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Human-centric zero-defect manufacturing: State-of-the-art review, perspectives, and challenges

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ABSTRACT

Zero defect manufacturing (ZDM) aims at eliminating defects throughout the value stream as well as the cost of rework and scrap. The ambitious goal of zero defects requires the extensive utilization of emerging technologies. Amidst the major drive for technological advancement, humans are often kept out of the loop because they are perceived as the root cause of error. The report from the European Commission on Industry 5.0 emphasizes that human-centric is a key pillar in building a more resilient industry and is vital to incorporate the human component into the manufacturing sector. However, we did not find any publications that explain what human-centric ZDM is, nor what the roles of humans are in advancing ZDM. As a contribution to bridging this gap, a systematic literature review is conducted using different databases. We collected 36 publications and categorised them into 3 different human roles which are managers, engineers, and operators. From our search, we found out that managers play a vital role in cultivating ZDM in the entire organization to prevent errors despite the fact they often do not have direct contact with the production line as operators. Operators can help advance ZDM through knowledge capturing with feedback functions to the engineer to better design a corrective action to prevent errors. Assistive technologies such as extended reality are efficient tools used by operators to eliminate human errors in production environments. Human-centric is now a goal in the future manufacturing sector, but it could face barriers such as high technological investments and resistance to changes in their work tasks. This paper can contribute to paving the roadmap of human-centric ZDM to bring defects to zero and reposition the manufacturing sector to become more resilient.

1. Introduction

Before the industrial revolutions led to the mass adoption of digital- and automation technologies, humans were used for manual work including repetitive tasks and heavy lifting (Bejarano et al., 2019). While being a central resource in most industries, including the manufacturing sector, humans have been perceived as the weakest link because manual tasks are prone to human errors that cause variation and defects (Welfare et al., 2019). Hence, the human component was distanced from the manufacturing processes, and the human roles were gradually replaced by technology.

Leveraged by recent developments in digital production, Zero Defect Manufacturing (ZDM) is becoming a viable manufacturing paradigm in which humans play a bigger role. Zero defects started as a quality program in the 1960 s with the fundamental goal that no defects were to reach the hands of the customers (Fouch, 1965; Psarommatis et al., 2022). Modern ZDM aims at eliminating defective products throughout the value stream, effectively reducing lead times, as well as the cost of rework and scrap. As an emerging paradigm, ZDM goes beyond traditional quality approaches and aims for the complete elimination of defects (Powell et al., 2022). However, the ambitious goal of zero defects requires the integration of digital technologies including the enabling technologies of industry 4.0 and smart factories with human components (Psarommatis et al., 2020b).

The human-centric approach in ZDM could yield new insights and improvements in quality because manufacturing quality is significantly impacted by human actions (Psarommatis et al., 2020a). Despite crusading to distance humans from the production environment to eliminate human error, research indicates that including a human component can increase productivity (Pacaux-Lemoine et al., 2017). While innovative technology is important to keep up with the competition, businesses must also invest in knowledge and skills (Cattaneo et al., 2017; Synnes and Welo, 2016). The cultivation of human resources has been introduced as a third important policy in ZDM,

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alongside correction and compensation, where *"[…] automation must be capable of facilitating the mutual learning of humans and machines"* (Powell et al., 2021, p. 1353).

In 2021, The European Commission published a report on Industry 5.0 emphasising the human-centric "*revolution*" as a reaction to the highly techno-centric industry 4.0 paradigm (European Commission, 2021a). While the true form of industry 5.0 remains unclear, the European Commission predicts a move towards purposefulness where "human-centric", "resilient", and "sustainable" are the core elements (European Commission, 2021b). The role of humans in cyber-physical manufacturing systems is still being defined, and the meaning of human-centric ZDM in this context remains unclear.

Various literature reviews have re-iterated that humans are critical assets in the manufacturing sector (Powell et al., 2022; Psarommatis et al., 2020a). Currently, no literature explains and maps out what human-centric ZDM means. Therefore, this work aims to provide a clearer understanding of what human-centric ZDM entails, and what are the roles of humans in future developments in ZDM. Furthermore, the challenges and barriers have to be identified to re-align researchers and practitioners within the manufacturing sector to move towards a more holistic ZDM.

A systematic literature review is conducted to identify gaps and facilitate discussions on future directions. This provides the basis for a roadmap for further research on the human aspect of ZDM. This study aims to answer the following research questions (RQs):

- RQ 1: What are the perspectives on human-centric ZDM?
- RQ 2: What are the different roles of humans in ZDM?
- RQ 3: What are the challenges to incorporating human-centric ZDM?

This paper begins with a background explanation of human-centricity and ZDM in Section 2. Section 3 explains the research methodology in conducting the systematic literature review and material collection. Section 4 discusses the perspectives and the roles of humans in ZDM before conclusions and final remarks are made in Section 5.

2. Human-centricity and ZDM

Advanced manufacturing systems are commonly viewed as a chain of technologies with as little human intervention as possible because quality is significantly impacted by humans (Psarommatis et al., 2020a). Such techno-centric approaches are important not only to develop the industries to produce large quantities, but it is also a key factor to meet the demand for product quality and strive to reach zero-defect (Tatipala et al., 2018). For example, machines can handle repetitive work longer and faster without feeling tired, while data-driven technology which utilizes process and machine data can detect and predict error. However, this leads to a question of whether techno-centric alone is sufficient to reach zero-defects in manufacturing.

In a recent policy brief by the European Commission, the industry is urged to re-calibrate to a more human-centric approach (as opposed to one of emerging technologies) by placing human needs and interests at the heart of the production process (European Commission, 2021b). This necessitates a paradigm shift in which technologies are developed to enhance human capabilities and adapt to human needs, rather than operators adapting to new technology. In short, there is a shift from a techno-centric to a more human-centric industry.

People-centric, anthropocentric, and human-centric are terms used throughout manufacturing and other sectors to denote similar concepts, namely a focus on humans over e.g., technology (Delmastro et al., 2016; May et al., 2015; Tan et al., 2019; Zeng and Xiang, 2021). The definition of system boundaries inevitably affects the evaluation of system performance. Since our current work is situated in the manufacturing domain, the term human-centric is used herein to refer to operators, engineers, and managers. In the context of this paper, the role "manager" refers to any position of authority from top management to middle- and lower-level management. "Engineers" are those who design and develop products, as well as the machines and systems used in manufacturing. Finally, "operators" are those using the tools, systems, and machines developed by engineers. These three human roles are also highlighted in the ManuFUTURE Vision 2030 report as key research focuses on a human aspect to re-position the European manufacturing industry (ManuFUTURE, 2018).

The ZDM paradigm lends itself to many applications, and the perspective on ZDM shapes the perception of it. According to Crosby (2006, p. 59), *"[a] defect is a characteristic that does not conform to its quality standard—a mistake or an error"*. This rigid view of ZDM entails that any error or mistake – no matter how insignificant – constitutes a violation of ZDM. While Vinod et al. (2015) suggested that a mistake only becomes a defect when it reaches the customer. Intuitively, this makes more sense from a human perspective with the fundamental idea that mistakes are inevitable, and that human makes mistakes.

The human aspect has been discussed in quality management discourse where, for instance, lean manufacturing emphasizes the empowerment of employees (Sanders et al., 2016). Nevertheless, with the increased focus on the implementation of new technologies, the human aspect may easily be overlooked. Contrary to lean manufacturing, the human aspect of ZDM has received little attention and more work is required to investigate this crucial aspect of manufacturing (Powell et al., 2022). As manufacturing is increasingly digitized, for example, human interfaces in cyber-physical systems must be properly designed to enable efficient operations (Brauner and Ziefle, 2015). This translates to preventing defects in the ZDM context, while also reducing lead time.

Psarommatis et.al (2020a) developed a ZDM framework with four strategies: (i) detection, (ii) repair, (iii) prediction, and (iv) prevention (DRPP) that can be deployed in a manufacturing industry. They also present two approaches in ZDM, namely the product-oriented approach which seeks to eliminate defects in the product, and the process-oriented approach which takes the root cause perspective to find the defective process. A third approach, namely the human approach, was later emphasized in a literature review by Powell et al. (2021) where they observe that effort to incorporate humans in advancing ZDM has received little attention. ZDM paradigm plays a crucial role in minimizing defects and errors in industries with different types of technologies to increase the throughput and quality (Caiazzo et al., 2022). However, there is no work focused primarily from the point of view of humans and the current state of the art is lacking in the ZDM field.

3. Research method

A scoping review was conducted to explore the current state of the art in academic research with the widest possible coverage of all the published publications. The reporting of this scoping review was guided by PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-analysis extension for Scoping Reviews) (Tricco et al., 2018). To be as comprehensive as possible, the publications were searched on Scopus, IEEE Xplore, ScienceDirect and Web of Science because these platforms have a high coverage for high-impact and well-known publications.

To capture both human-centric and zero defect across different industries or sectors, generic keywords such as "zero defect", "human", people" and "person" were used as research criteria in the title, abstract and keywords (Scopus, ScienceDirect and Web of Science) or all metadata (IEEE Xplore) to collect relevant publications. The key strings are formulated as shown below:

In Scopus, ScienceDirect and Web of science.

- (("Zero defect" OR "Zero defects") AND ("human" OR "people" OR "person")).

In IEEE Xplore

- Zero defect* AND human
- Zero defect* AND people
- Zero defect* AND person

This study includes both journal articles and conference proceedings with no restriction on place or date of publication to gain a broader overview of the research topic. After removing duplicates, the titles and abstracts were screened for relevance before moving on to the full-text review. At this stage, the authors were unable to obtain the full-text versions of eight papers detected by Scopus. Consequently, these papers were excluded from the study, and the final sample included 36 papers that were exported to Zotero and Microsoft Excel for analysis. The selection process for the scoping review is summarized in Fig. 1.

4. Results

The final selection of publications included 36 articles where the human component could be identified together with ZDM as summarised in Table 1. The earliest included publication is the article of Cassidy (1991) who highlighted that zero defects is an obtainable goal by empowering employees. This indicates that human-centricity as a component, to complement ZDM has been emphasized for almost three decades. A common approach to reaching zero-defects is to reduce human intervention through technology such as machine learning or robots because humans generate around 50–90 % of quality-related issues in the assembly line (Pasquale et al., 2018). Schulte et. al (2020) designed a decision support system based on recorded inspection data and ML techniques to reduce human verification efforts. Tatipala et al. (2018) have a similar approach where they propose an automated procedure to analyse, interpret and configure data measured from the production system without human intervention.

Another form of a human-centric approach is to incorporate humans in the decision-making process supported by technology (Dengler et al., 2021). For example, Dengler et al. (2021) develop a system based on machine learning that presents information in understandable forms for humans to make an informed decision. A case study by Hou et al. (1993) demonstrated that a hybrid visual inspection system (human and automated system) has a high level of performance with the lowest number of false alarms compared to both human and automated inspection modes. Although these publications demonstrated promising results when incorporating humans and technology to reduce error, it is difficult to say which approach is more effective and feasible. Nonetheless, we agree with Cattaneo et.al (2017) that it is vital to invest in people skills because focusing solely on the newest technology alone will not provide the required system's capabilities in reaching the paradigm of zero-defect manufacturing.

From Fig. 2, there is a gradual and apparent increase in academic interest in human-centric ZDM starting around 2012. Most of the publications are journal articles (17/36), followed by conference publications then book chapters (7/36). The largest number of publications can be observed in 2021. This may be explained by a growing research interest and a call for more research among researchers, industry, and policymakers alike on the human aspects of ZDM. More than half of the collected publications are case studies (20/36) on how to reduce errors in different types of industries. About 26 % (9/26) of the collected publication have designed frameworks to re-position humans with technology to reach ZDM. 5 review papers are also collected where Psarommatis et al. (2020a) highlighted how human aspects are still largely neglected in ZDM. Narottam et. al (2021), a review book chapter, suggested that to achieve human-centric ZDM, in addition to human and robot interaction, environmental health and safety aspects are important to achieve zero-defects. Two (6 %) argumentative publications are

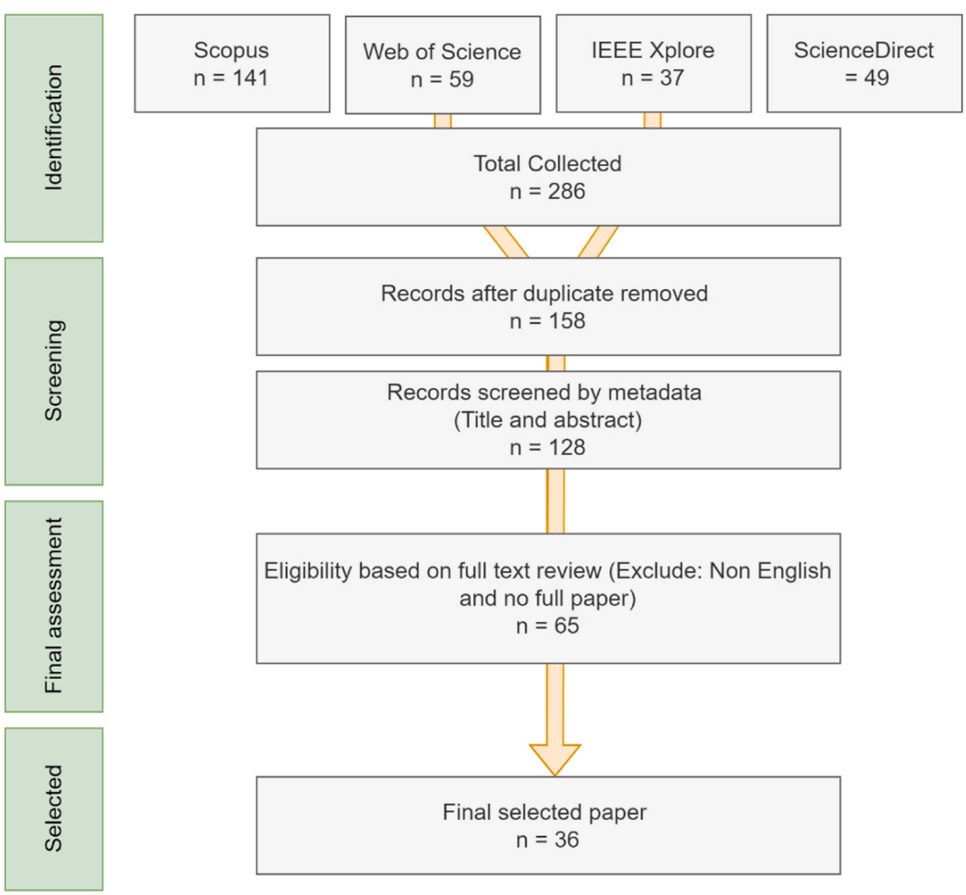

Fig. 1. Schematic overview of the screening procedure employed in the current study.

Table 1
Overview of the selected publications.

Authors	Types	Approach	Key points
(Alessio et al., 2022)	Conference	Framework	Propose an optimization framework of the assembly sequence through Robust Adversarial Reinforcement Learning to improve human-robot collaboration (e.g., non-significant mistakes should be allowed or corrected during work)
(Alogla and Alruqi, 2021a, 2021b)	Article	Case study	Identify the deeper causes of defects by considering the psychological mechanisms behind human error
(Jin et al., 2021)	Article	Framework	Develop a new correctness verification and integrity validation method in the form of a human-machine dialogue to minimize the workload and systematically control risks
(Konstantinidis et al., 2021).	Conference	Review	Machine vision is employed to automate the procedures and should integrate with the existing system to enable ZDM at the human and system level
(Powell et al., 2021)	Conference	Framework	Introduce the 3Cs: Correction, compensation, and cultivation
(Cañas et al., 2021)	Article	Review	New learning methodologies by incorporating AR will drastically change the education and training of professionals apt to work in I4.0.
(Brito et al., 2020)	Conference	Framework	Design a framework which enables humans to interact with robots using sensors (reinforced learning) to support corrective actions
(Schulte et al., 2020)	Conference	Case study	Develop a decision support system based on recorded inspection data and ML techniques to reduce human verification efforts
(Minnetti et al., 2020)	Article	Case study	Humans can be considered as a part of quality control systems when they decide on the quality aspects of automated control systems.
(Al Ayyubi et al., 2020)	Conference	Case study	Design a system to prevent problems by using the FMEA method with an automatic Poka-Yoke system to prevent human errors in preparing materials
(O'Brien and Humphries, 2019)	Conference	Case study	Computer vision has an advantage over human vision with tasks where variability is low.
(Kang et al., 2019)	Article	Framework	Design a framework by combining monitoring and simulation processes to help a worker to observe the states of the object and verify the effectiveness of control commands before applying them to a real production environment
(Ostadi and Masouleh, 2019).	Article	Case Study	FMEA methodology can identify errors in the production line. Errors caused by humans are the most frequent compared to technology and process.
(Bejarano et al., 2019)	Conference	Case study	A task requiring high-level of dexterity requires human intervention
(Reiff et al., 2018)	Conference	Framework	Design a webGL to store operators' experience and feedback, when non-conformances are identified to achieve ZDM of high-quality part through knowledge, capturing
(Wojcik and Ekielski, 2017)	Article	Case study	TPM should be considered from human and machine perspectives. One of the ways to improve operators' technical skills is that all operators should take an active role in the production line.
(Jiang et al., 2000)	Conference	Framework	An inspection system can operate in three different modes: human inspection mode, automated inspection mode and hybrid inspection mode
(Hou et al., 1993)	Article	Framework	Hybrid (human and automated system) shows a high level of performance in visual inspection, with the fewest false alarms
(Cassidy, 1991)	Article	Case study	Empowered employees can make continuous quality improvements, and demonstrates that zero-defects is an obtainable goal.
(Tatipala et al., 2018)	Article	Case study	Propose an automated procedure to analyse, interpret and configure data measured from the production system without human intervention
(Verhoosel and van Bekkum, 2017)	Book Chapter	Case study	Developed knowledge model using a data-driven approach that supports the operator with instruction and adaptive support for human/cobots instruction
(Cattaneo et al., 2017)	Book Chapter	Review	Investing in the newest technology alone will not provide the required system's capabilities, but it is crucial to invest in knowledge and people skills
(Toussaint, 2013)	Article	Argumentative	The role of the manager is to remove barriers so that the 'front line' can do their job effectively
(Crosby, 2006)	Article	Argumentative	Argues for *7 Laws of Defect Prevention* to reach zero defects
(Dengler et al., 2021)	Article	Case study	Develop a system based on machine learning to detect errors and present the information in understandable forms for humans to make an informed decision.
(Eddy et al., 2020)	Book Chapter	Case study	Introduces how FMEA/DMAIC can be automated with AI (machine learning) to assure zero defects from

(*continued on next page*)

Table 1 (*continued*)

Authors	Types	Approach	Key points
			a given inspection process to replace manual procedures
(Navarre et al., 2018).	Book Chapter	Case study	Similar interfaces at the presentation and interaction levels can reduce error and increase learnability for operators
(Beluško et al., 2016)	Article	Case study	Standardize work instruction (procedures, phases and tasks) can enhance human effectiveness in production, particularly in a semi-automated production line
(Hong et al., 2007)	Article	Case study	By training operators to have greater insights wrt. machine and process yield higher performance, and higher job satisfaction.
(Aggarwal, 2021)	Article	Framework	Explain how aligning 5 P's—People, Process, Plant (infrastructure), Parts & Product (services) can win customers' trust.
(Vinod et al., 2015)	Article	Case study	Prevention of defects accelerates a company to achieve zero-defect manufacturing
(Castillo-Pérez et al., 2019)	Book Chapter	Case study	Interdependent self-designed teams have better performance than traditional teams.
(Putri et al., 2016)	Article	Case study	Cultivating teamwork based on Toyota way philosophy can achieve the company's quality goals
(Ng et al., 2012)	Conference	Case study	Identifies barriers to implementation of TPM to reach zero defect – all of which are related to humans
(Narottam et al., 2021).	Book Chapter	Review	Environmental, health and safety, as well as people development, are important to achieve zero-defects.
(Psarommatis et al., 2020a)	Article	Review	Manufacturing quality is significantly impacted by people, but the human aspect is largely neglected.

collected where the authors argue for changes in the manager's role (Toussaint, 2013) and the implementation of "Seven laws of defect prevention" (Crosby, 2006) to reach human-centric ZDM.

Much of the published work on ZDM cannot be attributed to a single industry, and therefore falls in the category of General Manufacturing (19/36) as displayed in Fig. 3. These are typically papers that discuss the general manufactory sectors rather than within a specific industry. Beyond this observation, one may also note the relatively large number of papers originating from the automotive industry (4/36). This may come as no surprise as the industry is known for the early adoption and development of quality initiatives such as total quality management and lean. The occurrence in both healthcare (2/36) and aviation (1/36) emphasizes that the consideration of the human component to reach zero-defects goes beyond manufacturing.

The collected literature was categorized according to the four ZDM strategies from Psarommatis et al. (2020a) as displayed in Fig. 4 and tabulated in Table 2. Within the domain of human-centric ZDM, strategies related to prevention (83 %) and detection (47 %) appear most frequent which also aligns with the results from the review papers by Caiazzo et al. (2022) and Psarommatis et al. (2020a). However, our result shows more collected publications focus on prevention over detection strategies, which is the opposite, as compared to the two review papers mentioned earlier. This could be because humans are often perceived as the source of error and the common solution is to prevent humans from introducing errors in manufacturing or to replace humans in the production line. From Table 3, automation, and robots along with user interface are some of the prevention strategies in ZDM. Lean and poka-yoke are tools that are adopted in both detection and prevention strategies. From our search, both prediction and repair are the least adopted strategies, 11 % each, in moving towards ZDM. Psarommatis and Kiritsis (2022) suggested a hybrid automating decision-making using real-time production data and past knowledge not only for defect analysis but also to suggest alternative repair plans to improve production performances.

The Venn diagram in Fig. 5 illustrates how the collected publications relate to the three human roles following the classification introduced in Section 2, namely managers, engineers and operators. A total of 18 publications are aimed solely toward operators, while only 7 publications excluded the roles of operators, with 3 publications on managers and 2 on engineers. The large number of publications related to the operator role may be explained by the direct contact between operators and the product, which makes the effects of the operator's actions more easily observable. The role of the engineer is often interconnected with the operators through the development and deployment of new systems and technologies. Therefore, a significant number of papers concerns both operators and engineers. As illustrated in Fig. 5, only two publications focus on all three roles in moving towards ZDM. For example, people development by boosting the morale of and providing a healthy and safe environment for all employees can help the process of reaching zero-defect (Narottam et al., 2021). From our literature review, we agree with Psarommatis et al. (2020a) that current work on different human roles in manufacturing remains under-searched and a more holistic approach in human-centric is needed to improve the overall manufacturing effectiveness.

5. Discussion

Fig. 6 encapsulates human-centric ZDM and illustrates how the human roles prevent defective products from reaching the hands of the customers. Quality originates within the system and moves through the subsequent roles before reaching the customer. The manager is placed within this system for two reasons; (i) managers are the ones who set the direction and goals of ZDM activities; and (ii) situating managers inside the system emphasizes the integral role of management in the operation. The perceived quality may increase with each layer for instance by engineers developing tools and processes for operators to use. The quality standard put down by management also emanates through the organization and affects the quality of the final product. A rippling effect may amplify the results of minor interventions in management to become larger than analogous changes closer to the customer. The final layer in Fig. 6 is a layer of technologies that buffers between the humans in the organization and the customers. This includes all technologies utilized to move towards ZDM, either that is manufacturing technologies or information technologies. Various perspectives on the human aspect of ZDM affect the perception of human roles and create barriers to human-centric ZDM. The following subsections address the three research questions with a particular focus on the three roles of humans in ZDM.

5.1. Perspectives on the human aspect of zero-defect manufacturing

The perspective on humans as the source of error is perhaps the most prevalent in literature, and the technologies and solutions to this problem have matured over many decades (Ostadi and Masouleh, 2019). This may, however, be an underestimation of human capabilities and the role of humans in ZDM. The different perspectives on human-centric

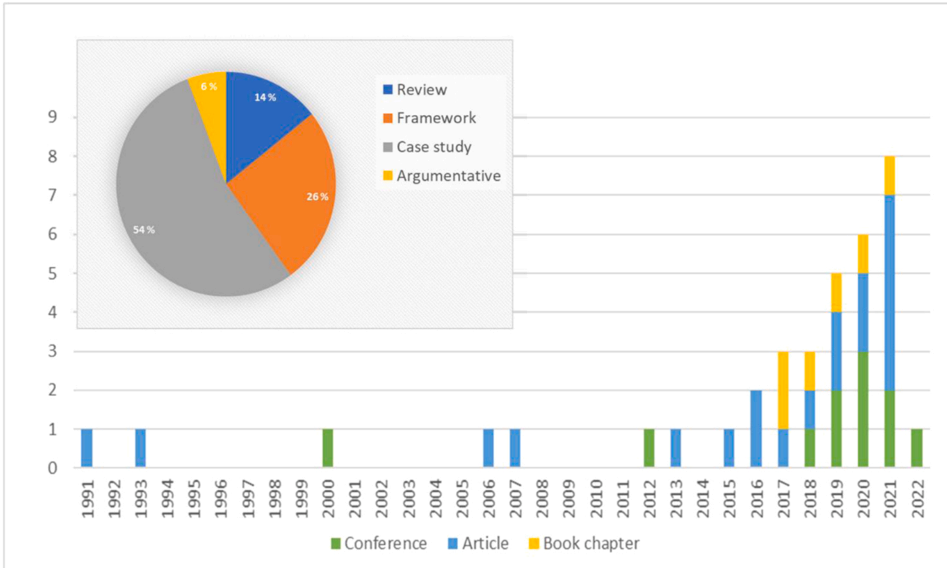

Fig. 2. Number of publications per year included in the final selection.

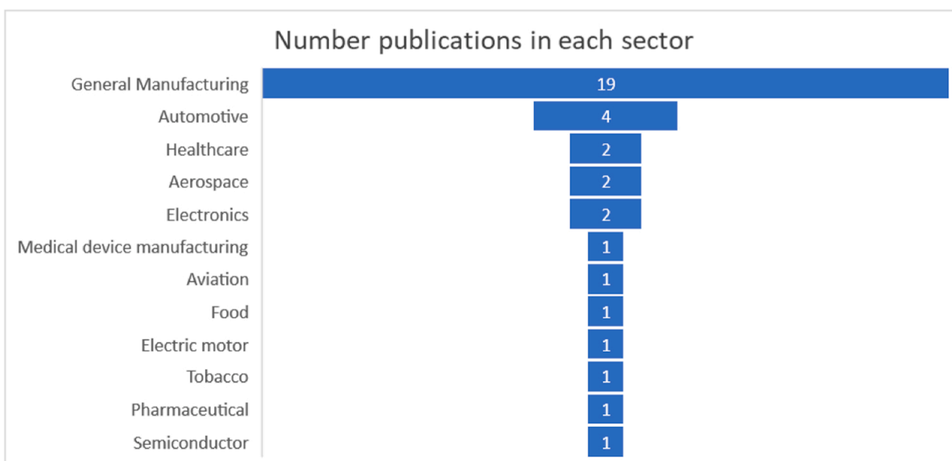

Fig. 3. Number of publications per industry among the selected publications.

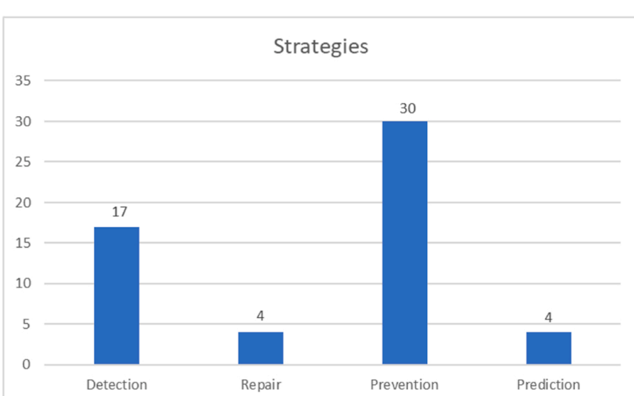

Fig. 4. Classification of publications according to the four strategies of zero-defect manufacturing (Psarommatis et al., 2020a).

ZDM lay the foundation for how we envision the future role of humans in manufacturing. Several collected publications describe how defects attributable to human error may be avoided through a combination of detection, repair, prediction, and prevention (Psarommatis et al., 2020a).

Some reflections point toward a different perspective on humans in ZDM, namely that humans are indeed capable of achieving zero-defects – not by being removed from the system, but with technological support. This implies that technology provides the quality inspection capabilities that are required to avoid defects for instance by utilizing machine vision and machine learning (Dengler et al., 2021; Konstantinidis et al., 2021). Technologies highlighted as enabling technologies of industry 4.0 are effective in predicting and detecting defects (Angelopoulos et al., 2019). However, this perspective still favours technology over people, where people are considered a source of error that must be alleviated in the system. Therefore, it is important to map out the role and reposition humans in the manufacturing sector and move towards ZDM.

In line with the industry 5.0 paradigm outlined by the European Commission (2021b), the two previous perspectives are much too technology-oriented and fail to enhance human capabilities. On the contrary, the focus of these perspectives has been on controlling and containing the damage done by human actors in the manufacturing system. However, by empowering and integrating humans with technology, the inherent capabilities of humans will enjoy the power and

Table 2
Publication sorted based on industry, strategy and ZDM tools.

Authors	Industry	Strategy	ZDM tools
Human role: Operator			
(Alogla and Alruqi, 2021a, 2021b)	Aerospace	Prevention	Poka-Yoke
(Jin et al., 2021)	Healthcare (laboratory)	Prevention	Automation
(Konstantinidis et al., 2021).	Automotive	Detection, repair	Machine vision
(Powell et al., 2021)	General manufacturing	Detection, repair, prediction and prevention	Digitalization
(Cañas et al., 2021)	General manufacturing	Prevent, detect, predict	Review
(Brito et al., 2020)	General manufacturing	Prevention	Robots and Machine learning
(Schulte et al., 2020)	Electronics	Detection	Machine learning
(Minnetti et al., 2020)	Automotive	Detection	Sensors
(Al Ayyubi et al., 2020)	General manufacturing	Detection, prevention	Poka-Yoke, FMEA
(O'Brien and Humphries, 2019)	Medical device manufacturing		
	Detection	Extended reality	
(Kang et al., 2019)	General manufacturing	Prevention	Digital Twin
(Ostadi and Masouleh, 2019).	Tobacco	Prevention	FMEA, Poka-Yoke
(Bejarano et al., 2019)	General manufacturing	Prevention	Robots
(Reiff et al., 2018)	General manufacturing	Detect, repair	Information sharing
(Wojcik and Ekielski, 2017)	Food industry	Prevention	Total Productive Maintenance (TPM)
(Jiang et al., 2000)	General manufacturing	Detection	Visual inspection
(Hou et al., 1993)	General manufacturing	Detection	Visual inspection
(Cassidy, 1991)	Electronics	Prevention	Poka-Yoke
Human role: Engineer			
(Tatipala et al., 2018)	Automotive	Prediction, prevention	Automation
(Verhoosel and van Bekkum, 2017)	General manufacturing	Prevention	Digitalization
Human role: Manager			
(Cattaneo et al., 2017)	General manufacturing	Prevention	Lean and Industry 4.0.
(Toussaint, 2013)	Healthcare	Detection, prevention	Lean
(Crosby, 2006)	General manufacturing	Prevention	Culture
Human role: Engineer and operator			
(Alessio et al., 2022)	General manufacturing	Detection, prevention	Robots, machine learning
(Dengler et al., 2021)	Pharmaceutical	Detection	Machine learning
(Eddy et al., 2020)	Aerospace	Prevention	Digitalization and Failure Modes and Effects Analysis (FMEA)
(Navarre et al., 2018).	Aviation	Prevention	User interfaces
(Beluško et al., 2016)	General manufacturing	Prevention	User interface
(Hong et al., 2007)	Automotive	Detection	Poka-Yoke
Human role: Engineer and manager			
(Aggarwal, 2021)	General manufacturing	Prevention, detection	Digitalization
		Prevention	Poka-Yoke
(Vinod et al., 2015)	General Manufacturing		
Human role: Manager and operator			
(Castillo-Pérez et al., 2019)	Electrical motor manufacturing	Prevention	Lean
(Putri et al., 2016)	General manufacturing	Prevention	Lean
(Ng et al., 2012)	Semiconductor	Prevention	TPM
Human role: Engineer, manager and operator			
(Narottam et al., 2021).	General manufacturing	Prevention, detection	Lean
(Psarommatis et al., 2020a)	General manufacturing	Detection, repair, prediction and prevention	Review

Table 3
ZDM enabling tools in each detection, repair, prediction and prevention (DRPP) strategy.

ZDM enabling tools	Detection	Repair	Prevention	Prediction
Review papers	2	1	3	2
Digitalization	2	1	4	1
Lean	2	0	4	0
Poka-Yoke	2	0	5	0
Machine learning	3	0	2	0
Automation	0	0	2	1
Robots	1	0	1	0
FMEA	1	0	3	0
User interface	0	0	2	0
TPM	0	0	2	0
Visual inspection	2	0	0	0
Machine vision	1	1	0	0
Information sharing	1	1	0	0
Sensors	1	0	0	0
XR	1	0	0	0
Digital twin	0	0	1	0
Culture	0	0	1	0
TOTAL	17	4	30	4

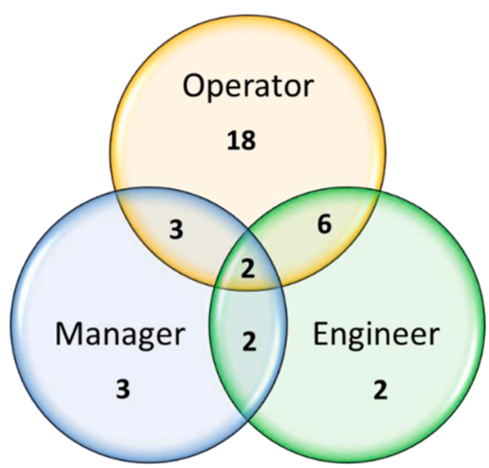

Fig. 5. Number of publications aimed toward the three different human roles.

precision of technology (Bejarano et al., 2019). This preserves the flexibility and creativity of humans, allowing them to exceed the limits imposed on technology (i.e., the boundaries within which technology operates, such as the tools available to a machining centre for instance). We argue that humans are the key to sustainable ZDM as humans exhibit important traits such as flexibility and creativity. Beyond completing tasks requiring these special abilities, the human function in the quality system is that of moderator and facilitator. Humans strategically deploy

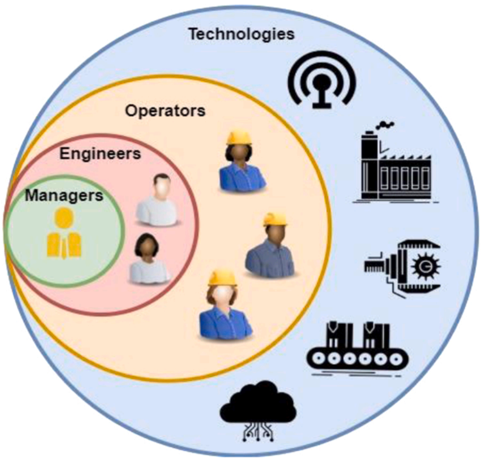

Fig. 6. Illustration of human centric zero-defect manufacturing.

technology as enabling factors for quality improvements. Consequently, human-centric ZDM needs to adopt the perspective of humans as the core of operations, support this resource with technology, and digitally enhance core competencies and capabilities.

5.2. The role of humans in zero-defect manufacturing

5.2.1. Manager

The managers of the organization play a core role in advancing ZDM, although managers are not directly involved in production. The common understanding and strategy in ZDM are to reduce potential errors caused by operators as they directly impact product quality. Crosby (2006) highlighted seven rules of zero-defects, and the first rule is that zero-defects start with the leader of the organization. Managers play a role in defining a clear vision and mission in achieving what the customers want and setting the correct performance standard in production (Putri et al., 2016). As illustrated in Fig. 6, managers have to share what zero-defects mean for the organization because this helps to bridge the employees – engineers, operators and managers alike – to prevent defective goods from reaching the hands of the customers (Aggarwal, 2021). From Fig. 5, there are only 3 publications that highlighted the need for managers' roles within a ZDM context. This may indicate that there is a trend toward redefining the role of managers in ZDM.

Managers should embrace the Gemba walk, "the real place" in Japanese, to bring problems at the production line to the surface and identify root causes (Dombrowski and Mielke, 2013; Seidel et al., 2019). Toussaint (2013) argues that managers at a hospital should not avoid Gemba walk just because they lack practical know-how, but that their role is to enable and facilitate the work being done. For example, in the healthcare sector, the managers can help to remove barriers experienced by the front-line healthcare staff in the hospital. Similarly, in the manufacturing context, managers should do Gemba walk from time to time to remove challenges faced by operators and engineers, that oftentimes are out of their control (Castillo-Pérez et al., 2019). This can also promote a culture of teamwork while also empowering operators and engineers to make continuous improvements in manufacturing (Putri et al., 2016).

5.2.2. Engineer

The engineers are responsible for avoiding or removing systemic errors and identifying the root causes of defects in the manufacturing system. Alogla and Alruqi (2021a) (2021b) developed a framework to identify the root cause of defects by considering the psychological mechanism behind human error in the aerospace industry. For example, description similarity errors in different production stages can confuse operators in an assembly line and give rise to defects. Additionally, Ostadi and Masouleh (2019) suggested conducting a field study focusing on factors such as wages, work-related stress, or other forms of existing disparities experienced by operators on the shop floor to prevent errors due to carelessness or lack of adequate motivation. Hence, efforts in correcting the identified root causes such as the operating procedures or the lack of motivation experienced by workers should come before redesigning the manufacturing system to be cost and time effective.

Engineers should investigate how to incorporate digital tools such as machine learning to improve the efficiency of quality control such as fault detection. Machine vision in combination with convolutional neural networks (CNNs) enables in-line inspection with unprecedented accuracy (Smith, 2021). The power of this combination was demonstrated by Su et al. (2019) who integrated the technology with augmented reality (AR) to visualize assembly operations using object state and pose estimation. AR can also be utilized as a human-centric approach to assist operators in detecting errors in real-time (Zhao et al., 2022). The utilization of such innovations relies on the knowledge and competency of engineers to support technology integration.

Digitising work instructions for specific operating procedures or processes may improve the quality and consistency of the finished products (Beluško et al., 2016). Visual work instruction, such as pictures or videos, can help operators to better remember the information compared to written instructions. Despite visual learning having a higher knowledge transfer, particularly for tasks in complex production systems, engineers need to consider steps such as the education and skill level of the operators. Clear language and a wise choice of words are needed to ensure the work instructions are properly understood by the operators (Beluško et al., 2016). For this purpose, engineers need to engage with operators in the day-to-day work, using the language of the shop floor to develop clear and concise instructions (Olson and Villeius, 2011).

5.2.3. Operator

Knowledge capturing from the operator's feedback is essential in moving towards ZDM (Reiff et al., 2018). The experience and knowledge retained in human resources complemented with digital solutions for identifying non-conformances are pivotal for achieving ZDM (Gebus and Leiviskä, 2009). To achieve such synergy effects, Reiff et al. (2018) developed web-based software with an interface where operators can provide feedback to a machine-readable classification when they identified a defect. This tool can identify and visualize the location of the defect, and if corrective action is required or executed. Most importantly, all the captured defects are recorded in the system and can be analysed by quality managers to identify the defect propagation path and preventive solution.

Operators must adapt to new workspaces with robots. The repetitive work is gradually replaced by robots due to their excellent repeatability and indefatigability (Brito et al., 2020), while operators are essential for a task which requires a high level of dexterity (Green et al., 2008). The collaboration between robots and humans is not only cost-effective (del Toro et al., 2007), but this might be an effective technical solution in the manufacturing industry in reducing error (Bejarano et al., 2019). Brito et al. (2020) developed a system architecture where operators can teach the robot the necessary or new path to carry out a quality inspection to create a safe space for them by machine learning approach. With the rapid development of automation and digitalization in the manufacturing sector, operators might need to develop and acquire higher skills including day-to-day robot maintenance or even basic programming skills.

Apart from robots, the integration of enabling industry 4.0 technology like AR with operators is growing (Gorecky et al., 2014) because it has demonstrated that AR can reduce the number of errors significantly and the mental workload of operators (Loch et al., 2016). For example, AR can facilitate online quality control by visualizing defects and potential challenges by projecting onto the physical object and the display positions and orientations of components in assembly operations

(Blanco-Novoa et al., 2018). Utilizing AR in assembly operations is an example of a human-centric approach where technology enhances the capabilities of the operator by making information accessible on demand in an intuitive manner. The industrial revolution is ongoing with the introduction of disruptive and innovative technologies and will not stop. Thus, operators, engineers and managers must be able to cope and integrate with the new technologies to reduce the gap between smart factories and skilled workers.

5.3. Challenges to incorporating human-centric ZDM

Major steps towards ZDM are enabled by employing new technology. However, the cost of obtaining and incorporating new technology into the manufacturing system may be substantial. Considering training and maintenance, the cost of introducing new technologies constitutes a significant barrier – especially for small- and medium-sized enterprises (SMEs). High costs may render key technologies unavailable to manufacturers in the same way that off-the-shelf solutions rarely exist until the technologies have fully matured. This effectively leaves the development of customized solutions up to the corporation which again adds to the cost of technology. Access to key technologies and competency is a barrier that may be significant at all levels of an organization as it applies to shop-floor technologies such as extended reality and cooperative robots, engineers in terms of CAD/CAM systems, and managers in terms of strategic management systems and decision-making tools.

Any organizational change is subject to resistance or inertia in the system. This can be a reluctance to adopt new tools and strategies, or simply the time it takes to accomplish cultural change in an organization. The resistance to change is one of the critical failure factors in advancing ZDM (Psarommatis et al., 2020b). Moving towards human-centric ZDM entails an organizational change across all levels of the organization, where the CEO must lead the way by adopting this paradigm (Crosby, 2006). For example, the act of going for a Gemba walk is an important tool to identify and address issues throughout the organization (Toussaint, 2013). Furthermore, the act of Gemba will contribute to the overall adoption of a human-centric approach to ZDM. Humans are inherently reluctant to change and will attempt to maintain the status quo unless specifically avoiding this behaviour. Integration of new strategies, therefore, requires organizations to have the capacity for change at all levels to achieve a common goal (Jones et al., 2021).

A common pitfall is to introduce new technology, often reducing human intervention, thinking it could close the gap of zero-defects. Instead, a strong focus on understanding the needs and difficulties experienced by different roles in the manufacturing sectors should be prioritized over the introduction of new technologies (Psarommatis et al., 2020b). Low-hanging fruits such as managers paying attention to the wellbeing of all employees, engineers designing instruction manuals which is clear to operators as well as operators providing feedback on the challenges should be prioritized first before investing in new technologies. Since it is impossible to remove humans entirely from the manufacturing system, we should start looking for solutions from the human perspective. This approach can be most effective and more importantly, SMEs are like to be able to cope with this approach.

Moving towards human-centric ZDM entails overcoming psychological, as well as organizational and technological challenges. Not only will it require a shift in the organization and its fundamental view on human resources, but this mindset must be reflected in all the employees. For the organization, this means that the structure and information flow must support a human-centric approach to ZDM which may require both minor and major changes to the organizational structure. Finally, the technology that best augments the abilities, and complements the capabilities of the human counterpart must be found.

6. Conclusion

Humans are now regarded as assets rather than sources of error. The European Commission and the scientific community are urging industries to re-position humans in manufacturing as a strategy to reach ZDM. However, the human-centric aspect of ZDM has received little attention and is often overlooked. To this day, the roles of humans (manager, engineer and operator) in the manufacturing sector remain unclear.

We selected a total of 36 publications through a systematic literature review using four different databases. The literature was sorted based on the involved human roles, which industry was concerned, and what ZDM tools and strategies was used. Our literature review revealed a stronger focus of existing publications on the role of the operator in various production environments. Engineers and managers appear less frequently in the human-centric ZDM publications, due to the perceived distance from the defects occurring on the shop floor. From our work, we discovered that prevention strategy is the most common approach to reaching ZDM as compared to the results of other review papers. This could be because humans are still regarded as the source of error, for which the strategy is to prevent human intervention.

Human-centric approaches to ZDM are facing technological, psychological, and organizational barriers when being implemented in manufacturing systems. These barriers may manifest differently for the three human roles in the manufacturing sector, but the journey towards ZDM becomes more manageable by recognizing the various difficulties faced by the different roles. Based on our findings, managers have a pivotal role in moving toward ZDM and could ease the transformation, even though they are often not directly involved in the shop floor. For example, managers need to define a clear ZDM goal throughout the organization and promote a culture of teamwork to strive towards zero-defect. Lastly, a common pitfall on the journey towards ZDM is to implement cutting-edge technology, thinking that it will eliminate defects without prioritizing the role of humans in the manufacturing system.

To close the gap on human-centric ZDM, future research focusing on the roles of engineers and managers is needed. For example, the integration of humans and technology in manufacturing environments requires interdisciplinary research including hardware and software, as well as interaction design, cognitive psychology, and system engineering. Both the working environment and well-being of employees are also two important aspects of future research in moving toward human-centric ZDM.

After years of pushing for increased automation, the idea of increased manual labour may seem counterintuitive. Industry 5.0 calls for human-centric manufacturing where technology supports humans and not the other way around. By considering the needs of people in the development and deployment of new technology, synergy effects between man and machine will bring the industry closer to the ZDM vision. The introduction of disruptive technologies is ongoing and will not stop. Therefore, all human roles must be able to collaborate, integrate, and cope with new technologies while moving toward the goal of zero-defects in manufacturing.

CRediT authorship contribution statement

Paul Kengfai Wan: Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Torbjørn Langedahl Leirmo:** Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing, Visualization.

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.

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