality of each part of the product before its production, e.g., via specific models and historical data analyses (Caiazzo et al., 2022). The main exploited methodologies are applying mathematical modelling and AI techniques. Bhowmik and Ray (2019) present a Fuzzy Logic-based framework to predict roughness in an abrasive water jet machining process in green manufacturing. García et al. (2019) introduce regression models to predict both those physical quality indices in a tube extrusion process. Li et al. (2019) introduce a mathematical model and a framework involving anomalous data retrieval sensors for the improvement of RUL prediction. Liu et al. (2019a), (2019b) present a joint-loss convolutional neural network for bearing fault recognition and Remaining Useful Life (RUL) prediction. Wang et al. (2019) introduce a generative neural network model that combines an unsupervised feature-extraction step with a supervised learning method for automatically predicting work-in-progress product quality. Wang et al. (2020) propose an extended deep belief network to fully exploit useful information and capable of extracting quality-relevant features in batch processes. However, this strategy is one of the most underutilised because defining accurate prediction models is a very difficult and complex task and requires a vast amount of data in order to be accurate (Psarommatis et al., 2020a). The strategy support foremost the optimization of production planning and machine scheduling by integrating optimal maintenance actions. The timely performing preventive replacements allow both to reduce unexpected failures and minimize total maintenance costs (Petrillo et al., 2020; Tian, 2012; Xu et al., 2019). In this context, future health condition and thus the RUL of both equipment and products are the main objectives in the investigations.

Prevention strategies focus on providing quality control and inspection tools for monitoring machinery and corresponding produced quality (Caiazzo et al., 2022). The processes are known in depth and machine state analysis are done so that process conditions leading to defects or possible deviations of the product from expected outcome are proactively identified and countermeasures introduced (Powell et al., 2022). Further, ZDM prediction strategies are often the predecessor of ZDM prevention strategies. Predicted defect and affected parameters are identified and flagged, prevention actions are planned and scheduled to avoid production line downtime and interruptions (May and Kiritsis, 2019). The main exploited methodologies in prevention are applying Failure Mode and Effect Analysis (FMEA), digital twin and AI techniques.

Huang et al. (2018) proposes deep decoupling convolutional neural network intelligent compound fault diagnosis and capable of considering the machinery relationships between composite components. Cao and Deng (2019) introduce a geometric mean FMEA method enabling a more flexible expert judgment. Chen et al. (2019) present a novel fault diagnosis approach integrating Convolutional Neural Networks and Extreme Learning Machine to enhance the fault classification performance and learning speed. Liu et al. (2019a), (2019b) to introduce data-driven framework to address the problem of noisy environmental conditions in data acquisition. Principi et al. (2019) proposes an unsupervised method for diagnosing faults of electric motors and compare the results with several Deep Autoencoder models for overcoming the frequent limitation of anomalous data availability. Soualhi et al. (2019) introduce an Adaptive Neuro-Fuzzy Inference System allowing an early fault detection, diagnostic and prevention actions for critical components of the gear reducer, in particular gear and bearing defects.

Repair strategies focus on the reworking/re-manufacturing of products throughout circular supply chains (Caiazzo et al., 2022). Once a repairable defect is detected, online or offline repair is carried out focusing to minimize time and effort and maximize production performance and flow. For many companies, the linked actions are usually time-consuming and expensive, and it so is preferable to discard defective items (Psarommatis et al., 2020). However, with increased focus on sustainability, repair strategies can have a significant impact on zero-defect and zero-waste (Powell et al., 2022). Therefore, improved repair methods focus mostly on accelerated repair times without disturbing the overall production flow. For example, Gautam et al. (2019) propose a model for defect management that also considers factors such as carbon emission. Nadimpalli et al. (2020) introduces Friction Stir Processing to maintain the micro-structural advantages of Ultrasonic Additive Manufacturing. Li et al. (2019) presents an approach for the repair of metal defects based on the usage of groove monitoring, Wire and Arc Additive Manufacturing, and finishing machining.

Defect mitigation or compensation strategies reduce rework and repair activities through defect compensation using preventive, proactive, and reactive methods (Chen, 2016). For instance, defects are matched and integrated into the multi-stage machining or assembly systems without off-line rework (Powell et al., 2022). In traditional quality management strategies, feedback control loops are usually implemented at single-process levels to detect and repair defects, but lead to production performance inefficiencies. Modern defect mitigation or compensation strategies aim at proactively identifying defects or potential defects and attempt to find methods that avoid rework. Defects and deviations are compensated downstream in the process chain by means of feedforward control. The ZDM paradigm grounds on the integration of product and process data coming from multi-source process chains. Methodologies such as stream-of-variation can be applied to adapt the downstream process to avoid the propagation of dimensional and geometrical deviations of the measured part (Magnanini et al., 2019). If a model-based solution is not available, because of line complexity, specific downstream compensation actions can be generated, without the need of off-line rework (Eger et al., 2018; Eldessouky et al., 2019). Further in assembly systems, components vary within the predefined tolerance and may result in a defective assembled product due to the intrinsic parts variability. Selected assembly methods focus on matchmaking components to minimize the expected assembled product deviation (Colledani et al., 2014a, 2014b). Such compensation strategies can reduce rework or even end-of-line inspection resulting in scrap products.

2.2. ZDM approaches

ZDM approaches can be grouped in (I) single-stage, multi-stage, or supply chain, (II) process and product-centric, or (III) people-centric (Powell et al., 2022).

Single-stage, multi-stage, or supply chain approaches can support the quality control and production improvement on different stages. Single-stage optimizations support individual and discrete production processes and have received more than 70% of research attention in previous years (Powell et al., 2022). The optimization of a single process can still lead to defect generation in the form of deviations that propagate in subsequent process steps (Magnanini et al., 2019). More recent research has focused on multi-stage manufacturing systems that include entire production lines and consist of many discrete processes (Eger et al., 2018). For instance, these studies apply cyber-physical systems (Colledani et al., 2018; Kang et al., 2019) and smart, collaborative production systems (Lindström et al., 2019; Shiokawa and Ishii, 2019) to reduce defects in multi-stage manufacturing systems. Beyond multi-stage manufacturing systems, supply chains or digital supply networks share information and collaborate to reduce defects and increase production performance. Bosi et al. (2020) propose an Industrial Internet of Things (IIoT) platform for Agile Manufacturing in Plastic and Rubber Domain to make the processes in production networks more automated, interconnected and moreover to support ZDM strategies.

Process and product-centric approaches have different starting points for investigating the reduction of defects in manufacturing systems (Psarommatis et al., 2020a). Process-centric approaches study defective manufacturing equipment and move the investigation from shopfloor to product level. Based on the different levels, it is evaluated whether the manufactured products are defective or not. The research in this context focuses strongly on manufacturing processes (e.g., process monitoring and process control) and it his has been a common theme in ZDM. Many studies build on statistical process control concepts, where the process is central with respect to other system components and resources (Powell et al., 2022). Additionally, product-centric approaches study the defects on actual parts and try to find a solution to reduce defects on healthy machines (Psarommatis et al., 2020a). Latest research trends lean more towards product-centricity (Powell et al., 2022).

People-centric approaches has recently received a strong focus due to the recognition of human's expertise in manufacturing systems and Industry 5.0 research trends. The roles of humans (e.g., both white- and blue collar) in manufacturing systems are, despite strong efforts in automating manufacturing processes, still unreplaceable. Manufacturing systems rely strongly on human workers due to cognitive and motor skills. Human factors must be integrated in manufacturing systems to reduce defects and increase production performance (Romero et al., 2016; Romero and Stahre, 2021). However, the role of humans in ZDM has until now been vastly overlooked and most of the examples seem to be rather coincidental, often coming secondary to a focus on the process dimension (Powell et al., 2022).

2.3. ZDM methods, technologies, and tools

Industry 4.0 has pushed the development of technologies supporting

Table 2
ZDM methods, technologies and tools.

ZDM methods, technologies, and tools	Description	Published articles distribution*
Artificial intelligence	Data-driven techniques for automated data analysis and decision making	43%
Big data analytics	Elaboration, analysis, and visualization of the massive amount of industrial data	6%
Cyber-Physical Systems and digital solutions	Control strategies combining physical and digital resources	7%
Digital inspection and monitoring	Solutions for the measurement and monitoring of product and process resources	19%
Architecture and Standards	Integration and communication protocols of industrial software	7%
Process mining	Providing better understanding of process variations that can be decreased and improved	3%
Failure Mode and Effect Analysis:	Approach for identifying possible failures in a design, a manufacturing or assembly process, or a product or service.	1%
Digital Twin combined with simulation and modelling	Optimization and decision support for processes	13%
Extended Reality and visualization technology	Visualization of information to improve decision making processes	1%

* Note: average distribution result of the ZDM literature reviews (Caiazzo et al., 2022; Powell et al., 2022; Psarommatis et al., 2020a)

ZDM strategies (Powell et al., 2022; Zheng et al., 2021). Conducting a meta-survey among recent literature reviews (Caiazzo et al., 2022; Powell et al., 2022; Psarommatis et al., 2020a) the main ZDM methods, technologies, and tools are presented and described in Table 2.

2.4. ZDM barriers and limitations

Across the empirical studies of ZDM, the most mentioned and relevant barriers are shown in Table 3.

Table 3
ZDM barriers.

Barriers	Reference
Low knowledge of ZDM strategies	(Magnanini et al., 2020; Psarommatis et al., 2020b; Schmidt and Hanitzsch, 2012; Vafeiadis et al., 2017)
Low ZDM implementation experience	(Psarommatis et al., 2020b)
Low ZDM method and tool training	(Psarommatis et al., 2020b)
Low digitalization level	(Magnanini et al., 2020; Myklebust, 2013; Nazarenko et al., 2021; Ngo and Schmitt, 2016; Pombo et al., 2020; Psarommatis et al., 2020b; Schmidt and Hanitzsch, 2012; Vafeiadis et al., 2017)
Low IT infrastructure	Nazarenko et al. (2021);Ngo and Schmitt (2016);Pombo et al. (2020);Psarommatis et al. (2020b);Schmidt and Hanitzsch (2012);Vafeiadis et al. (2017))
Low commitment of top management	(Psarommatis et al., 2020b)
Low commitment of shop-floor level or operators	(Psarommatis et al., 2020b)
Low capacity of resources to work on or apply ZDM	(Psarommatis et al., 2020b)
Established quality management system and reluctance to apply new or different ones	(Psarommatis et al., 2020b)
No suitable projects to work on or apply ZDM	(Psarommatis et al., 2020b)

Table 4
ZDM research limitations.

Limitations	Reference
Low focus on automatic collection and connection of information between machines to reduce defects. Traditional quality control tools regard production as a static system, thus neglecting additional information on machine states and process variables along production stages and among product types, especially needed for a more responsive quality control system.	(Powell et al., 2022; Psarommatis et al., 2020a)
Low focus on feed-forward control. Little to no proactive parameters regulation and control are allowed with traditional quality-oriented approaches due to the absence of integrated multi-sensor software architecture.	(Powell et al., 2022)
Low focus on using AI for defect detection. Little to no comprehension about the complex root-cause dynamics is provided to the users and, hence, deviations and errors are mainly solved by exploiting human experience.	(Caiazzo et al., 2022)
Low focus on "online" reworking and compensating for defects/waste. Only off-line reworking strategies are carried out once the defect has been generated, having no chance to implement proper online corrective actions.	(Caiazzo et al., 2022; Powell et al., 2022)
Low focus on multistage zero-defect systems, supply chains or digital supply networks. As traditional quality control tools are mainly adopted to the single-stage production process, they are troublesome to implement in multistage systems.	(Powell et al., 2022; Psarommatis et al., 2020a)
Low focus on Zero-waste value-chain strategies. The quality improvement and control methods are lacking in focusing on environmental (e.g., sustainability / circular economy) aspects.	(Caiazzo et al., 2022; Powell et al., 2022)
Low focus on First-Time-Right and quality ramp-up minimization. The quality improvement and control methods lack support before production starts.	(Powell et al., 2022)
Low focus on Human-in-the-loop. The quality improvement and control methods are lacking in including and providing support to operators to work towards zero defects.	(Powell et al., 2022; Psarommatis et al., 2020a)

Furthermore, recent ZDM literature reviews summarized the current research and practice limitations. The ZDM research and practice limitations can be found in Table 4.

2.5. Research gap for this study

In the last two decades, the interest and the number of published articles introducing ZDM strategies, approaches, methods, and tools has increased significantly. As the ZDM literature has matured, its scientific landscape has been mapped, structured and quantified. This allows comparing the current state of practice in companies with the scientific findings and research streams. Further, most studies based on empirical data are only single- or few multiple-case studies, making the impact of ZDM on production performance difficult to generalize. Therefore, the current state of practice of ZDM and its impact on a large scale of companies are still unknown. This study aims to close the gap by identifying the current state of practice of ZDM in manufacturing companies, its limitations, and barriers, and the impact of ZDM on the production performance of manufacturing companies. Furthermore, we compare this to extant literature to identify further ZDM research needs.

3. Method

This section explains the survey design, administration, analysis, and validity. The present empirical study adopted a questionnaire-based survey approach to answer the three research questions. The survey method is especially suited and applicable for a mature research area such as ZDM (Karlsson, 2016). It allows to create reliable questionnaires

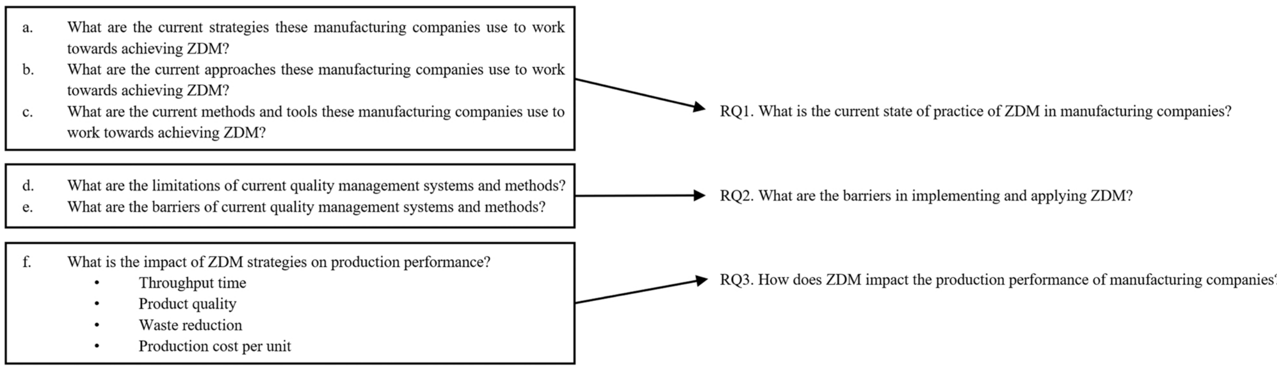

Fig. 1. Questionnaire and research questions construct.

based on established frameworks and methods and it enables the mapping of the current state of practice, compared to existing academic knowledge. Furthermore, this research method allows to collect and compile a considerably large amount of data in a given timeframe - which is especially useful for a global study (Fowler Jr, 2013; Wright and Schwager, 2008). Survey questionnaires are widely used within social sciences and allow the researcher to effectively collect data from broad populations in a practical manner that can easily be adapted to administering the study questionnaire online (Saunders et al., 2010). Many recent studies in production and quality management have adopted a survey methodology for empirical studies to map and identify the current state of practice of production strategies and methods, and their impact on production performance (Antony et al., 2019, 2021a; Buer et al., 2020, 2021; Zhang et al., 2016).

Our survey was conducted online using Google Forms to collect the data. An online survey has advantages over a manual survey in terms of cost, speed, reach, ease of use, clarity, and automation (Ball, 2019). The respondents' answers were collected in a timeframe of 6 months. After the survey deadline was passed, the data were exported directly from the online survey portal into IBM SPSS 29. The software supported the statistical analysis and visual representation of the results. The analysis of the responses to the questionnaire support responses to our three research questions as shown in Fig. 1.

Regarding missing data in responses, this was handled based on the extensiveness of the missing data. If only one item was missing in a summated scale, we calculated the average for the scale without sending a follow-up e-mail to respondents.

3.1. Questionnaire design

The survey questionnaire consisted of five parts and is based on the theoretical background provided in chapter two. In the first part, participants' background information (such as work function, work experience and functional level) was collected. The second part of the survey solicited respondents' company information (such as size, industry, production environment, digitalization level, etc.). The third part focused to capture the companies' involvement and application of ZDM strategies, approaches, methods, and tools. The next part focused to identify the barriers and limitations of ZDM in practice. Finally, the impact of ZDM strategies on production performance was captured.

The questionnaire contained 38 closed questions in total and the average duration to complete was 101 min. Questions 1–9 used nominal scales: participants were asked to choose from a number of possible answers, e.g., choose which production environment or service provision reflects best their company from a given list. Questions 10–38 used an ordinal scale: participants were asked to rate the applicability of ZDM strategies, approaches, methods, and tools in their companies, and the corresponding impact on production performance, e.g., indicate to what extent the ZDM prediction strategy applied in the company to work towards zero defects (very low, low, moderate, high, very high).

To ensure validity and reliability of the questionnaire, it was screened among several critics on web-based questionnaires and sent to experts for pilot testing. One of the most common criticisms of questionnaires is related to various biases. Addressing relevant biases in questionnaires is an important task to collect the most accurate data from respondents. Therefore, investigators must recognize and be able to prevent, or at least minimize, bias during the design of questionnaires. Choi and Pak (2005) identified 48 types of common bias in questionnaires. These recommendations were considered during the design and administration of the survey presented in this paper. For instance, asking sensitive questions such as age or working position may elicit inaccurate answers and can also negatively impact the interviewer-interviewee relationship, potentially affecting all subsequent responses. To address this, this survey was evaluated for ethical considerations and sensitivity of personal data by the Norwegian Centre for Research Data (with case number 472062) and received positive feedback. Additionally, we focused on removing leading questions and forced choice options. Some questions may be worded in a way that prompts respondents to choose an inaccurate answer or too few categories can force respondents to choose imprecisely among limited options. Therefore, the questions are based on previous well documented surveys for production management, digitalization, and performance (Antony et al., 2019; Buer et al., 2021, 2020; Forza, 2002). Moreover, a pilot questionnaire was distributed to an expert panel of five members (a ZDM academic, six sigma champion, six sigma master black belt, quality management consultant, and operational excellence manager) to test the pilot questionnaire. The pilot survey helped articulate the questionnaire more precisely. Also, it helped to develop a comprehensive construct relevant to the field of study. To test reliability, the Cronbach's alpha coefficient was calculated for each of the summated scales. All the summated scales have values above the recommended threshold of 0.6 (Forza, 2002). The reliability statistics of this survey has a Cronbach's Alpha of 0,927 and so, deemed reliable for further analysis.

3.2. Population and sampling

Once the revised and enhanced online questionnaire was deemed suitable for distribution, a link was sent to 381 subject matter experts who are practitioners and / or consultants. The respondents were selected based on the authors' networks. Each of the respondents was contacted via email. These methodologies were adopted based on similar research in the area (Antony et al., 2019, 2021a). In addition, the respondents were contacted based on the following criteria.

(1) Respondents must be working, practising, or involved in the ZDM projects.
(2) Respondents must have been involved in at least one ZDM project in their career and at least one in the present organisation.

Continent	Respondents	Proportion
Asia	35	29,2 %
Africa	17	14,2 %
North America	13	10,8 %
South America	12	10,0 %
Europe	43	35,8 %
Australia	0	0,0 %

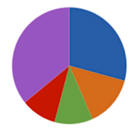

Fig. 2. Respondents' continent origin.

Company size	Respondents	Proportion
Small enterprise (1 to 49 pers.)	18	15,0 %
Medium-sized enterprise (50 to 249 pers.)	29	24,2 %
Large enterprise (250 or more pers.)	73	60,8 %

Fig. 3. Respondents' company size.

Production environments or service provisions	Respondents	Proportion
Complex customer order production	25	20,8 %
Configure-to-order production	20	16,7 %
Batch production of standardized products	31	25,8 %
Repetitive mass production	29	24,2 %
Aftermarket services	4	3,3 %
Other services	11	9,2 %

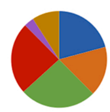

Fig. 4. Respondent company's production environment or service provision.

Company function	Respondents	Proportion
Research and development/Engineering	18	15,0 %
Design	1	0,8 %
Production	40	33,3 %
Quality management	48	40,0 %
Distribution	4	3,3 %
Customer service	2	1,7 %
Information technology	7	5,8 %

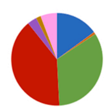

Fig. 5. Respondents' company function.

Years of experience	Respondents	Proportion
<5 years	34	28,3 %
5 - 10 years	26	21,7 %
10 - 20 years	32	26,7 %
>20 years	28	23,3 %

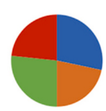

Fig. 6. Respondents' years of experience.

Function level	Respondents	Proportion
Top management	29	24,2 %
Middle management	49	40,8 %
Frontline management	21	17,5 %
Support staff / operations	21	17,5 %

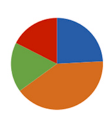

Fig. 7. Respondents' functional level.

(3) Respondents must have at least one year of experience in the execution of ZDM projects

(4) Respondents must be working in the manufacturing or service sector.

These selection criteria bring credibility to the findings and assist in drawing robust inferences. A total of 120 respondents participated in the survey over six months, with a response rate of 31%, which is acceptable in the survey research methodology (Antony et al., 2021b; Easterby-Smith et al., 2012). The companies in this survey are large enterprises mainly operating in Europe (see Figs. 2 and 3). They represent all production environments and service provisions (see Fig. 4; description can be found in appendix A). Most of the respondents work in production and quality management, have more than 10 years of experience in this field, and identify themselves as top- or middle management (as shown in Figs. 5, 6 and 7).

4. Survey results and findings

In this section, the survey results are presented and compared to the ZDM knowledge landscape (as described in Section 2), paving the way for future research in ZDM.

4.1. Current state of practice of ZDM in manufacturing companies

The ZDM strategies of detection and prevention are applied strongest in the respondents` companies (Fig. 8). The detection strategy has since the beginning been a cornerstone – receiving strong interest among academics and practitioners. Unsurprisingly, digital inspection and monitoring and FMEA are the most applied methods because they are mainly used for detection and prevention of defects (Fig. 9). FMEA is still strongly applied, but the ZDM research community sees this method as quite mature for defect prevention. In contrast, Industry 4.0 has pushed both the digitalization of companies and research activities in digital technologies. Besides digital inspection and monitoring, architecture and standards, and process mining are increasingly applied. An increase in company digitalization is seen as an enabler of more effective process-analyses and provides more insights.

However, not the full spectrum of digital technologies is growing and applied. Cyber-physical systems and digital twins are research areas receiving much attention in ZDM. Together, they are discussed in more than a quarter of research articles (as shown in Table 2). Despite this, they are still applied relatively infrequently in many companies. Empirical ZDM studies in these areas provide insights in specific industries and describe their benefits on ZDM, though frameworks describing their connection and applicability in ZDM are still lacking.

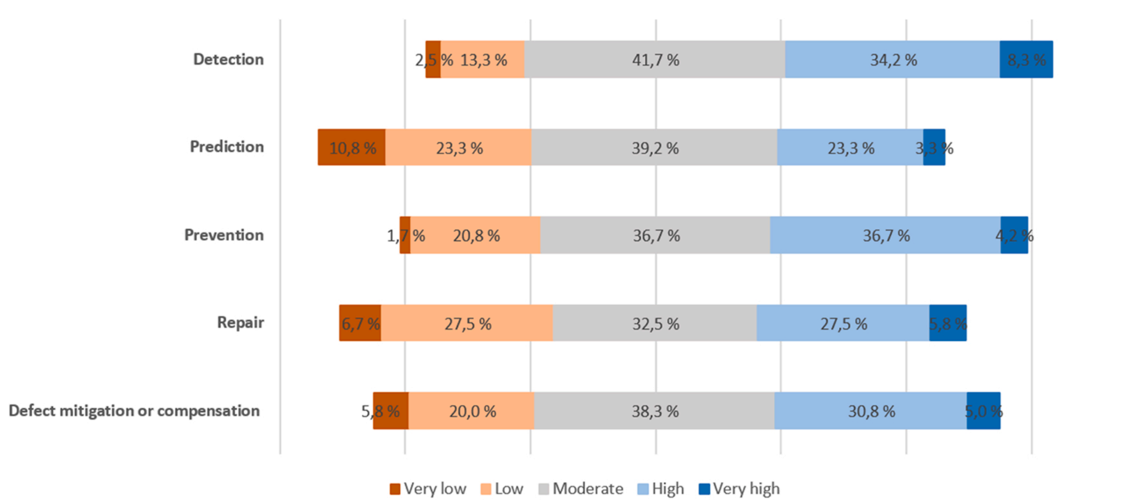

Fig. 8. Strategies applied in companies to achieve zero defects.

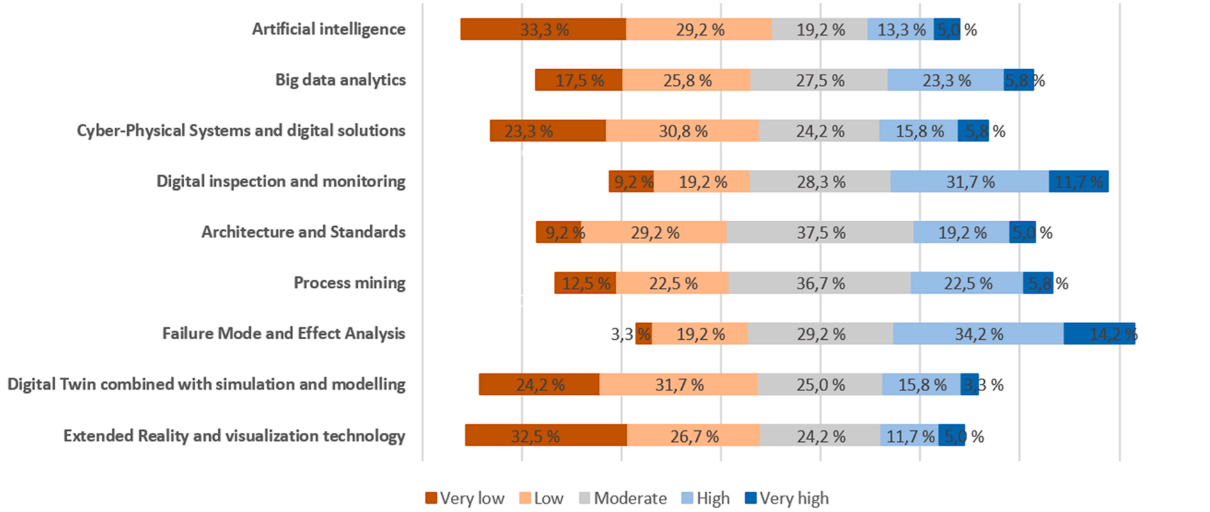

Fig. 9. Methods applied in companies to achieve zero defect.

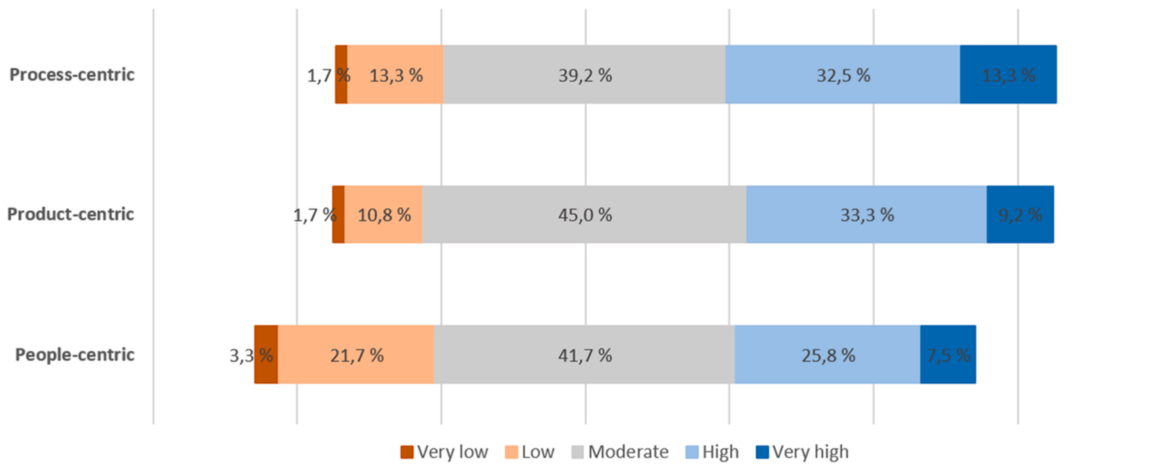

Fig. 10. Process, product and people-centric approaches applied in companies to achieve zero defects.

Moreover, future research should investigate Cyber-physical systems and digital twins in different industries. The industry-specific connections and relation need to be described to increase their implementation and usage in companies.

The potential of AI and big data analytics are still unexploited. Based on the research results, we can assume that generic or simple analyses are still the preferred means adopted for anomaly detection. Unsurprisingly, the prediction strategy is seldom applied in practice. Though more than 20% of the research studies in ZDM have focused on this strategy and introduced AI methods such as convolutional neural network, deep learning, machine learning, fuzzy logic, etc., the respondents' companies are still behind in applying this strategy and method. It is questionable, therefore, whether the companies' problems are poorly understood or if it is the provided methods that are

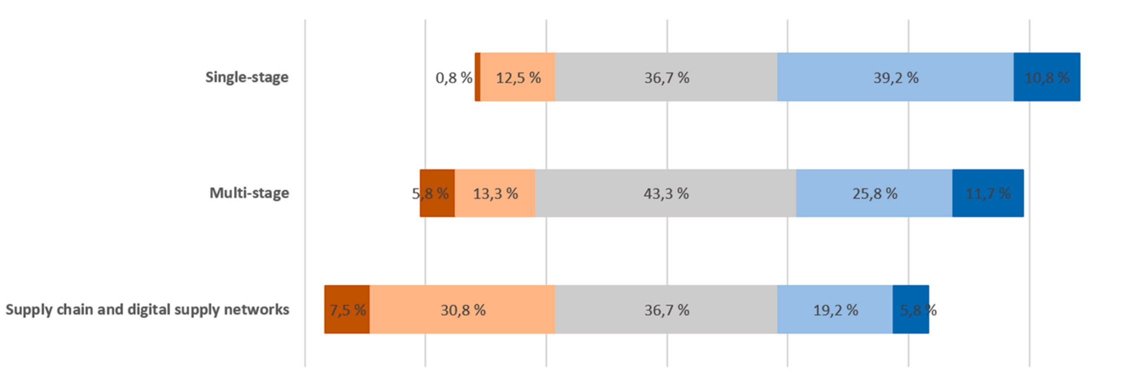

Fig. 11. Single-stage, multi-stage, supply chain and digital supply network approaches applied in companies to achieve zero defects.

inadequate in addressing the companies` problems.

Compared to the detection, prevention and prediction strategies, the defect mitigation and compensation has received relatively low attention from academia, but more of the survey respondents have applied this method in practice. It seems that companies try to mitigate or compensate defects instead of repairing them. The repair strategy is the second lowest applied strategy. Reworking/re-manufacturing of products throughout circular supply chains is still less integrated in companies' current business models. The ZDM paradigm needs to support companies in developing circular processes. However, frameworks, methods and studies moving ZDM towards sustainable development and zero waste are still lacking. The sustainability aspect in ZDM must therefore explore its environmental and social impact.

People-centric approaches are still far behind the other approaches (Fig. 10). As highlighted in previous studies and confirmed in this one (Powell et al., 2022; Wan and Leirmo, 2023), ZDM follows foremost process and product-centric approaches. People-centric approaches have still to catch up. Human factors need to be incorporated in manufacturing systems and their cognitive and motor skills should be enhanced to increase production performance. The role of humans in ZDM has until now been overlooked. Further, technologies to support them (such as extended reality) are some of the least applied in practice.

ZDM is still quite focused on individual and discrete production processes. Single-stage approaches in production systems are mainly investigated to improve production performance in both practice and academia (Fig. 11). Cyber-physical systems, digital twins and digital platforms have been promoted to increase information sharing and manufacturing collaboration to reduce defects. ZDM should also investigate and provide methods and technologies to support the transition from single- to multi-stage and/or supply chain and digital supply network approaches.

4.2. Limitation and barriers in implementing and applying ZDM

The main barriers in ZDM currently concern the low knowledge and training in implementing and applying ZDM strategies and methods (Fig. 12). The awareness of ZDM needs to be increased on a general level and academia must provide more guidelines and lessons learned in implementing and applying ZDM strategies and methods. Most respondents confirm that they have identified suitable projects for ZDM, and they have both commitment from top management to shop floor level to work towards ZDM. While ZDM has strong application potential, respondents suggest that it might receive low prioritization. This can further be seen with the respondents' expression on low resource capacity for ZDM strategies and methods.

Moreover, the respondents indicate that while their companies have a good IT infrastructure in place, they are still concerned about the overall level of digitalization in their companies. Additionally, companies need to provide training and education to help employees become familiar with and effectively utilize digital technologies.

Most of the respondents disagree that companies collect too little information automatically – otherwise inhibiting the potential to reduce defects (Fig. 13). However, the usage of AI methods should be applied more frequently to yield more insights and reduce defects on a larger scale. Companies collect vast amounts of data that are often not further processed, for example to find useful insights and reduce defects. The

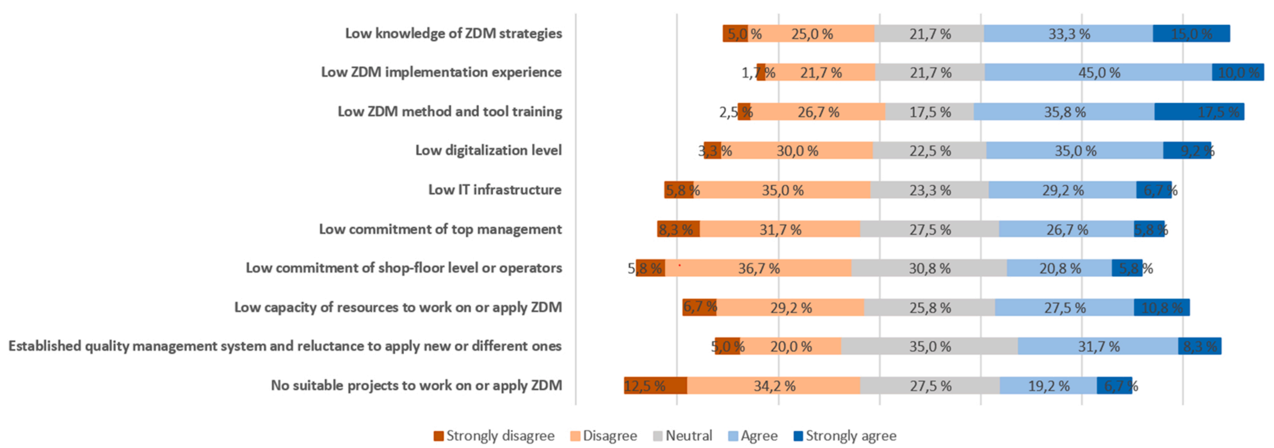

Fig. 12. Barriers of current quality management systems and methods.

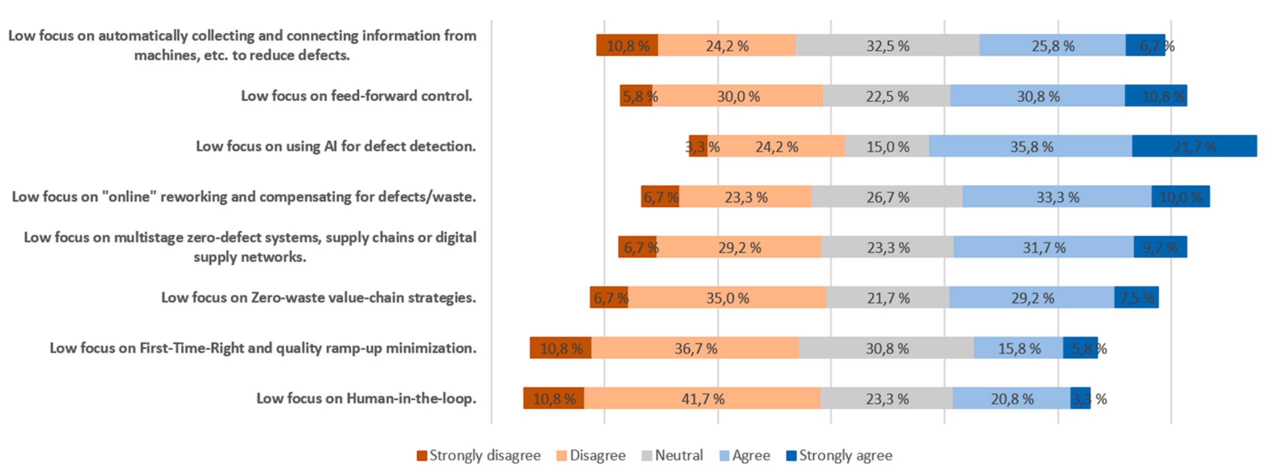

Fig. 13. Limitations of current quality management systems and methods.

identification of defects should in a stronger degree lead to feed-forward control in cyber-physical systems. This can support the reduction of an otherwise limited focus on multi-stage and digital network systems. Moreover, most of the respondents agree that there should be more focus on “online” rework and compensating defect or waste.

Respondents are undivided in their response about companies’ awareness of sustainability issues, where companies have a strong focus on both environmental aspects such as zero-waste value chains and social aspects such as human-in-the-loop. In contrast, the ZDM literature provides few empirical studies on sustainability issues. Furthermore, the respondents are clear that companies work mainly towards First-Time-Right and quality ramp-up minimization. Academics and ZDM researchers must acquire contemporary knowledge of companies’ current sustainability practices, and share this knowledge with the wider community.

4.3. ZDM impact on production performance of manufacturing companies

The strategies and methods related to detection, prediction and prevention have a strong positive impact on throughput time, product quality, waste reduction, and production cost per unit performance (as shown in Figs. 14, 15, 16, and 17). The respondents identify the prevention strategies and methods as most effective. Defect mitigation or compensation results in moderate to positive production performance effects. Repair strategies and methods are identified as having not only positive effects on production performance, but 16–22% of respondents report that repair activities in production also have a negative impact on the company’s performance. This perspective on the performance effects of repair methods is not well represented in the ZDM literature.

Overall, the ZDM strategies have the strongest positive impact on product quality performance, with the highest total value of 77.5% (as seen in Table 5). ZDM aims for the complete elimination of defects and errors, and serves as a mean of achieving an organization’s "first-time-right" (Raabe et al., 2018). As a result, most studies have quality performance as the main objective (Caiazzo et al., 2022; Powell et al., 2022). According to respondents, the prediction strategy has the strongest positive impact on production quality performance. Practitioners should consider this strategy when focusing on improving product quality performance. The study by Caiazzo et al., 2022 provides an overview of the most prominent methods for predicting product quality performance.

The detection, prediction, and prevention strategies have similar

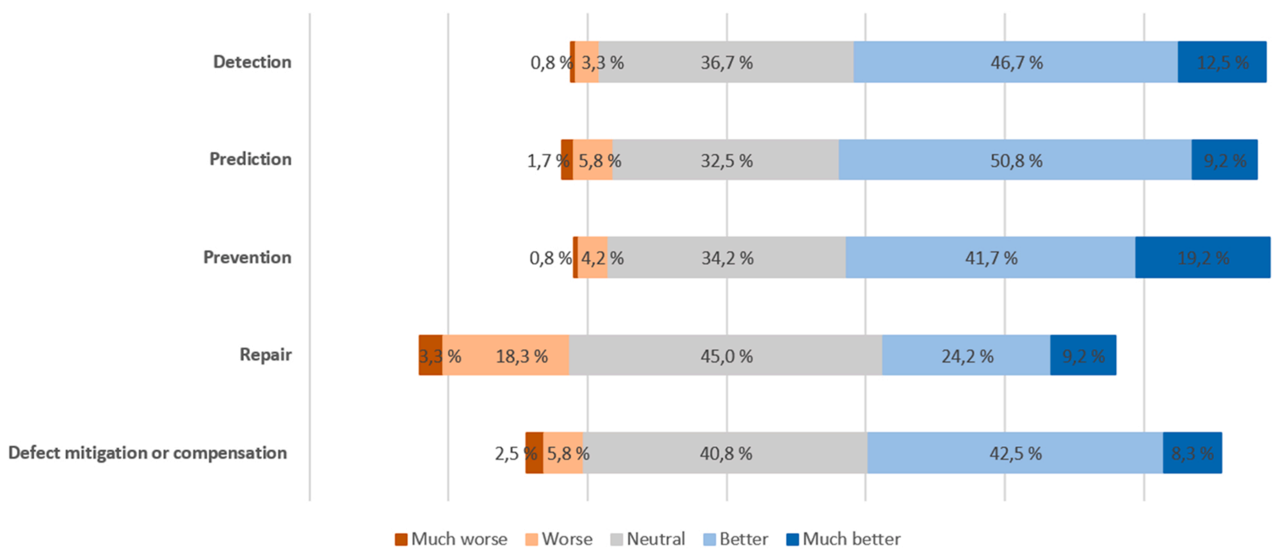

Fig. 14. Throughput time performance effects of applying ZDM strategies.

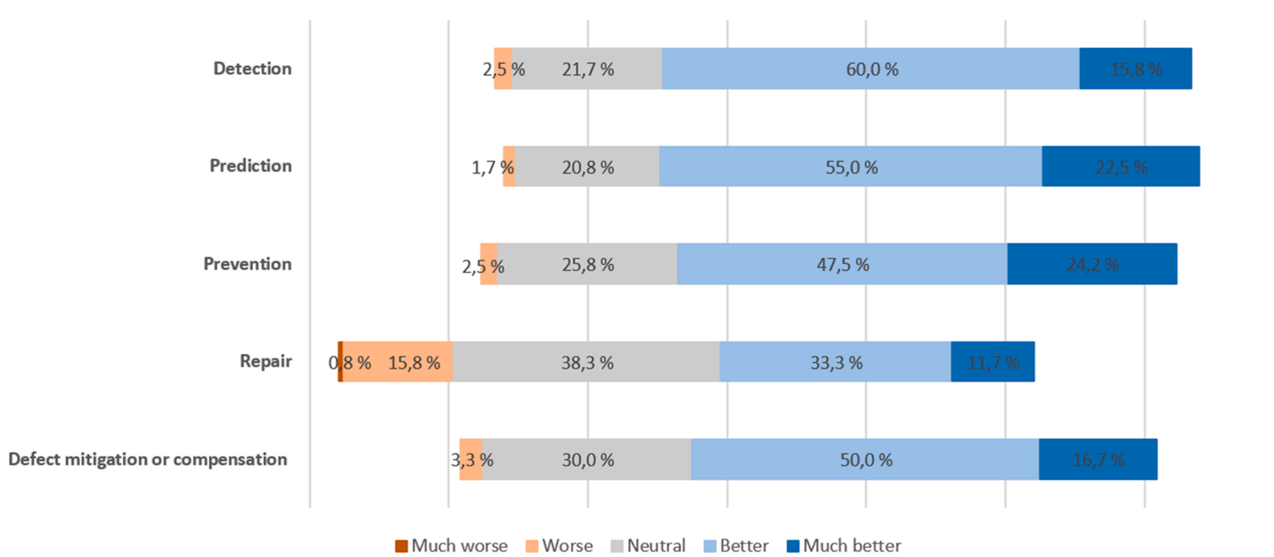

Fig. 15. Product quality performance effects of applying ZDM strategies.

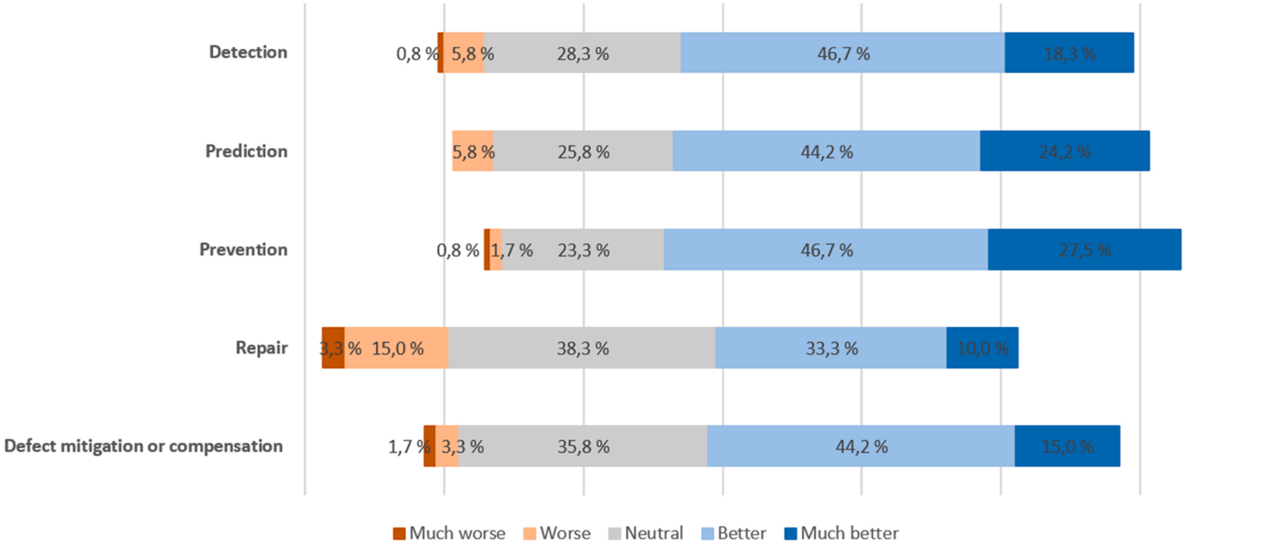

Fig. 16. Waste performance effects of applying ZDM strategies.

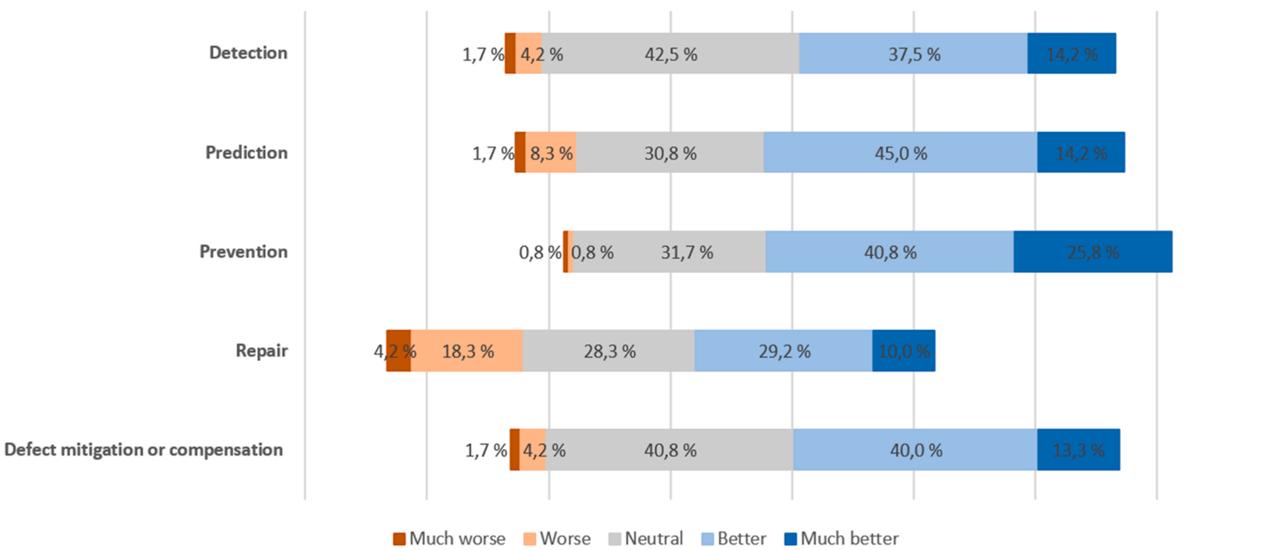

Fig. 17. Production cost per unit performance effects of applying ZDM strategies.

Table 5
ZDM strategies filtered on positive impact on production performance (Values show the % sum of "better" and "much better").

ZDM strategies	Throughput time	Product quality	Waste performance	Production cost per unit performance
Detection	59,2 %	75,8 %	65,0 %	51,7 %
Prediction	60,0 %	**77,5 %**	68,4 %	59,2 %
Prevention	60,9 %	71,7 %	74,2 %	66,6 %
Repair	33,4 %	45,0 %	43,3 %	39,2 %
Defect mitigation or compensation	50,8 %	66,7 %	59,2 %	53,3 %

* Green marked cells are the highest values within the single performance column
** Bold marked cell is the highest value across all performance columns

effects on throughput time. The prevention strategy is more effective (60.9%) and has a stronger yield (19.2%) compared to the others. According to ZDM literature, reducing defects and errors leads to improved throughput time. Caiazzo et al. (2022) suggests that combining ZDM strategies and methods may result in higher throughput time performance yield.

However, as the focus on sustainable production grows, it is essential for ZDM strategies to assist manufacturing companies to continuously deliver higher quality products of increasing complexity at lower cost, while simultaneously limiting the use (and particularly waste) of resources within entire industrial ecosystems (Colledani et al., 2014a). The prevention strategy has been found to have the greatest impact on reducing waste in ZDM. The primary method employed in prevention is FMEA (as outlined in Section 2) and as confirmed by this study (as shown in Fig. 9). As suggested by (Powell et al., 2022), ZDM should place a greater emphasis on implementing non-destructive inspection methods and quality monitoring solutions to detect defects without using or wasting materials, as well as methods for preventing defects and waste. The survey shows that companies are increasingly turning to digital inspection and monitoring (as seen in Fig. 9) in order to move towards a more sustainable approach.

Furthermore, ZDM strategies that target the reduction of defective parts, energy consumption, and scrap materials, among other performance indicators, are expected to lead to cost savings (Psarommatis et al., 2020a). However, only a limited number of studies have presented evidence or cost functions demonstrating the impact of ZDM on production costs per unit. The survey findings suggest that ZDM strategies have a significant impact on production costs per unit and the prevention strategy is the most suitable choice for attaining the highest performance yield.

5. Practical and managerial implications

For rapid improvement of production performance, companies should apply detection and prevention strategies for ZDM. Literature provides an extensive repertoire of methods and tools and the companies applying them achieve high impact over all the different measured performance dimensions of throughput time, product quality, waste performance and production cost per unit. Companies can of course continue to utilize traditional methods such as FMEAs, which can be enhanced by modern and innovative technologies such as digital inspection and monitoring.

Many companies experience that the prediction strategy can significantly improve production performance. The prediction strategy relies mainly on AI methods that often require additional resources and knowledge for companies to implement and successfully operate (PS). A majority of the companies have indicated that they struggle in the implementation of ZDM strategies and have low method training. Companies need to train and specialize their workforce in implementing and applying advanced analytical and predictive methods such as convolutional neural networks, deep learning, machine learning, fuzzy logic, etc. Companies should focus on closing this knowledge gap.

Further, companies still lack the application of advanced methods such as AI, Big data analytics, CPS, digital twin combined with simulation and modelling and extended reality and visualization technology to move towards ZDM. The IT infrastructure is for a great majority of companies at a sophisticated level. Companies need to shift their focus from simply establishing an IT communication system towards building on it and integrating advanced digital tools. Companies indicate that they have an abundance of projects to work on ZDM, with which comes great opportunity to advance production systems with digital technologies. Companies also need to establish the required working culture and increase the knowledge in applying digital technologies for ZDM.

Moving towards circular supply chains and focusing to decrease waste, companies need also to increase the efficiency of repair and reuse activities. Companies will soon become obligated to increase the repair of defective parts and products. The inefficiency in the workstations for “offline” repairing needs to be reduced and more “online” repairing should be applied. Repairing methods need to be harmonized with production systems instead of having separate inefficient and time-consuming repair points close to the production lines. Further, deviation and defects need to be detected instantly. Therefore, companies need to apply a wider degree of CPS and digital solutions across the production systems and connect them to multi-stage systems or networks. This will enable companies to detect deviations and increase the feed-forward control to compensate and mitigate defects.

Finally, increasing the digitalization maturity level in companies will not necessarily reduce the role of engineers and operators in manufacturing companies. Human cognitive and motor skills remain advantageous in many areas. However, human errors are inevitable. Applying ZDM methods can especially reduce the demand on humans in repetitive / tedious tasks to reduce defects. Many technological enablers still do not focus on supporting humans by providing the right data, in the right quantity / format, at the right place, and at the right time. Companies should therefore increase data visualization (e.g., through xR and dashboards) for their workforce and so improve decision making and production performance.

6. ZDM research needs

ZDM has evolved from a zero-defect concept to a zero-defect paradigm enhancing production management, quality management and maintenance management. Mapping the current state of ZDM practices in companies and its performance effects supports the forming of future research directions of ZDM. Our survey reflects a representative segment of today’s global ZDM practice in companies, and highlights the following future research needs:

6.1. ZDM strategies

- The prediction strategy has a strong positive impact on companies’ overall performances. However, this strategy is compared to the others, less implemented and applied. More empirical studies are needed to provide guidance and best practices in implementing and applying this strategy.
- Both academics and practitioners need to increase their focus on repair strategies. In the transition from linear- to circular economy, this strategy can strongly support the move towards a zero-defect, zero-waste paradigm. Therefore, future research should investigate repair and remanufacture methods.
- While companies increasingly work to mitigate defects, academia has not grasped this knowledge and shared crucial insights. More empirical studies are needed to strengthen the defect mitigation strategy.

6.2. ZDM approaches

- Moving towards Industry 5.0, production systems should focus more on human-centricity. Human-centric approaches are still lacking in ZDM. Future research must provide frameworks, methods and tools to support the human-in-the-loop perspective of production systems to improve production performance.
- The increase in digitalization should lead to an increase in communication between single-stage processes and machines. ZDM has a rich knowledge of single-stage and needs to develop it for system perspective. More studies and methods in connecting multi-stage processes are required.
- Increasing the decentralization of production systems and moving towards digital production networks can further yield in the reduction of defects. More studies are needed which provide methods to collaborate in digital production networks.

6.3. ZDM methods

- The increasing digitalization in companies allows application of advanced AI techniques and analysis of large amounts of data. Many studies introduced AI methods for ZDM, however, these methods are still less applied in practice. As described in this study and confirmed in a previous study, AI methods for ZDM should not only focusing on specific industry processes and industries (Caiazzo et al., 2022). Future research needs to introduce AI methods that are more applicable to a wider industrial audience.
- Shopfloor digitalization enables the development of digital twins and CPSs. Simulation modeling based on real-time data can improve the decision-making processes, however digital twins and CPSs are still less applied to improve production performance. Future research needs to provide digital twins for enhanced decision making and CPSs that address time-relevant issues (such as energy-efficiency) and connect production systems.
- Human-centric approaches support operators with a high amount of useful and useable data in decision-making processes. Extended reality (xR) and visualization technologies can significantly contribute to improving these processes. Future research should therefore investigate how to further support and augment the operator in working towards zero defects.

6.4. ZDM barriers and limitations

- Awareness of ZDM needs to be increased on a general level and shared in different communication channels. Further, academics and policymakers must provide more guidelines and lessons learned in implementing and applying ZDM strategies and methods.
- Manufacturing and service companies produce large amounts of data and often use only a small percentage of this data to improve processes. Companies need support in increasing the usage of data to yield more insights and reduce defects at a higher scale.
- Companies need not only to reduce physical waste, but also digital waste. Future research needs to provide methods to move away from inefficient “offline” rework towards efficient “online” defect prevention.

6.5. ZDM impact on production performance

- Approximately 1 in 5 of the respondents experienced that the repair strategy and methods negatively impacted on production performance. Future research needs to investigate the companies’ difficulties and provide methods that support their resolution. To transition and succeed with circular economy, academics must support practitioners in eliminating the inefficiencies in linked processes.
- Many of the respondents experienced a neutral impact on production performance after applying ZDM strategies and methods. Applying ZDM strategies, methods, and tools should in the future significantly increase the production performance. This is a significant finding of the research.
- The production cost per unit performance can in some case still be reduced. Future research should investigate the cost drivers for ZDM implementation and application and so introduce methods and tools to reduce the costs.

7. Conclusion

ZDM is a disruptive concept that provides traditional production strategies and methods with advanced digital / technological enhancement. While scientific knowledge within this area has exponentially increased, the actual extent of adopting such ZDM practices, and the impact of doing so, otherwise remains unknown. This paper set out to map the current state of practice in ZDM, to identify its impact on production performance, and to highlight future applied-research needs. The survey results show that ZDM strategies and methods are widely applied and can have a strong positive impact on production performance, though the potential has not yet been achieved. The findings also indicate that although digital technologies are increasingly used, the potential of both AI and xR is still less exploited. We contribute to the theory by detailing the ZDM research needs from the practitioner’s perspective and suggesting actions to enhance ZDM strategies and methods. Further, we provide practical and managerial suggestions to improve production performances and move towards sustainable development and zero waste.

However, some limitations of this research should be noted. When using self-administered questionnaires to gather data, there are risks associated with the respondents not understanding the question or under- or overestimating their actual implementation and application level. Although the measurement instrument was developed with this in mind, with clear descriptions of all questions, this limitation should be noted.

Next, the respondents were guaranteed anonymity. However, there might be a social desirability bias in their responses, in which they assess their implementation level and production performance to be higher than they actually are. As the respondents were promised anonymity and would not gain anything from making their responses seem more positive than was really the case, we expect that this is not a major concern in this study.

Finally, the sample size for a global study is slightly smaller than some of the prominent studies in this field. However, it is still within the recommendation of Forza (2002) and Hair et al. (2010) and so allowing to further analyse and interpret the empirical data. Therefore, future research should examine if there are correlations between specific ZDM methods and tools and production performance. Additionally, it should investigate if contextual factors such as company size, production environment, or service provision have a significant impact on the implementation and applicability of ZDM methods and tools. These investigations can support the application of ZDM methods and tools in diverse production environments (or indeed service providers) and so achieve significant improvement in production performance.

CRediT authorship contribution statement

Giuseppe Fragapane: Conceptualization, Methodology, Formal analysis, Visualization, Writing – original draft, Writing – review & editing. **Ragnhild Eleftheriadis:** Conceptualization, Investigation. **Daryl Powell:** Conceptualization, Investigation, Validation, Writing – original draft, Writing – review & editing**. Jiju Antony:** Conceptualization, Investigation, Validation.

Declaration of Competing Interest

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

Data Availability

Data will be made available on request.

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Appendix A

Production environment

Complex customer order production- This type of production implies a low volume, low standardization, and high product variety type of production. The most characteristic feature of this production environment is that the products are more or less designed and engineered to customer order (i.e. it is an engineer-to-order type of operation). Manufacturing batch sizes are typically small and equivalent to the customer order quantity. Products are complex with deep and wide bills of material. The manufacturing throughput times and the delivery lead times are long.

Configure-to-order production

The products produced in this environment have less complexity and are assembled in small batches, based on what kind of customization the customer wants. It can be characterized as an assemble-to-order or make-to-order type of operation, where many optional products can be configured and manufactured by combining standardized and stocked components and semi-finished items. The number of customer orders is rather large and the delivery lead times are much shorter than for complex customer order production.

Batch production of standardized products

This environment can mainly be characterized as make-to-stock of standardized products in medium- to large-sized quantity orders. These products are typically more complex and have a longer lead time than repetitive mass production.

Repetitive mass production

In this production environment, products are made in large volumes on a repetitive and more or less continuous basis. It involves standardized products made or assembled from standardized components characterized by having flat and simple bills of materials.

Aftermarket services

The provision of parts replacement services, repair services, maintenance services, and digital services to promote safe, secure, and comfort usage of equipment or products in the market (at the end-user).

Other services.

References

Antony, J., Lancastle, J., McDermott, O., Bhat, S., Parida, R., Cudney, E.A., 2021a. An evaluation of Lean and Six Sigma methodologies in the national health service. Int. J. Qual. Reliab. Manag.

Antony, J., McDermott, O., Sony, M., Fernandes, M.M., Ribeiro, R.V.C., 2021b. A study on the Ishikawa's original basic tools of quality control in South American companies: results from a pilot survey and directions for further research. TQM J.

Antony, J., Lizarelli, F.L., Fernandes, M.M., Dempsey, M., Brennan, A., McFarlane, J., 2019. A study into the reasons for process improvement project failures: results from a pilot survey. Int. J. Qual. Reliab. Manag.

Ball, H.L., 2019. Conducting online surveys. J. Hum. Lact. 35, 413–417.

Bhowmik, S., Ray, A., 2019. Prediction of surface roughness quality of green abrasive water jet machining: a soft computing approach. J. Intell. Manuf. 30, 2965–2979.

Bosi, I., Rosso, J., Ferrera, E., Pastrone, C., 2020. IIot platform for agile manufacturing in plastic and rubber domain. Presente IoTBDS 436–444.

Buer, S.-V., Strandhagen, J.W., Semini, M., Strandhagen, J.O., 2020. The digitalization of manufacturing: investigating the impact of production environment and company size. J. Manuf. Technol. Manag.

Buer, S.-V., Semini, M., Strandhagen, J.O., Sgarbossa, F., 2021. The complementary effect of lean manufacturing and digitalisation on operational performance. Int. J. Prod. Res. 59, 1976–1992.

Caccamo, C., Eleftheriadis, R., Magnanini, M.C., Powell, D., Myklebust, O., 2021. A Hybrid Architecture for the Deployment of a Data Quality Management (DQM) System for Zero-Defect Manufacturing in Industry 4.0. Presented at the IFIP International Conference on Advances in Production Management Systems. Springer, pp. 71–77.

Caiazzo, B., Nardo, Di, Murino, M., Petrillo, T., Piccirillo, A., Santini, S, G., 2022. Towards Zero Defect Manufacturing paradigm: a review of the state-of-the-art methods and open challenges. Comput. Ind. 134, 103548.

Cao, X., Deng, Y., 2019. A new geometric mean FMEA method based on information quality. IEEE Access 7, 95547–95554.

Chen, H.-T., 2016. Quality function deployment in failure recovery and prevention. Serv. Ind. J. 36, 615–637.

Chen, Z., Gryllias, K., Li, W., 2019. Mechanical fault diagnosis using convolutional neural networks and extreme learning machine. Mech. Syst. Signal Process. 133, 106272.

Choi, B.C., Pak, A.W., 2005. Peer reviewed: a catalog of biases in questionnaires. Prev. Chronic Dis. 2.

Colledani, M., Coupek, D., Verl, A., Aichele, J., Yemane, A., 2014a. Design and evaluation of in-line product repair strategies for defect reduction in the production of electric drives. Procedia CIRP 21, 159–164.

Colledani, M., Tolio, T., Fischer, A., Iung, B., Lanza, G., Schmitt, R., Váncza, J., 2014b. Design and management of manufacturing systems for production quality. CIRP Ann. 63, 773–796.

Colledani, M., Coupek, D., Verl, A., Aichele, J., Yemane, A., 2018. A cyber-physical system for quality-oriented assembly of automotive electric motors. CIRP J. Manuf. Sci. Technol. 20, 12–22.

Dalenogare, L.S., Benitez, G.B., Ayala, N.F., Frank, A.G., 2018. The expected contribution of Industry 4.0 technologies for industrial performance. Int. J. Prod. Econ. 204, 383–394.

Easterby-Smith, M., Thorpe, R., Jackson, P.R., 2012. Management Research. Sage.

Eger, F., Coupek, D., Caputo, D., Colledani, M., Penalva, M., Ortiz, J.A., Freiberger, H., Kollegger, G., 2018. Zero defect manufacturing strategies for reduction of scrap and inspection effort in multi-stage production systems. Procedia Cirp 67, 368–373.

Eldessouky, H., Flynn, J., Newman, S., 2019. On-machine error compensation for right first time manufacture. Procedia Manuf. 38, 1362–1371.

Eleftheriadis, R., Myklebust, O., 2016. A guideline of quality steps towards zero defect manufacturing in industry. Presente Proc. Int. Conf. Ind. Eng. Oper. Manag. 332–340.

Forza, C., 2002. Survey research in operations management: a process-based perspective. Int. J. Oper. Prod. Manag.

Fowler Jr, F.J., 2013. Survey Research Methods. Sage Publications.

Fragapane, G., Ivanov, D., Peron, M., Sgarbossa, F., Strandhagen, J.O., 2022. Increasing flexibility and productivity in Industry 4.0 production networks with autonomous mobile robots and smart intralogistics. Annals of operations research 308 (1–2), 125–143.

García, V., Sánchez, J.S., Rodríguez-Picón, L.A., Méndez-González, L.C., Ochoa-Domínguez, H., de, J., 2019. Using regression models for predicting the product quality in a tubing extrusion process. J. Intell. Manuf. 30, 2535–2544.

Gautam, P., Kishore, A., Khanna, A., Jaggi, C.K., 2019. Strategic defect management for a sustainable green supply chain. J. Clean. Prod. 233, 226–241.

Hair, J.F., Anderson, R.E., Babin, B.J., Black, W.C., 2010. Multivariate data analysis: A global perspective (Vol. 7).

Huang, R., Liao, Y., Zhang, S., Li, W., 2018. Deep decoupling convolutional neural network for intelligent compound fault diagnosis. IEEE Access 7, 1848–1858.

Kang, S., Kang, P., 2017. An intelligent virtual metrology system with adaptive update for semiconductor manufacturing. J. Process Control 52, 66–74.

Kang, S., Chun, I., Kim, H.-S., 2019. Design and implementation of runtime verification framework for cyber-physical production systems. J. Eng. 2019.

Karlsson, C., 2016. Research Methods for Operations Management. Routledge, London.

Kurz, D., De Luca, C., Pilz, J., 2014. A sampling decision system for virtual metrology in semiconductor manufacturing. IEEE Trans. Autom. Sci. Eng. 12, 75–83.

Li, Y., Han, Q., Horvath, I., Zhang, G., 2019. Repairing surface defects of metal parts by groove machining and wire+ arc based filling. J. Mater. Process. Technol. 274, 116268.

Lindström, J., Lejon, E., Kyösti, P., Mecella, M., Heutelbeck, D., Hemmje, M., Sjödahl, M., Birk, W., Gunnarsson, B., 2019. Towards intelligent and sustainable production systems with a zero-defect manufacturing approach in an Industry4. 0 context. Procedia Cirp 81, 880–885.

Liu, L., Guo, Q., Liu, D., Peng, Y., 2019a. Data-driven remaining useful life prediction considering sensor anomaly detection and data recovery. IEEE Access 7, 58336–58345.

Liu, R., Yang, B., Hauptmann, A.G., 2019b. Simultaneous bearing fault recognition and remaining useful life prediction using joint-loss convolutional neural network. IEEE Trans. Ind. Inform. 16, 87–96.

Magnanini, M.C., Eger, F., Reiff, C., Colledani, M., Verl, A., 2019. A control model for downstream compensation strategy in multi-stage manufacturing systems of complex parts. IFAC-Pap. 52, 1473–1478.

Magnanini, M.C., Colledani, M., Caputo, D., 2020. Reference architecture for the industrial implementation of zero-defect manufacturing strategies. Procedia CIRP 93, 646–651.

May, G., Kiritsis, D., 2019. Zero defect manufacturing strategies and platform for smart factories of industry 4.0. Presented at the International Conference on the Industry 4.0 model for Advanced Manufacturing. Springer, pp. 142–152.

Myklebust, O., 2013. Zero defect manufacturing: a product and plant oriented lifecycle approach. Procedia CIRP 12, 246–251.

Nadimpalli, V.K., Karthik, G., Janakiram, G., Nagy, P.B., 2020. Monitoring and repair of defects in ultrasonic additive manufacturing. Int. J. Adv. Manuf. Technol. 108, 1793–1810.

Nazarenko, A.A., Sarraipa, J., Camarinha-Matos, L.M., Grunewald, C., Dorchain, M., Jardim-Goncalves, R., 2021. Analysis of relevant standards for industrial systems to support zero defects manufacturing process. J. Ind. Inf. Integr. 23, 100214.

Ngo, Q.H., Schmitt, R.H., 2016. A data-based approach for quality regulation. Procedia CIRP 57, 498–503.

Park, P., Marco, P.D., Shin, H., Bang, J., 2019. Fault detection and diagnosis using combined autoencoder and long short-term memory network. Sensors 19, 4612.

Petrillo, A., Picariello, A., Santini, S., Scarciello, B., Sperlí, G., 2020. Model-based vehicular prognostics framework using Big Data architecture. Comput. Ind. 115, 103177.

Pombo, I., Godino, L., Sánchez, J.A., Lizarralde, R., 2020. Expectations and limitations of cyber-physical systems (CPS) for advanced manufacturing: a view from the grinding industry. Future Internet 12, 159.

Powell, D., Magnanini, M.C., Colledani, M., Myklebust, O., 2022. Advancing zero defect manufacturing: a state-of-the-art perspective and future research directions. Comput. Ind. 136, 103596.

Principi, E., Rossetti, D., Squartini, S., Piazza, F., 2019. Unsupervised electric motor fault detection by using deep autoencoders. IEEECAA J. Autom. Sin. 6, 441–451.

Psarommatis, F., May, G., Dreyfus, P.-A., Kiritsis, D., 2020a. Zero defect manufacturing: state-of-the-art review, shortcomings and future directions in research. Int. J. Prod. Res. 58, 1–17.

Psarommatis, F., Prouvost, S., May, G., Kiritsis, D., 2020b. Product quality improvement policies in industry 4.0: characteristics, enabling factors, barriers, and evolution toward zero defect manufacturing. Front. Comput. Sci. 2, 26.

Raabe, H., Myklebust, O., Eleftheriadis, R., 2018. Vision based quality control and maintenance in high volume production by use of zero defect strategies. Presented at the International Workshop of Advanced Manufacturing and Automation. Springer, pp. 405–412.

Romero, D., Stahre, J., 2021. Towards The Resilient Operator 5.0: The Future of Work in Smart Resilient Manufacturing Systems. Presented at the 54th CIRP Conference on Manufacturing Systems.

Romero, D., Stahre, J., Wuest, T., Noran, O., Bernus, P., Fast-Berglund, Å., Gorecky, D., 2016. Towards an operator 4.0 typology: a human-centric perspective on the fourth industrial revolution technologies. Presented at the proceedings of the international conference on computers and industrial engineering (CIE46), Tianjin, China, pp. 29–31.

Saunders, M.N., Skinner, D., LEWICKI, R., 2010. 16 Emerging themes, implications for practice, and directions for research. Organ. Trust 407.

Schmidt, G., Hanitzsch, T., 2012. Managing data for a zero defect production-the contribution of manufacturing automation to a corporate strategy. Presented at the 2012 IEEE International Conference on Automation Science and Engineering (CASE), IEEE, pp. 70–73.

Shiokawa, H., Ishii, N., 2019. A method of collaborative inspection planning by integrating a production planning system. Procedia Manuf. 39, 727–736.

Soualhi, M., Nguyen, K.T., Soualhi, A., Medjaher, K., Hemsas, K.E., 2019. Health monitoring of bearing and gear faults by using a new health indicator extracted from current signals. Measurement 141, 37–51.

Susto, G.A., Pampuri, S., Schirru, A., Beghi, A., De Nicolao, G., 2015. Multi-step virtual metrology for semiconductor manufacturing: a multilevel and regularization methods-based approach. Comput. Oper. Res. 53, 328–337.

Tabernik, D., Šela, S., Skvarč, J., Skočaj, D., 2020. Segmentation-based deep-learning approach for surface-defect detection. J. Intell. Manuf. 31, 759–776.

Tian, Z., 2012. An artificial neural network method for remaining useful life prediction of equipment subject to condition monitoring. J. Intell. Manuf. 23, 227–237.

Vafeiadis, T., Ioannidis, D., Ziazios, C., Metaxa, I., Tzovaras, D., 2017. Towards robust early stage data knowledge-based inference engine to support zero-defect strategies in manufacturing environment. Procedia Manuf. 11, 679–685.

Wan, P.K., Leirmo, T.L., 2023. Human-centric zero-defect manufacturing: State-of-the-art review, perspectives, and challenges. Comput. Ind. 144, 103792.

Wang, G., Ledwoch, A., Hasani, R.M., Grosu, R., Brintrup, A., 2019. A generative neural network model for the quality prediction of work in progress products. Appl. Soft Comput. 85, 105683.

Wang, Y., Pan, Z., Yuan, X., Yang, C., Gui, W., 2020. A novel deep learning based fault diagnosis approach for chemical process with extended deep belief network. ISA Trans. 96, 457–467.

Wright, B., Schwager, P.H., 2008. Online survey research: can response factors be improved? J. Internet Commer. 7, 253–269.

Xu, Y., Sun, Y., Liu, X., Zheng, Y., 2019. A digital-twin-assisted fault diagnosis using deep transfer learning. IEEE Access 7, 19990–19999.

Yuan, X., Zhou, J., Huang, B., Wang, Y., Yang, C., Gui, W., 2019. Hierarchical quality-relevant feature representation for soft sensor modeling: a novel deep learning strategy. IEEE Trans. Ind. Inform. 16, 3721–3730.

Zhang, A., Luo, W., Shi, Y., Chia, S.T., Sim, Z.H.X., 2016. Lean and Six Sigma in logistics: a pilot survey study in Singapore. Int. J. Oper. Prod. Manag.

Zheng, T., Ardolino, M., Bacchetti, A., Perona, M., 2021. The applications of Industry 4.0 technologies in manufacturing context: a systematic literature review. Int. J. Prod. Res. 59, 1922–1954.

Zhou, Q., Chen, R., Huang, B., Liu, C., Yu, J., Yu, X., 2019. An automatic surface defect inspection system for automobiles using machine vision methods. Sensors 19, 644.