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Review

Application of automation for in-line quality inspection, a zero-defect manufacturing approach

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A R T I C L E I N F O

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A B S T R A C T

Contemporary manufacturing must prioritise the sustainability of its manufacturing processes and systems. Zero Defect Manufacturing (ZDM) focusses on minimising waste of any kind using data-driven technology, hence enhancing the quality of all manufacturing aspects (product, process, service, etc.). Making things right on the first try is the central tenet of ZDM. In recent years, the application of automation for in-line quality inspection systems has begun to attract the interest of both practitioners and academics because of its capability to detect defects in real-time, and thus adapt the system to disturbances. In this work, we provide a systematic review of the literature on current trends in the application of automation for in-line quality inspection with the ultimate objective of achieving ZDM. Additionally, bibliometric and performance analyses have been performed to gain a complete picture of the field. In this work, we have collected bibliometric data from the most widely referred search engines for academic engineering papers, i.e. Scopus, Web of Science, and IEEE Explorer, involving a total of 145 academic publications from 2011 to 2021. Uniquely for this study, we used three research attributes for the analysis of the selected articles, that is, the level of automation, the condition for quality inspection, and the contribution to ZDM dimensions. The literature suggests that there is a lack of research on the use of in-line detection data for the prediction of defects or repair. Based on the results and our interpretation of the literature, an adapted framework of ZDM (Psarommatis et al., 2020a) and multi-layer quality inspection (Azamfirei et al., 2021a) is presented.

1. Introduction

In the contemporary manufacturing landscape, product quality is a critical aspect for manufacturers. Poor product quality can have an effect on a variety of levels, including direct financial losses, increased environmental impact, and waste of resources. Therefore, quality management is crucial for manufacturing companies who wish to maintain or improve their operational and financial performance [1]. Poor quality can also have negative social impacts, affecting the reputation of a company through its substandard products and unsatisfied clients [2]. Furthermore, the modern manufacturing industry must prioritise the sustainability of its manufacturing processes and systems. True sustainability requires companies to balance economic, social, and environmental factors [3,4] in addition to the environment. Today, manufacturing systems produce a significant amount of waste of any kind, including materials, production time, energy, and other natural resources, contrary to sustainability goals [5].

The shift from mass production to mass customisation is what defines the manufacturing industry today. A concept known as mass customisation entails creating items that are specifically catered to the wants of the consumer while taking full advantage of economies of scale. The key to achieving widespread personalisation is big data [6] and high-quality [7,8]. The modern manufacturing industry is critically dependent on product personalisation. In 2015, Deloitte reported that 36% of consumers want to buy a personalised product, and 50% of them are willing to wait a longer time to get it. Furthermore, 20% of them indicated that they would be willing to spend 20% extra for a personalised product [9]. According to Dassault Systems, the processes of connecting the data, contextualising the data and collaborating on the data must be taken to successfully implement mass customisation [10]. Due to the shift in lot sizes, from mass production to mass customisation and lot size one, a departure from classic quality improvement methodologies is now necessary. A successful example of mass customisation is the 'The Customer-Oriented Sales and Production Process (COSP)' program offered by BMW group. Customers receive new levels of service from COSP, including easy online buying, instant binding order confirmation and delivery date, flexibility for

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adjustments, order progress information, and on-time delivery [11]. Production is slowed by a number of causes, most notably on-site inspection procedures due to the ongoing push to shorten manufacturing cycles for quick delivery by customers [8,12,13]. This highlights how existing quality-focused manufacturing practices fall short of the Industry 4.0 vision and highlights the need to eliminate data silos and achieve full system integration and interoperability.

Manufacturers must use at least one quality improvement method to produce high-quality products with little performance loss [14]. Although manufacturers have used classic quality improvement techniques such as six-sigma, lean manufacturing, the theory of constraints, and comprehensive quality management for more than three decades, there is still much to be done. This is due to the fact that such methods were developed using the production standards of the era without taking into account recent technological developments related to Industry 4.0 [15] in general data-driven approaches. For manufacturing firms that want to adopt Industry 4.0 and efficiently produce products with zero errors and waste, the comprehensive approach of Zero-Defect Manufacturing (ZDM) is crucial.

Sustainable manufacturing can be achieved through the implementation of ZDM [7,8]. By minimising waste of any kind using data-driven technology, it seeks to enhance the quality of all manufacturing aspects (product, process, service, etc.). Making things right on the first try is the central tenet of ZDM. In doing so, quality is enhanced and sustainability is raised, which ultimately results in higher customer satisfaction, which is crucial for a manufacturing company's success [16]. In contrast to current optimisation techniques, ZDM takes a holistic approach that addresses all areas of manufacturing while taking into account how they interact with one another [16,17]. Four strategies make up ZDM: detect, predict, repair, and prevent, which are action methods, and which are the triggering variables [7,18]. Each of those strategies—one from the triggering and one from the action strategies—is put into practice in pairs; for example, detect–prevent, detect–repair, predict–prevent, and predict–repair. Rapid technological transformations, together with the growing competition and sustainability demands, have resulted in an unprecedented level of automation. With the maturity of Industry 4.0, the amount of manufacturing data available has been drastically increasing, thus allowing for concepts such as ZDM to become a reality [7,8,18,19]. ZDM allows single-stage and multi-stage manufacturing systems to improve process efficiency and product quality by minimising, eliminating, or compensating for defects and process errors [18,20,21]. The foundation for the ZDM implementation and in general quality assurance is the product inspection. Currently, there is an increasing interest and demand for intelligent systems for automatic in-line quality inspection solutions.

Given that human behaviour has a substantial impact on manufacturing quality, the human-centric ZDM method could produce new insights and improvements in quality [7]. Research shows that incorporating a human component can boost efficiency despite campaigns to remove humans from the production environment to reduce human error [22]. Businesses must invest in knowledge and skills in addition to innovative technologies to be competitive [23]. A third significant strategy of ZDM, after correction and compensation, is the development of human resources [24]. The European Commission released a study on Industry 5.0 in 2021 that placed a strong emphasis on the human-centric 'revolution' in response to the extremely technocentric Industry 4.0 paradigm [25]. The European Commission forecasts a shift towards purposefulness where 'human-centric', 'resilient', and 'sustainable' are the key aspects of Industry 5.0 even though its exact form is still unknown [26]. Human-centric ZDM's significance in this context is still uncertain as the function of humans in cyber–physical manufacturing systems is still being established. Rather than being seen as a source of error, humans are now seen as assets. As a plan to achieve ZDM, the European Commission and the scientific community are advising businesses to reposition humans in production. But the human-centred element of ZDM has gotten little attention and is frequently disregarded [27].

Achieving sustainable manufacturing is a mandatory goal for current and future manufacturing systems. Product quality is a key factor for achieving sustainable manufacturing [8]. Taking into consideration all the above, it is evident that quality inspection is a topic very important for manufacturers and at the same time very difficult considering the fast and complex production conditions [28]. Therefore, in the current paper, a systematic literature review is conducted to present the current status of the quality inspection domain. More specifically, the analysis aims to reveal how quality inspection is currently performed. Furthermore, the current study aims also to identify issues and weaknesses of the current practices that need to be tackled in future research studies and will help towards ZDM and Zero-Waste productions.

This paper is structured as follows. Section 2 introduces the research methodology and data collection. Section 3 presents the literature review by describing the main findings based on thematic, content, and taxonomic analyses (Performance analysis, Bibliometric analysis, Literature review). Section 4 discusses the main findings and research gaps in the literature. Finally, Section 5 concludes and identifies emerging patterns in the field and presents future research directions.

2. Review methodology

A literature review is a systematic, explicit, and reproducible method of identifying, evaluating, and synthesising the existing body of completed and recorded works produced by researchers, scholars, and practitioners on a specific topic [29]. The methodology used for the literature review comprises the following steps: (i) problem formulation; (ii) literature search; (iii) literature collection; (iv) quality assessment; (v) analysis and synthesis; (vi) interpretation; (vii) presenting the results. Fig. 1 graphically represents the sequence of actions performed during the literature search, collection, and quality assessment part of the process, the analysis, and the synthesis.

In this state-of-the-art study, we have gathered bibliometric data from the most widely referred search engines for academic engineering papers, i.e. Scopus, Web of Science, and IEEE Explorer. The search fields for each paper were the title, abstract, and keywords specified by the author/s in the papers, with variations depending on the database: (i) with Scopus, the tag combination was TITLE-ABS-KEY; (ii) in Web of Science, tags TI-AB-AK were used; and (iii) with IEEE Xplore, the advanced search options were "Document Title", "Abstract", and "Author Keywords". The search has been performed on 24th February 2022 and the search string was compounded by five groups of keywords:

- Manufacturing industry: "manufact*" OR "production"
- Automation: "automat*" OR "robot*"
- Zero-defect: ("zero" PRE/0 "defect") OR "ZDM"
- Condition for quality inspection: "inline" OR (("in" OR "on") PRE/0 ("line" OR "machine" OR "process" OR "situ"))
- Quality inspection: "quality" OR "inspect*" OR "measur*" OR "metrology"

The search was limited to articles from 2011 to 2022, written in English, and within the field of computer science or engineering. Furthermore, we focused on discrete manufacturing, excluding the food, textile and chemical industries. Since each paper can be categorised into several subject areas, we excluded: "Earth and Planetary Sciences", "Biochemistry, Genetics and Molecular Biology", "Agricultural and Biological Sciences", "Health Professions", "Medicine", and "Pharma*".

Given the complexity and magnitude of the queries, to simplify them, four different combinations have been made based on "group 1" AND "group 2" AND "group 3" AND "group 4", i.e., (i) "automated in-line quality inspection" (ii) "automated quality detection" (iii)"automated quality inspection for zero defect manufacturing"; and (iv) "automated detection for zero defect manufacturing". After filtering duplicates from the different searches and databases, a total of 368 documents were extracted that constitute: 54.4% (192) Conference

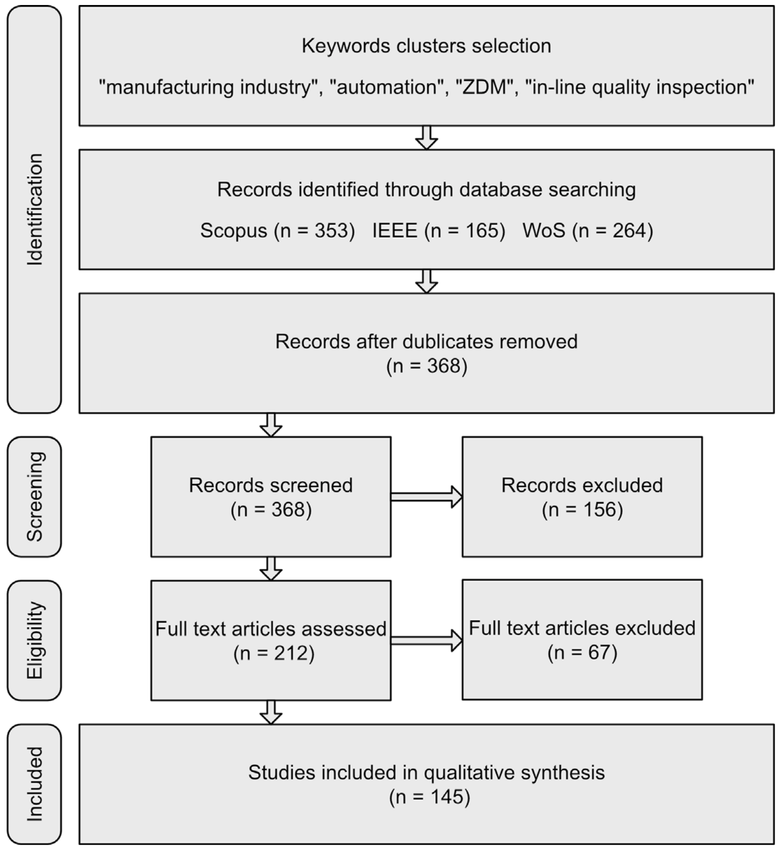

Fig. 1. PRISMA Research Process Flow Diagram.

Paper, 40.8% (144) Article, 2% (12) Conference Review, 3.4% (3) Book Chapter, 0.8% (1) Review, 0.3% (1) Short Survey, 0.3%.

The visualisation of the presented data was performed using the software VOSviewer [30] version 1.6.17. The software was used to construct and examine in full detail bibliometric maps of authors, journals, and keywords. The viewing capabilities of VOSviewer are especially useful for maps containing at least a moderately large number of items (e.g., at least 100 items). VOSviewer only employs distance-based mapping, in which the distance between two items reflects the strength of the relation between the items, e.g., smaller distances indicate stronger relationships [30].

Our focus in this research has been on:

- **Performance analysis**: Total Papers (TP) is the total number of publications from the source; Total Citations (TC) is the total number of citations received by the publication; Citations per Paper (CPP) is the total number of received citations count divided by total publications; Citations per Year (CPY) is the total number of received citations count divided by time span.
- **Science mapping**: a co-occurrence network approach. Keywords represent the basic content of scientific publications. A co-occurrence network was created in VOSviewer using author and indexed keywords [31].
- **Literature content analysis**: summarise and synthesise the findings of existing literature on the research topics encountered using the science mapping analysis.

Research attributes used for analysis

The term 'in-line' is commonly used in the manufacturing industry to condition the place and time where measurements are taken, that is, on the production line or during value-added processes. The idea behind such reasoning is to identify defects at the root and avoid the propagation of defects using quick corrective activities on both product and operation processes. Since a workpiece is typically manufactured from the raw material to the final product by a manufacturing chain composed of a number of machines, people, and processes, several 'in-line' sub-terms have been given through the years. Such conditions are clarified and classified in [32,33]; see Fig. 2. In addition, Gao et al. [32] highlighted the synonymous usage of 'in-situ' for 'on-machine' and 'in-process' in some manufacturing papers. By conducting this literature review, most articles that use such terms interchangeably are within Additive Manufacturing (AM). Once the measurement process condition is given, quality inspection follows the same protocol as conceived in 1945 by Juran [28], that is, (i) interpretation of specification, (ii) measurement of the quality of the characteristic, (iii) comparison between "interpretation of specification" (i) and "measurement" (ii), (iv) judgement on conformance, (v) process of conforming items, (vi) disposition of nonconforming items, and (vii) record of obtained data. The difference between the concepts is explained further below and depicted in Fig. 2.

- In-situ quality inspection: measurement of the work-piece surface is carried out on the same work floor and in the same manufacturing environment, without isolating the workpiece from the manufacturing environment. In-situ has been used freely between at-line quality inspection and any sub condition of in-line quality inspection [34,35].
- In-line quality inspection: measurement of the workpiece surface carried out on a production line without moving the workpiece outside the production line.
- On-machine quality inspection: measurement of the workpiece surface carried out on a manufacturing machine where the workpiece is manufactured.
- In-process quality inspection: the measurement is carried out while the manufacturing process is taking place. Contrary to [32],

Table 1
LoA scales for computerised and mechanised tasks within manufacturing (Frohm et al. 2008).

LoA	Mechanical and equipment	Information and control
1	**Totally manual** - Totally manual work, no tools are used, only the users human sensoring.	**Totally manual** - The user creates his/her own understanding for the situation, and develops his/her course of action based on his/her earlier experience and knowledge. E.g. The users earlier experience and knowledge
2	**Static hand tool** - Manual work with support of static tool. E.g. Screwdriver	**Decision giving** - The user gets information on what to do, or proposal on how the task can be achieved. E.g. Work order
3	**Flexible hand tool** - Manual work with support of flexible tool. E.g. Adjustable spanner	**Teaching** - The user gets instruction on how the task can be achieved. E.g. Checklists, manuals
4	**Automated hand tool** - Manual work with support of automated tool. E.g. Hydraulic bolt driver	**Questioning** - The technology question the execution, if the execution deviate from what the technology consider being suitable. E.g. Verification before action
5	**Static machine/workstation** - Automatic work by machine that is designed for a specific task. E.g. Lathe	**Supervision** - The technology calls for the users' attention, and direct it to the present task. E.g. Alarms
6	**Flexible machine** - Automatic work by machine that can be reconfigured for different tasks. E.g. CNC-machine	**Intervene** - The technology takes over and corrects the action, if the executions deviate from what the technology consider being suitable. E.g. Thermostat
7	**Totally automatic** - Totally automatic work, the machine solve all deviations or problems that occur by it self. E.g. Autonomous systems	**Totally automatic** - All information and control is handled by the technology. The user is never involved. E.g. Autonomous systems

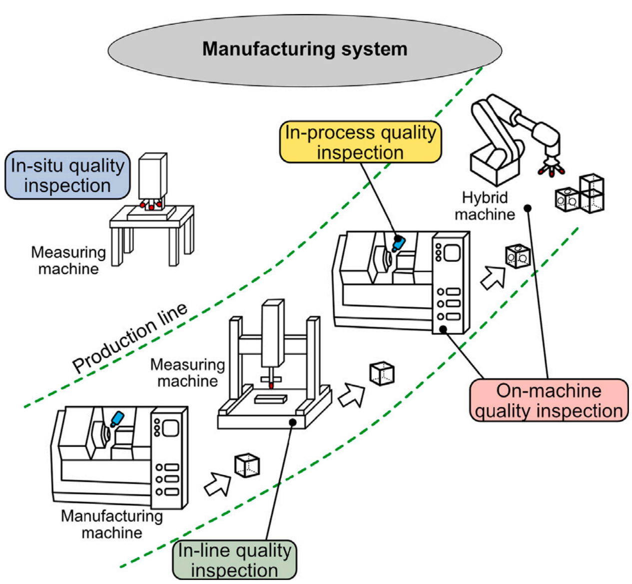

Fig. 2. Scheme of condition for quality inspection in a manufacturing system, inspired by Gao et al. [32].

where in-process quality inspection is a subcategory of on-machine, we believe certain applications allow to perform of in-process inspection without being mounted on a machine, as, for example, optical cameras allow long-distance measurement. In-process inspection should be a subcategory of on- and off-machine inspection.

More precisely, this article focuses only on quality inspection performed by automation, e.g. industrial robots or Control Measurement Machines (CMM). Different Level of Automation (LoA) can be applied on a physical and cognitive level to perform such in-line quality inspection. Frohm et al. [36], Jayasekara et al. [37] argue that there are seven different LoA on a physical and cognitive basis; see Table 1.

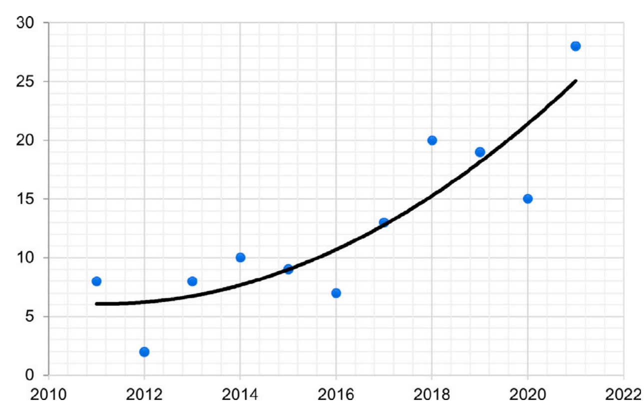

Fig. 3. Annual distribution of publications.

3. Literature analysis

In this section, the selected n=145 papers presented in Fig. 1 and Appendix A are reviewed using (1) performance analysis, (2) bibliometric analysis, and (3) literature content analysis. The results are presented and analysed.

3.1. Performance analysis

In this section, we evaluate the contribution to the field in three key factors, i.e. the distribution across the period of 2011 to 2021, journals and productive authors. For that, the metrics of total papers, total citations, and citations per paper have been used.

Fig. 3 shows that interest in the topic has increased exponentially in the last 10 years. Using a polynomial expression of order two, we approximate the growth of the field. In 2018, there was a visible increase in interest in research of automation in conjunction with quality inspection techniques. Although the field experiences two years of stagnation, it was in 2021 that it experienced another growth of almost half.

Fig. 4 presents the type of publication of the selected articles. Since the search includes the research field of computer science, it is natural that a large number of conference papers have been encountered

Table 2
Distribution across the top 10 journals in the field.

Journal	TP	TC	CPP	Journal	TP	TC	CPP
IEEE Transactions on Automation Science and Engineering	6	79	13.16	Sensors	3	16	5.3
IEEE Robotics and Automation Letters	5	56	11.2	CIRP Annals	3	121	40.3
Procedia CIRP	5	33	6.6	International Journal of Advanced Manufacturing Technology	2	13	6.5
IEEE Transactions on Instrumentation and Measurement	4	52	13	Measurement: Journal of the International Measurement Confederation	2	10	5
IEEE Transactions on Semiconductor Manufacturing	3	28	9.3	Additive manufacturing	2	158	79
				Others (n = 1)	42		

Table 3
Most productive authors from the selected papers.

Author	TP	TC	CPP
Yang, Haw Ching	7	55	7.86
Franke Jorg	6	16	2.66
Cheng, Fan Tien	7	83	11.85
Hung, Min Hsiung	3	41	13.66
Tieng, Hao	3	40	13.33
Leitao, Paulo	3	26	8.66
Queiroz, Jonas	2	20	10
Barbosa, Jose	2	16	8

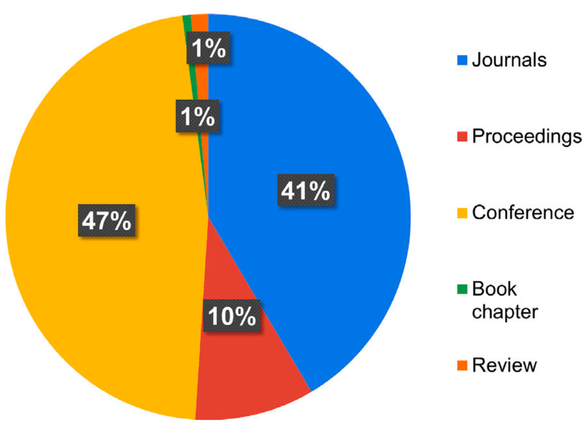

Fig. 4. Document types.

at 47%. Journal publications are the second largest group at 41%. Proceedings are considered separately at a 10%. Finally, only 1% have been encountered to include Book chapters and Reviews.

To identify the main contribution to research, the distribution according to the journals is given in Table 2. The three metrics have been used to detect the journals with the most papers contributed, the papers with the highest impact, and the average impact in terms of citations.

Table 3 shows the authors that have made the largest contribution in the field of application of automation for in-line quality inspection. Cheng Fan Tien is the most productive and cited author in the field with 7 publications and 83 total citations. Nonetheless, it is his co-author Hung Min Hsiung the most successful author when considering citations per paper. Yang Haw Ching is the second most cited author on our list and also a co-author with Cheng Fan Tien. Franke Jörg follows with 6 publications but without too much impact in terms of citations. Finally, The Queiros Jonas, Leitao Paulo and Barbosa Jose trio are following, all being within the multi-agents field and co-authors.

Table 4 illustrates the universities and research institutes that are the most represented according to the affiliation of the authors. Two institutes from Taiwan are the first on our list with a third one on top five. It is expected as Taiwan is the main silicon manufacturer in the world and the field of in-line quality inspection is of great interest to the area. Following is Portugal with the multi-agents trio. Though forth, the research institute from China is the most successful when considering citations per paper. Finally we have the German institute for factory automation and production systems with three total publications and eight citations.

3.2. Bibliometric analysis

In this section, we present the results of the bibliographic analysis [38]. The selected articles, presented in Section 2, were collected in PDF format, introduced in Mendeley, and a RIS file was inserted into VOSviewer v.1.6.16. Based on the RIS file of the reviewed research articles, (i) a co-occurrence map of keywords was drawn up, where clusters of interrelated keywords are visualised, see Fig. 5, and (ii) a co-authorship map of most productive authors and their interrelations was depicted, see Fig. 6.

3.2.1. Co-occurrence

Keywords represent the core content of scientific publications. The principle of analysis is based on the occurrence of multiple keywords in multiple studies. In other words, how closely related are they in terms of the concepts they deal with. This analysis gives a network of topics that are grouped into closely conceptual clusters. From the cluster analysis, Fig. 5, it can be seen that the field has evolved into seven large clusters: (1) zero defect manufacturing, (2) industry 4.0, (3) visual inspection, (4) additive manufacturing, (5) monitoring, (6) quality control, and (7) quality inspection.

From the data, some interpretations come naturally. ZDM is closely related to industry 4.0. Highlighted keywords in this close interconnection are decision-making, factory automation, production of new materials, business ecosystem, collaborative cyber–physical systems, system interoperability, predictive maintenance, and automatic scheduling. In the centre of the network plot is 'quality control'. It is the dimension that connects everything. Monitoring triggers are connected to in-process inspection and other forms of inspection. In this cluster highlighted keywords are: in-process inspection, robot non-destructive testing, automatic process, fault detection, and data analytics. Furthermore, other clusters connected to 'quality control' are quality inspection and visual inspection. The interesting part is the position of visual inspection. Despite the fact that this is part of quality inspection, it is the only type of inspection connected to Industry 4.0, providing the assumption that it is the most researched type of inspection.

Within Industry 4.0 and quality inspection, additive manufacturing has also received much interest. AM requires a complete redesign and consideration of the traditional processes. AM is preferred for high-cost industries such as aerospace, and the end result must be perfect. In-situ quality inspection, commonly used in additive manufacturing for in-line inspection for in-process monitoring, is increasingly being used for system adaptability to disturbances. Defects are inevitable, and given the possibility of AM repairing/adapting geometry during the process, defects need to be detected in real-time and predicted in the future. Highlighted keywords are in-situ metrology, machine vision inspection, fault recognition, and intelligent metrology.

Table 4
Distribution of affiliations.

Affiliation	TP	TC	CPP	Category	Country
National Cheng Kung University	8	85	10.62	University	Taiwan
Institute of Manufacturing Information and Systems	7	76	10.85	Research institute	Taiwan
Research Centre in Digitalization and Intelligent Robotics (CeDRI), Instituto Politécnico de Bragança	4	26	6.5	University	Portugal
Harbin Institute of Technology	4	55	13.75	Research institute	China
National Kaohsiung University of Science and Technology	3	10	3.33	University	Taiwan
Institute for Factory Automation and Production Systems (FAPS)	3	8	2.66	Research institute	Germany

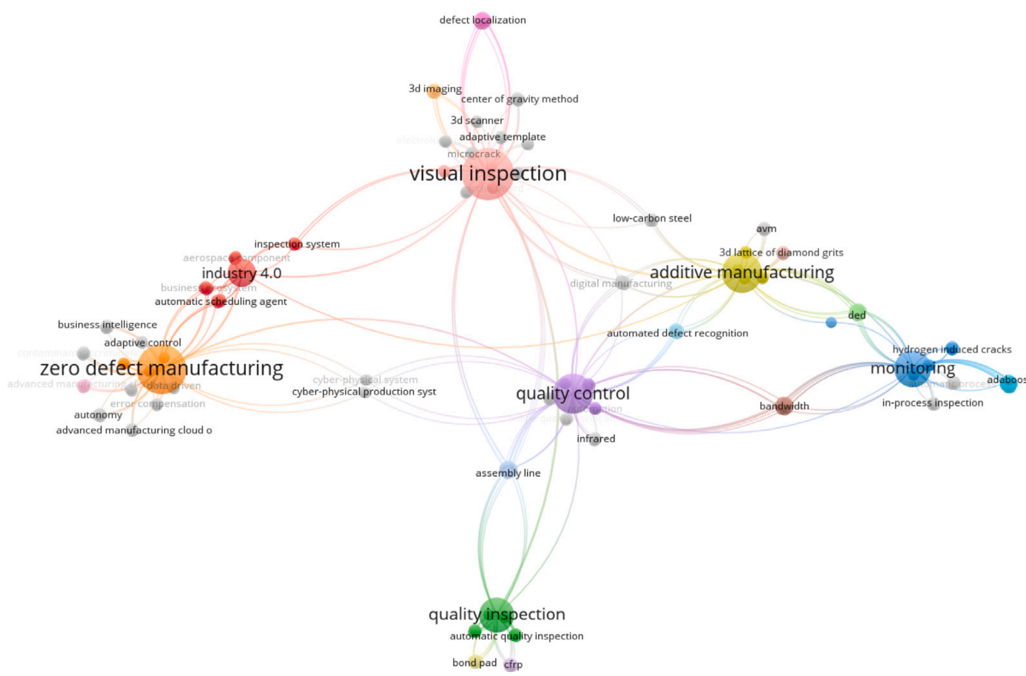

Fig. 5. Co-occurrence network of authors' keywords.

3.2.2. Co-authorship

Fig. 6 outlines a network of coauthors of the most productive researched of selected papers. Using a filter of minimum of 3 publications, the network consists of eight items forming three different clusters. The network shows that research related to automated in-line quality inspection is fragmented and multidisciplinary. (1) Cheng Fan Tien and Yang Haw Ching, (2) Leitão Paulo and Babose Jose, and (3) Franke Jörg,

Cluster 1 red, Cheng Fan Tien and Yang Haw Ching, with a speciality on virtual metrology, algorithms, AI and AM, focusses on the technological aspect of the field, such as architecture, sensoring technologies, and their application. Automatic virtual metrology was investigated in [39–42]. In [43] applied the concept of Industry 4.1, i.e., ZDM in a wheel machining automation case. Based on our bibliometric analysis, Cheng Fan Tien is mostly co-writer in this field together with Yang Haw Ching, Tieng Hao, and Hung Min Hsiung [39–45].

Cluster 2 green, Leitão Paulo and Babose Jose have participated in the European project "GO0D MAN - Agent-Oriented Zero Defect Multi-Stage Manufacturing". Their focus is on the applications of the multi-agent systems to support ZDM strategies in multi-stage environments [20,46]. Additionally, in [47] they have considered the usage of robotic in-line quality inspection as a multi-agent for ZDM. Leitão Paulo, based on our bibliometric analysis, is mostly co-writer in this field together with Barbosa Jose, and Queiroz Jonas [20,46,47].

Cluster 3 blue, Franke Jörg is the leader of the Department of Mechanical Engineering and Working group: "Institute for Factory Automation and Production Systems". Franke Jörg has contributed in the investigation of in-line measurement and quality monitoring of

Fig. 6. Co-authorship of most productive authors from the selected papers.

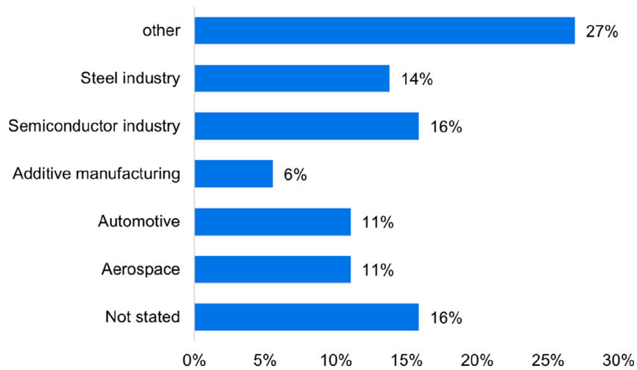

Fig. 7. Distribution of industry domain.

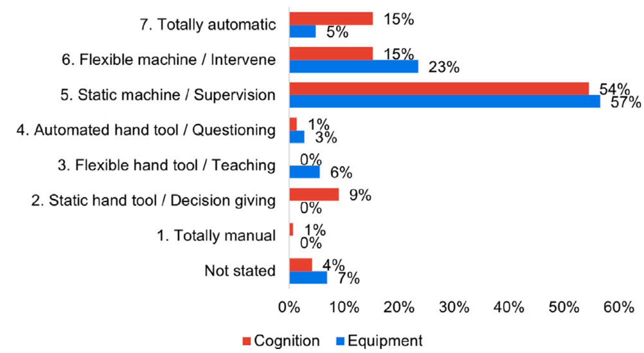

Fig. 8. Distribution of the Level of Automation used in selected papers.

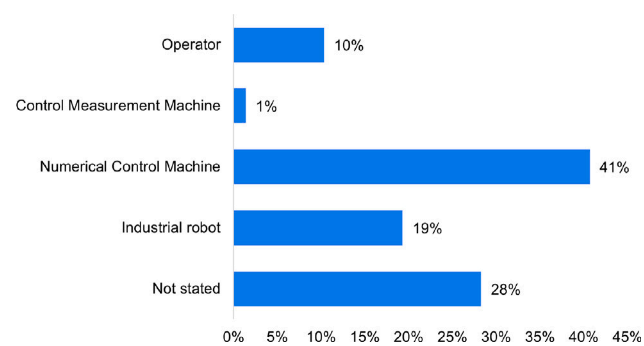

Fig. 9. Distribution of the usage of actuators for in-line quality inspection.

different industrial applications [48–53]. Franke Jörg, based on our bibliometric analysis, writes with several different less-known authors in the field.

3.3. Literature content analysis

In this section, the selected n=145 articles are reviewed through thematic and content analysis. It was identified the: (1) industry domain and process; (2) level of automation; (3) actuators used for quality inspection; (4) condition for quality inspection (5) set-up and evaluated environment (6) contribution to ZDM; and (7) Dedicated improvements.

3.3.1. Industry domain and process

Fig. 7 provides an overview of the most researched industrial domains. The application of automation for in-line quality inspection has been mostly researched for the semiconductor industry, followed by what we interpret as generic manufacturing, steel industry, automotive, aerospace, and additive manufacturing. A large amount of the articles, 27%, contribute are scattered industries and processes. Furthermore, Yasuda et al. [54] assessment on the aerospace literature revealed a scarcity of publications in the aircraft inspection area and a lack of complete intelligent inspection systems.

3.3.2. Level of automation

An essential point of investigation was related to the level of automation used for both physical and cognition of these quality inspection activities; see Section 2. Fig. 8 shows that a large proportion of quality inspection systems were triggered by static machines (56.55%) and limited themselves to only supervising (54.48%) if a defect was encountered. The second most popular level was the usage of both physical flexible machines (23.45%) such as industrial robots or control numerical machines and cognitive capacity to intervene (15%). From this point on, there is an inconsistency in the usage of physical and cognitive levels of automation. Totally automatic cognitive capacity (15%) is much higher than totally automatic physical capacity (5%). Finally, human quality inspection represents 6% in physically inspecting using flexible hand tools, and 9% in using inspection orders.

3.3.3. Inspection actuators

A critical point in the inspection process that controls the effectiveness and productivity of the corresponding manufacturing system is the actuator of the inspection process. Fig. 9 illustrates the results from the paper's analysis corresponding to the actuator of the inspection process. The inspection actuators have been classified using five categories, the operator, which means that the operator handles the inspection equipment and performs the process, which covers only 10% of the total sample. Visual inspection plays an essential part in not only quality inspection but also equipment maintenance, overhaul, and repair [54–56]. The highest percentage is 41% for numerical control machines, which are all the devices that are integrated into the production line and are initiated automatically when an inspection is required. The second highest percentage, 19% is for the category of industrial robots, which are separated from the numerical control machines because their complexity and capabilities are superior to numerical control machines that are only capable of one functionality [57]. Furthermore, 28% of the analysed papers were not stating how the inspection process was actuated. Finally, in less than 1% of the papers the inspection process was performed using a CMM machine, which is reasonable because they are time-consuming and reduce significantly the productivity of the production systems.

3.3.4. Condition of quality inspection - Level of integration of quality inspection equipment

Another important aspect of quality control is the level of integration of the inspection equipment into the main production line. Fig. 10 presents the results from the analysis, where in total six categories were used for the classification. The most dominant category is the in-line level of integration, with 62%, followed by the on-machine and in-process at 10%. In-line inspection is the most popular because it constitutes the ideal setting for inspection in terms of productivity and flexibility. On-machine inspection means that once the machine has finished a process the part is inspected without leaving this machine to the next manufacturing stage. In-process inspection is an advanced inspection technique that the inspection equipment is installed again in the machine but the difference with the on-machine is the fact that the quality is continuously monitored throughout the entire manufacturing process. Only 3% were using an off-line inspection, which is reasonable due to performance reasons. An interesting observation is that 99% of the analysed papers were clearly presenting the level of integration of their quality inspection system, something that is not the case for many of the defined attributes of the current study.

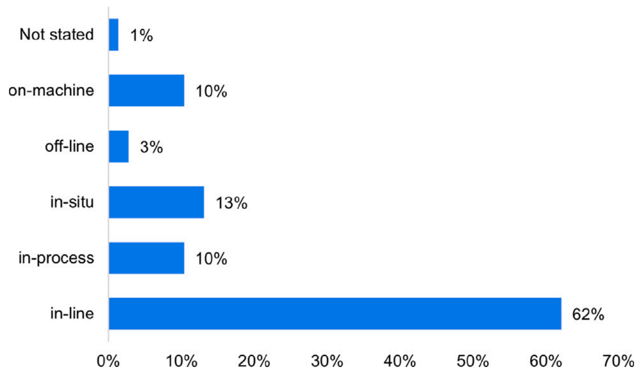

Fig. 10. Distribution of condition used for quality inspection.

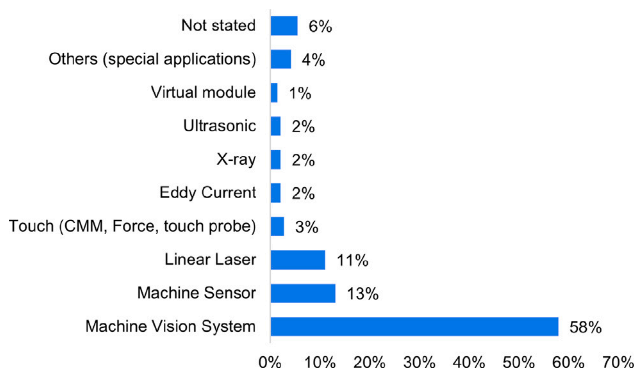

Fig. 11. Distribution of inspection equipment type used for quality inspection.

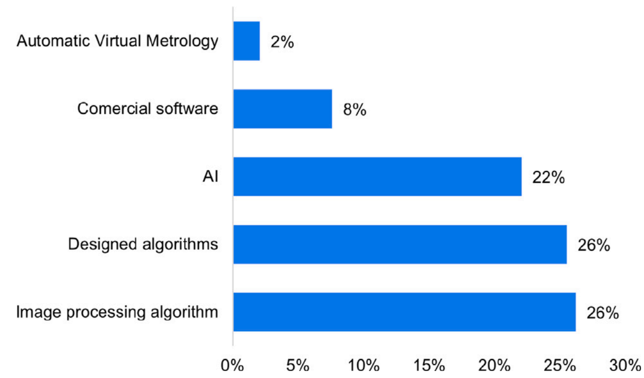

Fig. 12. Distribution of inspection analysis method type used for quality inspection.

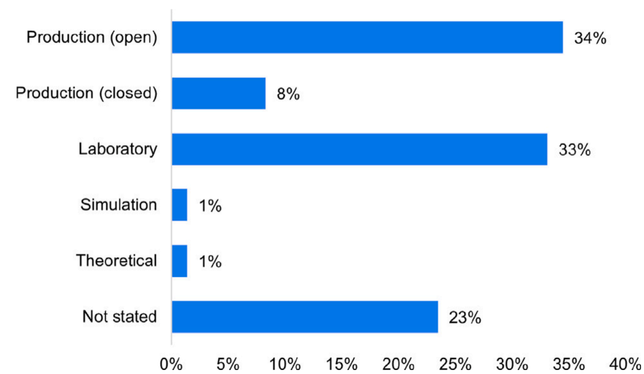

Fig. 13. Distribution of used set-up for quality inspection.

3.3.5. Type of inspection equipment used

A critical point in the quality inspection process is the equipment used for such a task. The equipment will predetermine the accuracy, repeatability, and speed of the quality inspection task. Additionally, not all measurement equipment provides an equal amount of data that can be used for other stages of ZDM. Fig. 11 illustrates that the most researched type of inspection equipment is ‘machine vision systems’ at 58% of the articles [58]. Since one inspection application can contain different types of inspection equipment, the numbers will exceed 100%. This is in line with the bibliometric analysis on keywords, see Fig. 5. Second most used inspection equipment is actually no equipment, at a 13%. It consists of exploiting the data already available from the machines. Additionally, virtual modules made the list with a 1% interest. The third category could be classified under the first one. Though, Linear Lasers are much faster than optical cameras, and thus deserve their own category. Linear Lasers present an 11% of usage, especially in large-scale manufacturing [59]. Touch type of inspection only presents a 3% of the studies. It is well known that such inspection equipment sacrifices time over accuracy and repeatability. This category encompass the usage of CMM, touch probes, and force sensors. Finally, specific industrial domain applications represent 2% individually for Eddy Current, X-ray, and Ultrasonic, and 4% for very specific one-of-a-kind solutions.

3.3.6. Method for data analysis

In the current sub-section, we overview the most commonly used methods for analysing the measured data for the quality inspection task. The data analysis method is one of the most critical aspects of quality inspection. As described in [28], the data analysis module should not only decide upon conformity of the product but also question the inspection data and ask for re-inspection if needed. Fig. 12 illustrates the results from the literature analysis concerning the different inspection technologies that are most commonly used for the analysis of the quality inspection data. The most dominant category was the ‘image processing algorithms’, with 26%. This is an expectable and reasonable result since machine vision systems are the most common device for acquiring product quality information. Additionally, the semiconductor industry (at a 16% representation) is well known for improving the yield rate through the wide application of visual inspection devices in the design, layout, fabrication, assembly, and testing processes of production lines [60]. The second category is custom-made algorithms that use low-end modules that cannot be classified under Artificial Intelligence (AI) or other types of data mining methods. AI has 22%, of which 12% is Machine Learning, 7% Neural Networks, and 3% is unspecified. As the amount of manually segmented and labelled data is limited, machine learning technologies such as multi-instance learning are increasing their usage as they can be trained with weakly labelled images [61]. Surprisingly, only 2% were using the ‘virtual metrology’ concept, but this will change in the future, as it is the most promising approach for product quality data analytics.

3.3.7. Set-up and evaluated environment/inspection conditions and environment

A factor that can significantly affect the accuracy of the quality inspection is the environmental conditions. The interesting finding is that modern technological advancements allow performing accurate inspection even in open production environments, which constitutes 34% of our total sample. On the other hand, high accuracy with very tight tolerances products is still inspected in laboratory setups, which is the 33% of our sample. Some studies have successfully integrated controlled inspection conditions using closed inspection setups integrated with the main production, which is 8% of our total sample. Finally, 28% of the sample did not state the conditions that the inspection performed.

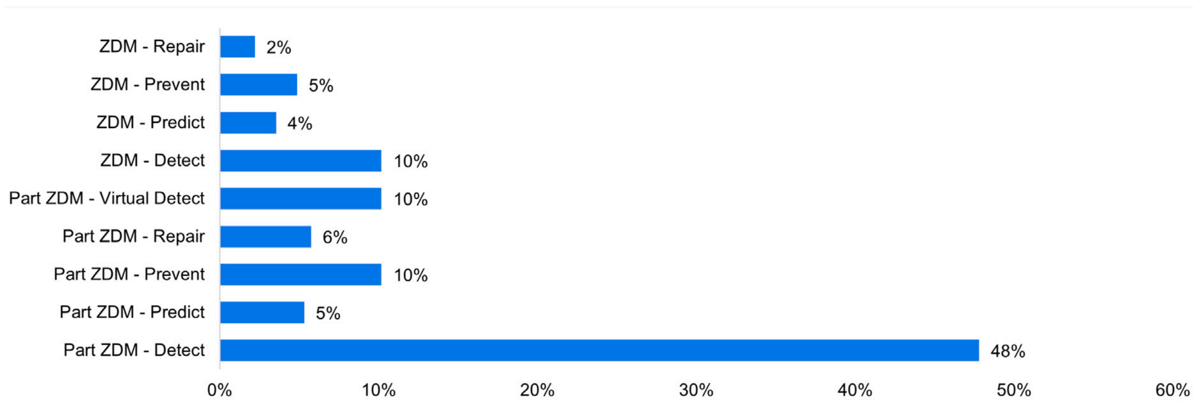

Fig. 14. Distribution of ZDM contribution.

3.3.8. Contribution to ZDM

The current sub-section is devoted to analysing the literature regarding the ZDM domain. The four ZDM strategies, i.e. 'detect', 'predict', 'repair' and 'prevent' [7], were used as attributes. Also, based on the findings of our analysis, two categories arise and have to do with whether they mention explicitly ZDM or they are using the principles of ZDM but they do not refer explicitly to ZDM. Fig. 14 illustrates the results from our analysis regarding the use of ZDM and part ZDM strategies. The most dominant category is the part ZDM-Detect, with 48%, which was an expectable result because the detection is the foundation of quality control. All the processes start and use data from the inspection of products or processes. The second place is taken by three categories with 10%, the actual ZDM detection, the partial virtual detection and the partial prevention. Virtual detection is a category that is highly aligned with ZDM concept, very most of the time, it refers to as prediction of quality, which is inaccurate. Virtual detection is a concept that lies within the concept of virtual metrology and has the goal of measuring the desired quality characteristics of a product without physical access to the part. The term 'prediction' is misused as it refers to something in the future, but virtual detection estimates the quality of an already manufactured product, as stated by Psarommatis et al. [7], Dreyfus et al. [62]. The fact that the highest percentage of partial detection is reasonable as the modern ZDM framework that authors are following was developed in 2020 by Psarommatis et al. [7].

3.3.9. Dedicated improvements

The current section is devoted to presenting the distribution of what are the improvements that the developed inspection systems achieved at the deployed manufacturing system. The analysis revealed that achieving higher accuracy to the inspection systems is the top category with 21% followed by the achievement of real-time inspection with 19% [63]. In the third place is the achievement of 100% inspection, which is one of the key aspects that are necessary when implementing ZDM, with 18%. The next two categories at the cost reduction and the increase of the reliability of the inspection equipment at 15% and 14%, accordingly.

4. Discussions

In this section, the analysis presented from our performance, bibliometric and literature analysis is discussed. To surpass the identified shortcomings, an adapted ZDM framework and future research directions are proposed.

4.1. Adapted ZDM framework

With the aim of bringing all communities together and allowing the reader to gain a clear understanding of the big picture of the literature analysed and clustered, we created a comprehensive framework to summarise our findings; see Fig. 16. In the current study, the ZDM framework that was developed in 2020 by Psarommatis et al. [7] is utilised, and it has become a standard by CEN/CENELC-CWA-17918 [64]. This framework imposes that there are four ZDM strategies, 'detect', 'predict', 'repair' and 'prevent'. In the current study, we expand this framework to add intermediate steps and notions. Besides the additions, the proposed model aligns fully with the original ZDM framework [7].

A top-bottom approach is used to describe the framework obtained. First, the ZDM paradigm takes advantage of advanced technologies with true sustainability in mind. To do so, second, triggering factors such as 'detection' and 'prediction' need to be placed. They are responsible for identifying that there are quality issues. Additionally, we added 'monitoring', as the 'prediction' mechanism should identify deviations whether that might be in the product or the process [65]. Third, the quality evaluation layer, where the product conformity and process characteristics are evaluated for diagnosing the potential quality issue. Fourth, action strategies are established to compensate for the quality issue. Those strategies are being used in pairs meaning that a triggering strategy will always be combined with an action strategy. Furthermore, in the action layer, the addition of the planning process was made in order to demonstrate that the decisions need to be planned as stated in [18,66,67]. Planning should be made for the repair or prevention of defects [68]. Preventive actions should be performed to not only prevent similar future defects from re-occurring but catch them even earlier in the process. Finally, all activities helped in reaching truly zero-defect and zero-waste.

4.2. Discussion of analysis and future directions

The shortcomings of the current state-of-the-art have revealed ten distinctive areas for improving the research topic.

4.2.1. Research and industrial communities should adopt the ZDM approach and terminology

Based on the results of the literature analysis, it was revealed that research studies were using the principles of ZDM, but they did not explicitly mention the ZDM. The adoption of the ZDM approach will also mean that the standardised ZDM terminology from the [64] would be utilised and align all researchers together.

4.2.2. Industries that are developing solutions for quality inspection

The application of automation for in-line quality inspection has mostly been researched for the semiconductor industry, followed by what we interpret as generic manufacturing, steel industry, automotive, aerospace, and additive manufacturing, see Fig. 7. Dispersed industries and processes comprise a significant portion of the articles, 27%. When considering the research growth of the field, see Fig. 3, it can be argued that such dispersed interest is a good one and the seek for a ZDM result is a common one across industries.

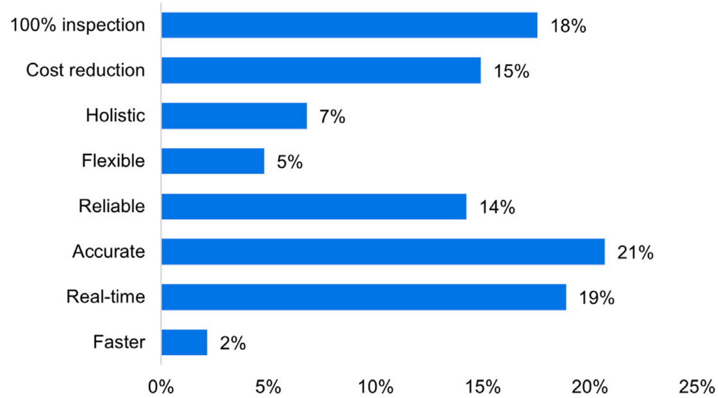

Fig. 15. Distribution of quality inspection improvement focus.

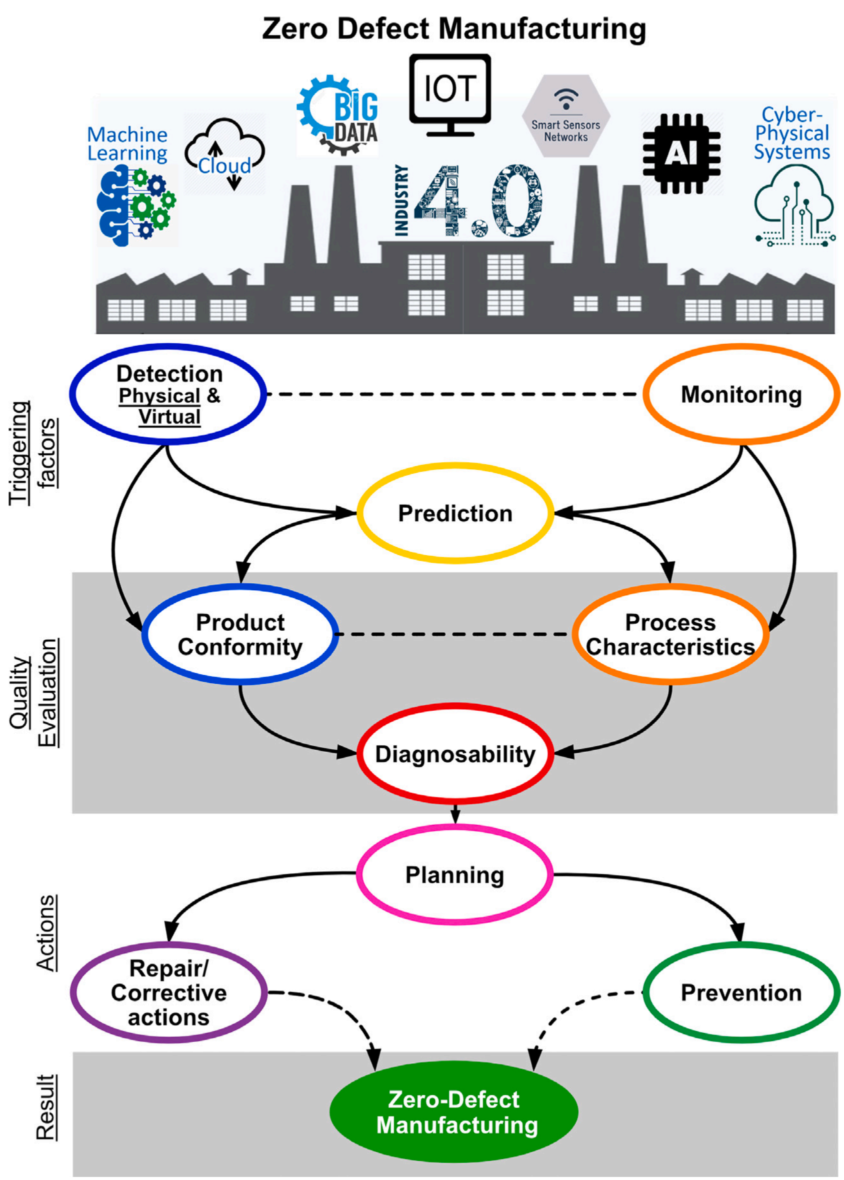

Fig. 16. Quality inspection framework for ZDM.
Source: Adapted from [7].

4.2.3. Research groups should collaborate among each other

Our analysis of the authors' contributions reveals that the majority of writers have interests in a variety of areas related to automated quality inspection, including multi-agent systems, virtual metrology, inspection technologies, and architectures, to mention a few. It was surprising that these several departments, with their vast experience in the sector, did not work together; see Fig. 6. The lack of cross-field collaboration is reflected in different analyses of our study. There are multiple downsides because of the lack of cross-field collaboration between researchers and groups in the same field. First, the research is slowing down because the same knowledge is generated more than one time, leading to a 'waste' of time when it could be used for going one step further. If researchers in the same field join forces will increase the research efficiency and, at the same time, increase the sustainability of the research process. In the current study, this phenomenon was observed in the quality inspection domain, but the same happens to other domains as well. Furthermore, more collaboration in the same research field will save a lot of funds and other resources, which can be used for other purposes and not for repeating and generating the same knowledge with the other institutes in the same domain. Additionally, there is a lack of standardisation in the different solutions developed, which causes confusion in the community and in the industry. Performing collaborative research will align researchers in a better and more efficient way.

4.2.4. Precision vs speed of inspection

Despite CMM machines being more precise, our analysis depicts an increase in the usage of other actuators for quality inspection that is faster and more reliable. Numerical control machines are still used more than industrial robots. One reason is the low accuracy of industrial robots present. There is a need to increase the accuracy and repeatability of relative measurement systems such as vision cameras.

4.2.5. Theory vs. practice

Only 1% of the selected articles focused on contributing to theoretical advancement or simulation for the field; see Fig. 13. We believe with the standardisation of ZDM by CEN/CENELC-CWA-17918 [64] and the proposed framework, there will be a mutual consensus in terms of theory. Nonetheless, the simulation for ZDM and quality inspection needs to be further researched. The results also revealed that a theoretical contribution on how the field connects the technological, processes, and human aspects is missing, and also the concept of Virtual detection and quality simulation is also lacking.

4.2.6. Static inspection equipment

It is evident that the distribution of the level of automation used for the developed inspection systems from the analysed papers revealed that the majority of the papers were focusing on the development of static inspection systems. On top of that, the developed inspection equipment was designed only to supervise and not towards the full automation of the inspection procedure. This means that the level of flexibility of the majority of inspection systems is low and if the operation that they perform changes then either the inspection setup is becoming obsolete or significant effort is required for the adaptation of the inspection system to the new conditions. This is also verified by the results that show that a holistic and flexible quality inspection is the least researched one; see Fig. 15. Other phases of ZDM that require a holistic approach have also been mostly disregarded; see Fig. 14.

4.2.7. Digital twins a key technology for increasing inspection quality and speed

The usage of Digital Twin (DT), i.e. a virtual model designed to accurately reflect a physical object to mimic reality, provides a perfect environment for the three ZDM dimensions of (i) prediction, (ii) diagnosability, and (iii) planning. DT are considered the technology of the future, with endless capabilities. DT are considered as the next wave of simulation and can offer higher efficiency, quality and performance during the design and operational optimisation towards ZDM [69]. A digital twin could enable feedback between the real physical system and the digital model of cyberspace [70]. The coordination of the digital and physical areas during the course of the complete life cycle can be ensured in this way. The DT directly conducts validation and testing that can quickly identify the cause of malfunction and inefficiency, rule out errors, and assess the viability and safety/security of the physical solution in use [71]. Quality inspection is one of the leading concepts in the Smart manufacturing approach [28]. Furthermore, the use of the DT notion in the design process is still unclear, and significant effort is required towards maturity. The research on the logical incorporation of digital twins technology into the Smart manufacturing system design must therefore be explored and organised [72]. In [18] a DT was developed for the proper quantification of the specification of the inspection equipment for achieving ZDM, but to authors' best knowledge, there are no other studies using DT technology to design a manufacturing system for achieving ZDM. In the context of the quality inspection process, DT can be very beneficial by the realisation of deviation pattern identification and intelligent decision on diagnosability and planning [28,73].

4.2.8. Real-time inspection would help in achieving ZDM

The synergy between operational technologies and information technologies will help reach the goal of ZDM [20]. Operational technologies are responsible for the manufacturing operations included in the process plan of the product or product family of interest. Such value-added technologies include control numerical machines, industrial robotics, and/or inspection stations. Value-added stations that additionally perform in-line quality inspection can provide a more constant interpretation of the real world to the data analysis model in the digital world. Such closeness to the origin of defects will not only provide more time for the data analysis model to detect but also to plan and perform corrective actions at the origin of deviation.

4.2.9. Simulation for optimum inspection cycles and flexibility

For ZDM to be a profitable manufacturing philosophy, the cost of appraisal must be lower than the cost of defect, customer dissatisfaction, and scrap. Customer dissatisfaction can be caused by the delivery of defects but also by not complying with the specified delivery times. Optimum inspection cycles must be constantly calculated for manufacturing companies to maintain the planned times. Simulation tools have the potential for more accurate planning of the manufacturing process that includes in-line inspection and in-line corrective actions.

4.2.10. Towards 100% inspection

Performing 100% inspection is the only way to assuring that the desired quality levels have been achieved and the product delivered to the customers is the correct one. Another aspect of 100% is that no defective items will ever leave the factory, minimising the harmful effects of production on the environment without increasing the workload associated with production [74]. Additionally, in [75] 100% in-situ inspection is used to increase the resilience of Cyber-Physical System (CPS) against cyber attacks. Besides the positive effects of 100% inspection, there are a few also negative. The employment of this level of inspection has a number of drawbacks, including a significant cost rise caused by the need for extra employees or measuring equipment, as well as time consuming. Additionally, implementing 100% inspection is unreliable when destructive inspection techniques are required, such as when mandated by law. To enable early defect identification and prevent its spread through the growth of in-process inspection, also known as in-line inspection or quality control, 100% production inspection is becoming essential for smart factories. Implementing 100% inspection might have a negative impact on the performance of the manufacturing system, but compared to the losses brought on by a defective product at the customer's end, these losses would be far smaller. Fenech and Perkins [9] indicated that 36% of customers want to buy a personalised product, with 50% saying they would accept a longer length of time for doing so, to counteract this little performance loss.

Table A.5
Selected papers for this study.

No.	Author & Year	Title	Source title	TC
1	Gobert et al. [76]	Application of supervised machine learning for defect detection during metallic powder bed fusion additive manufacturing using high resolution imaging	Additive manufacturing	134
2	Juarez and Gregory [77]	In Situ Thermal Inspection of Automated Fiber Placement for manufacturing induced defects	Composites part b-engineering	0
3	Aminzadeh and Kurfess [78]	Vision-based inspection system for dimensional accuracy in powder-bed additive manufacturing	Proceedings of the ASME 11th international manufacturing science and engineering conference, 2016	4
4	Aminzadeh and Kurfess [79]	Layerwise automated visual inspection in laser powder-bed additive manufacturing	Proceedings of the asme 10th international manufacturing science and engineering conference, 2015, VOL 2	2
5	Mersmann [80]	Industrializing metrology-Machine vision integration in composites production	CIRP ANNALS - manufacturing technology	4
6	Hopkins et al. [81]	Challenges and Solutions for Ultrasonic Phased-Array Inspection of Polymer-Matrix Composites at Production Rates	45th annual review of progress in quantitative nondestructive evaluation	1
7	Pierer et al. [82]	Zero-error-production through inline-quality control of press-hardened automotive parts by multi-camera systems	International deep-drawing research group conference (IDDRG 2021)	0
8	Grasso et al. [83]	Data fusion methods for statistical process monitoring and quality characterization in metal additive manufacturing	15TH CIRP conference on computer aided tolerancing, CIRP CAT 2018	9
9	Wu et al. [84]	Inline Inspection with an Industrial Robot (IIIR) for Mass-Customization Production Line	Sensors	4
10	Bauer et al. [85]	Fast FMCW Terahertz Imaging for In-Process Defect Detection in Press Sleeves for the Paper Industry and Image Evaluation with a Machine Learning Approach	Sensors	0
11	Zhu et al. [86]	Automatically High Accurate and Efficient Photomask Defects Management Solution for Advanced Lithography Manufacture	Metrology, inspection, and process control for microlithography XXVIII	0
12	Colosimo and Grasso [87]	Spatially weighted PCA for monitoring video image data with application to additive manufacturing	Journal of quality technology	20
13	Han et al. [88]	A Robot-Driven 3D Shape Measurement System for Automatic Quality Inspection of Thermal Objects on a Forging Production Line	Sensors	12
14	Oromiehie et al. [89]	Characterization of process-induced defects in automated fiber placement manufacturing of composites using fiber Bragg grating sensors	Structural health monitoring-an international journal	30
15	Suárez et al. [90]	Wire arc additive manufacturing of an aeronautic fitting with different metal alloys: From the design to the part	Journal of manufacturing processes	4
16	Zhang et al. [91]	Hurdle Modeling for Defect Data with Excess Zeros in Steel Manufacturing Process	IFAC papersonline	2
17	Tieng et al. [40]	Automatic Virtual Metrology and Deformation Fusion Scheme for Engine-Case Manufacturing	IEEE Robotics and automation letters	9
18	Lednev et al. [92]	In situ multi-elemental analysis by laser induced breakdown spectroscopy in additive manufacturing	Additive manufacturing	24
19	Lednev et al. [93]	Laser induced breakdown spectroscopy for in-situ multielemental analysis during additive manufacturing process	Beam technologies and laser application	3
20	Huber et al. [94]	Automated NDT inspection based on high precision 3-D Thermo-Tomography model combined with engineering and manufacturing data	2nd CIRP conference on composite material parts manufacturing	0
21	Newell et al. [95]	Detection of Electrical Defects with SEMVision in Semiconductor Production Mode Manufacturing	Metrology, inspection, and process control for microlithography XXX	0

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Table A.5 (*continued*).

No.	Author & Year	Title	Source title	TC
22	Ferralli et al. [96]	Manufacturing and metrology for IR conformal windows and domes	Window and dome technologies and materials XV	0
23	Zörrer et al. [97]	Using Business Analytics for Decision Support in Zero Defect Manufacturing of Composite Parts in the Aerospace Industry	IFAC Papers Online	3
24	Magnanini et al. [98]	A control model for downstream compensation strategy in multi-stage manufacturing systems of complex parts	IFAC Papers Online	1
25	Tatipala et al. [99]	Data-driven modelling in the era of Industry 4.0: A case study of friction modelling in sheet metal forming simulations	Journal of Physics: Conference Series	7
26	Xu et al. [100]	In-process adaptive dimension correction strategy for laser aided additive manufacturing using laser line scanning	Journal of Materials Processing Technology	1
27	Couto et al. [101]	Mapping of Bead Geometry in Wire Arc Additive Manufacturing Systems Using Passive Vision	Journal of Control, Automation and Electrical Systems	0
28	Zeng et al. [102]	Laser ultrasonic inspection of defects in wire arc additive manufactured samples with different surface profiles	Measurement: Journal of the International Measurement Confederation	3
29	Javadi et al. [103]	High-temperature in-process inspection followed by 96-h robotic inspection of intentionally manufactured hydrogen crack in multi-pass robotic welding	International Journal of Pressure Vessels and Piping	1
30	Ren et al. [104]	Quality monitoring in additive manufacturing using emission spectroscopy and unsupervised deep learning	Materials and Manufacturing Processes	2
31	Yang [105]	Promote In-Process Measurement Technology Application in Intelligent Grinding Production	Lecture Notes in Electrical Engineering	0
32	Martinez et al. [106]	Intelligent vision-based online inspection system of screw-fastening operations in light-gauge steel frame manufacturing	International Journal of Advanced Manufacturing Technology	8
33	Javadi et al. [107]	Continuous monitoring of an intentionally-manufactured crack using an automated welding and in-process inspection system	Materials and Design	13
34	Wang et al. [108]	Feasibility investigation for online elemental monitoring of iron and steel manufacturing processes using laser-induced breakdown spectroscopy	ISIJ International	5
35	Liang et al. [109]	In-line inspection solution for codes on complex backgrounds for the plastic container industry	Measurement: Journal of the International Measurement Confederation	10
36	Xiong et al. [110]	Increasing stability in robotic GTA-based additive manufacturing through optical measurement and feedback control	Robotics and Computer-Integrated Manufacturing	13
37	Ucan et al. [111]	Production technologies for lightweight structures made from fibre–metal laminates in aircraft fuselages	CEAS Aeronautical Journal	2
38	Strohmeier et al. [112]	Optical inline inspection detecting 3D defects on complex free-form surfaces in harsh production environments	Technisches Messen	4
39	Caggiano et al. [113]	Machine learning-based image processing for on-line defect recognition in additive manufacturing	CIRP Annals	111
40	Putz et al. [114]	A multi-sensor approach for failure identification during production enabled by parallel data monitoring	CIRP Annals	6
41	Szabo et al. [115]	Automated defect recognition as a critical element of a three dimensional X-ray computed tomography imaging-based smart non-destructive testing technique in additive manufacturing of near net-shape parts	Applied Sciences (Switzerland)	5
42	Liu et al. [116]	On-stream inspection for pitting corrosion defect of pressure vessels for intelligent and safe manufacturing	International Journal of Advanced Manufacturing Technology	5
43	Snel et al. [117]	In-line height profiling metrology sensor for zero defect production control	Proceedings of SPIE - The International Society for Optical Engineering	2
44	Wang et al. [118]	Research and application of online measurement system of tire tread profile in automobile tire production	Proceedings of SPIE - The International Society for Optical Engineering	1

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Table A.5 (*continued*).

No.	Author & Year	Title	Source title	TC
45	Lee and Liu [119]	High precision optical sensors for real-time on-line measurement of straightness and angular errors for smart manufacturing	Smart Science	9
46	He et al. [120]	The Intelligent Composite Panels Manufacturing Technology Based on Tape-laying Automatic System	Procedia CIRP	4
47	Zoesch et al. [121]	Zero defect manufacturing: Detection of cracks and thinning of material during deep drawing processes	Procedia CIRP	14
48	Ružarovskỳ et al. [122]	Automated in-process inspection method in the flexible production system iCIM 3000	Applied Mechanics and Materials	1
49	Kraemer et al. [123]	Quality control in the production process of SMC lightweight material	Procedia CIRP	10
50	Montironi et al. [124]	Adaptive autonomous positioning of a robot vision system: Application to quality control on production lines	Robotics and Computer-Integrated Manufacturing	16
51	Kalms et al. [125]	Nondestructive testing in an automated process chain for mass manufacturing of fiber-reinforced thermoplastic components	Proceedings of SPIE - The International Society for Optical Engineering	0
52	Xiong and Zhang [126]	Online measurement of bead geometry in GMAW-based additive manufacturing using passive vision	Measurement Science and Technology	53
53	Molleda et al. [127]	A fast and robust decision support system for in-line quality assessment of resistance seam welds in the steelmaking industry	Computers in Industry	10
54	Liang et al. [128]	The study of online detecting technique of steel production based on laser structured light	Advanced Materials Research	0
55	Psarommatis and Kiritsis [129]	A hybrid Decision Support System for automating decision making in the event of defects in the era of Zero Defect Manufacturing	Journal of Industrial Information Integration	4
56	Eger et al. [130]	Reaching zero-defect manufacturing by compensation of dimensional deviations in the manufacturing of rotating hollow parts	Procedia Manufacturing	1
57	Brito et al. [47]	A machine learning approach for collaborative robot smart manufacturing inspection for quality control systems	Procedia Manufacturing	10
58	Reiff et al. [131]	Smart centering for rotation-symmetric parts in multi-stage production systems for zero-defect manufacturing	Procedia CIRP	4
59	Bhanu Prasad et al. [132]	Machine vision solutions in automotive industry	Studies in Computational Intelligence	2
60	Wang [133]	Towards zero-defect manufacturing (ZDM)-a data mining approach	Advances in Manufacturing	72
61	Bao et al. [134]	Design of inspection system of glaze defect on the surface of ceramic pot based on machine vision	2017 IEEE 2nd Information Technology, Networking, Electronic and Automation Control Conference (ITNEC)	5
62	Younes et al. [135]	Online quality monitoring of perforated steel strips using an automated visual inspection (AVI) system	2011 IEEE International Conference on Quality and Reliability	2
63	Azamfirei et al. [33]	Towards fixtureless robotic in-line measurement assisted assembly, a case study	2021 IEEE International Workshop on Metrology for Industry 4.0 & IoT (MetroInd4.0&IoT)	1
64	Gao et al. [136]	Online quality inspection technology for electroplated diamond wire based on machine vision	2014 IEEE International Conference on Robotics and Biomimetics (ROBIO 2014)	0
65	Xu et al. [137]	Research on real-time quality inspection of PET bottle caps	2017 IEEE International Conference on Information and Automation (ICIA)	1
66	Tang and Wang [138]	Visual inspection of workpiece quality	2011 International Conference on Image Analysis and Signal Processing	1
67	Chu et al. [139]	Quality inspection algorithm based on machine vision for tube-sheet welding	2016 IEEE Workshop on Advanced Robotics and its Social Impacts (ARSO)	1
68	Bertoli et al. [140]	In-situ Quality Monitoring of Extrusion-based Additive Manufacturing via Random Forests and clustering	2021 IEEE 17th International Conference on Automation Science and Engineering (CASE)	0
69	Tremel and Franke [48]	Hall sensor line array for magnetic field inline measurements of PM-exited rotors	2012 2nd International Electric Drives Production Conference (EDPC)	7
70	Traxler et al. [141]	Experimental Comparison of Optical Inline 3D Measurement and Inspection Systems	IEEE Access	3

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Table A.5 (*continued*).

No.	Author & Year	Title	Source title	TC
71	Cao [142]	Design and Application of Robot Vision Inspection System for Semiconductor Metal Target	2021 3rd International Symposium on Robotics & Intelligent Manufacturing Technology (ISRIMT)	0
72	Wargulski et al. [143]	An In-line Failure Analysis System Based on IR Thermography Ready for Production Line Integration	2019 25th International Workshop on Thermal Investigations of ICs and Systems (THERMINIC)	5
73	Fujishiro et al. [144]	Minimization of CNN Training Data by using Data Augmentation for Inline Defect Classification	2020 International Symposium on Semiconductor Manufacturing (ISSM)	2
74	Yang et al. [45]	An Online AM Quality Estimation Architecture From Pool to Layer	IEEE Transactions on Automation Science and Engineering	2
75	Härter et al. [50]	Comprehensive correlation of inline inspection data for the evaluation of defects in heterogeneous electronic assemblies	2016 Pan Pacific Microelectronics Symposium (Pan Pacific)	7
76	Csencsics et al. [145]	Supplemental Peak Filters for Advanced Disturbance Rejection on a High Precision Endeffector for Robot-based Inline Metrology	IEEE/ASME Transactions on Mechatronics	4
77	An et al. [146]	Research on device and method of vision inspection of a vehicle dashboard framework	IEEE 2011 10th International Conference on Electronic Measurement & Instruments	0
78	Cannizzaro et al. [147]	Image analytics and machine learning for in-situ defects detection in Additive Manufacturing	2021 Design, Automation & Test in Europe Conference	1
79	Vaga and Bryant [148]	Industry 4.0 for Advanced Inspection	2019 Pan Pacific Microelectronics Symposium (Pan Pacific)	0
80	Di Leo et al. [149]	Online visual inspection of defects in the assembly of electromechanical parts	2014 IEEE International Instrumentation and Measurement Technology Conference (I2MTC) Proceedings	5
81	Meiners et al. [52]	Towards an Inline Quality Monitoring for Crimping Processes Utilizing Machine Learning Techniques	2020 10th International Electric Drives Production Conference (EDPC)	1
82	Chen et al. [150]	Online Surface Roughness Detection of Cold-Rolled Strip Steel Based on Adaptive Regression Smooth Filtering	2018 37th Chinese Control Conference (CCC)	2
83	Schlarp et al. [151]	Feature detection and scan area selection for 3D laser scanning sensors	2018 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM)	2
84	Kneidl et al. [53]	In-line Measurement Techniques of Resin-based Insulation Processes for Wireless Power Transfer Systems	2021 IEEE Conference on Electrical Insulation and Dielectric Phenomena (CEIDP)	0
85	Si and Zhang [152]	Research of online measurement and inspection approaches for 2.5 dimensional workpieces	2015 IEEE International Conference on Information and Automation	1
86	Xu et al. [153]	Surface Quality Assurance Method for Lithium-Ion Battery Electrode Using Concentration Compensation and Partiality Decision Rules	IEEE Transactions on Instrumentation and Measurement	7
87	Lee et al. [154]	In-Line Predictive Monitoring Framework	IEEE Transactions on Automation Science and Engineering	2
88	Tieng et al. [44]	An Automated Dynamic-Balancing-Inspection Scheme for Wheel Machining	IEEE Robotics and Automation Letters	1
89	Junhong et al. [155]	On-line Inspection System for Finished Circuit Board Based on Machine Vision	2021 China Automation Congress (CAC)	0
90	Gong et al. [156]	Adaptive Visual Inspection Method for Transparent Label Defect Detection of Curved Glass Bottle	2020 International Conference on Computer Vision, Image and Deep Learning (CVIDL)	1
91	Xiaojun et al. [157]	Online quality checking for large-scale centralized verification based on statistical process control	2021 IEEE Asia-Pacific Conference on Image Processing, Electronics and Computers (IPEC)	0
92	Deans et al. [158]	Solar wafer emitter measurement by infrared reflectometry for process control: Implementation and results	2014 IEEE 40th Photovoltaic Specialist Conference (PVSC)	5
93	Lanza et al. [159]	Automated optical detection of particles and defects on a Li-Ion-cell surface using a single-point analysis	2013 IEEE International Conference on Automation Science and Engineering (CASE)	2
94	Richter and Streitferdt [160]	Deep Learning Based Fault Correction in 3D Measurements of Printed Circuit Boards	2018 IEEE 9th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON)	1
95	Lin et al. [161]	Improvement of Multi-Lines Bridge Defect Classification by Hierarchical Architecture in Artificial Intelligence Automatic Defect Classification	IEEE Transactions on Semiconductor Manufacturing	1

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Table A.5 (*continued*).

No.	Author & Year	Title	Source title	TC
96	Cheng et al. [39]	Tutorial on Applying the VM Technology for TFT-LCD Manufacturing	IEEE Transactions on Semiconductor Manufacturing	25
97	Shan et al. [162]	Measuring Method of Involute Profile Error Based on Machine Vision	2021 IEEE International Conference on Real-time Computing and Robotics (RCAR)	0
98	Shui et al. [163]	Twofold Variation Propagation Modeling and Analysis for Roll-to-Roll Manufacturing Systems	IEEE Transactions on Automation Science and Engineering	7
99	Zhou et al. [164]	Automated inspection planning of freeform surfaces for manufacturing applications	2011 IEEE International Conference on Mechatronics and Automation	2
100	Cheri et al. [165]	An Online Intelligent Control Method for Surface Roughness of Cold-Rolled Strip Steel	2018 37th Chinese Control Conference (CCC)	1
101	Mohamed et al. [166]	Non-contact approach to roundness measurement	2011 IEEE 7th International Colloquium on Signal Processing and its Applications	4
102	Deng et al. [167]	A Multi-Sensor Data Fusion System for Laser Welding Process Monitoring	IEEE Access	2
103	Chua et al. [168]	Detection of Bond Pad Discolorations at Outgoing Wafer Inspections	IEEE Transactions on Semiconductor Manufacturing	3
104	Huang et al. [169]	Real-time structure-light-based 3D terrain sensing for mobile robot using CUDA	2013 IEEE International Conference on Cyber Technology in Automation, Control and Intelligent Systems	0
105	Yang et al. [42]	An Intelligent Metrology Architecture With AVM for Metal Additive Manufacturing	IEEE Robotics and Automation Letters	7
106	Alhwarin et al. [170]	Improving additive manufacturing by image processing and robotic milling	2015 IEEE International Conference on Automation Science and Engineering (CASE)	2
107	Zhang et al. [171]	Audible Sound-Based Intelligent Evaluation for Aluminum Alloy in Robotic Pulsed GTAW: Mechanism, Feature Selection, and Defect Detection	IEEE Transactions on Industrial Informatics	35
108	Leachman and Ding [172]	Excursion Yield Loss and Cycle Time Reduction in Semiconductor Manufacturing	IEEE Transactions on Automation Science and Engineering	24
109	Li et al. [173]	Research and Application of Online Quality Detection System Based on 3D Vision in Rectangular Steel Production Line	2018 IEEE International Conference on Mechatronics and Automation (ICMA)	1
110	Schneider and Franke [49]	Resonant method for the measurement of quality of laminated cores	2015 5th International Electric Drives Production Conference (EDPC)	2
111	Koch et al. [174]	Multisensor Contour Following With Vision, Force, and Acceleration Sensors for an Industrial Robot	IEEE Transactions on Instrumentation and Measurement	32
112	Liu et al. [175]	Efficient Optical Measurement of Welding Studs With Normal Maps and Convolutional Neural Network	IEEE Transactions on Instrumentation and Measurement	1
113	Zhang et al. [176]	A novel on-line alumina concentration measurement system	2015 IEEE International Conference on Mechatronics and Automation (ICMA)	2
114	Cui et al. [177]	Soft sensing of alumina concentration in aluminum electrolysis industry based on deep belief network	2020 Chinese Automation Congress (CAC)	1
115	Forbes et al. [178]	Using image data for Quality Assurance in Additive Manufacturing	2017 Systems and Information Engineering Design Symposium (SIEDS)	2
116	Kamalakannan and Rajamanickam [179]	Spatial smoothing based segmentation method for internal defect detection in X-ray images of casting components	2017 Trends in Industrial Measurement and Automation (TIMA)	3
117	Zhou and Liu [180]	Computer vision-based method for online measuring the moisture of iron ore green pellets in disc pelletizer	2021 China Automation Congress (CAC)	0
118	Khan et al. [181]	Analysis of defects on hot and cold roll coil using image processing methods	2017 13th International Conference on Emerging Technologies (ICET)	1
119	Zhao [182]	A Quality-Relevant Sequential Phase Partition Approach for Regression Modeling and Quality Prediction Analysis in Manufacturing Processes	IEEE Transactions on Automation Science and Engineering	44
120	Bao et al. [183]	Integration of Digital Twin and Machine Learning for Geometric Feature Online Inspection System	2021 IEEE 17th International Conference on Automation Science and Engineering (CASE)	0
121	Cui et al. [184]	Design and implementation of online measuring instrument for aluminum electrolytic anode current distribution	2015 IEEE International Conference on Information and Automation	1
122	Margraf et al. [185]	An Evolutionary Learning Approach to Self-configuring Image Pipelines in the Context of Carbon Fiber Fault Detection	2017 16th IEEE International Conference on Machine Learning and Applications (ICMLA)	8

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Table A.5 (*continued*).

No.	Author & Year	Title	Source title	TC
123	Wu and Li [186]	Machine Vision Inspection of Electrical Connectors Based on Improved Yolo v3	IEEE Access	9
124	Rodríguez-Araújo and García-Díaz [187]	Automated in-line defect classification and localization in solar cells for laser-based repair	2014 IEEE 23rd International Symposium on Industrial Electronics (ISIE)	3
125	Cannizzaro et al. [188]	In-Situ Defect Detection of Metal Additive Manufacturing: An Integrated Framework	IEEE Transactions on Emerging Topics in Computing	2
126	Zhou et al. [189]	Data-Driven Robust RVFLNs Modeling of a Blast Furnace Iron-Making Process Using Cauchy Distribution Weighted M-Estimation	IEEE Transactions on Industrial Electronics	43
127	Schirmer et al. [51]	Print Quality Assessment by Image Processing Methods for Printed Electronics Applications	2018 41st International Spring Seminar on Electronics Technology (ISSE)	1
128	Kassubeck et al. [190]	Optical Quality Control for Adaptive Polishing Processes	2020 IEEE Southwest Symposium on Image Analysis and Interpretation (SSIAI)	2
129	Teo et al. [191]	Design of an Imaging System for Characterizing Microcracks in Crystalline Silicon Solar Cells Using Light Transflection	IEEE Journal of Photovoltaics	5
130	Fang et al. [192]	Soft Sensors Based on Adaptive Stacked Polymorphic Model for Silicon Content Prediction in Ironmaking Process	IEEE Transactions on Instrumentation and Measurement	6
131	Liu et al. [193]	Design of a Submillimeter Crack-Detection Tool for Si Photovoltaic Wafers Using Vicinal Illumination and Dark-Field Scattering	IEEE Journal of Photovoltaics	8
132	Fan et al. [194]	Key Feature Identification for Monitoring Wafer-to-Wafer Variation in Semiconductor Manufacturing	IEEE Transactions on Automation Science and Engineering	1
133	zur Jacobsmühlen et al. [195]	Compound quality assessment in laser beam melting processes using layer images	2017 IEEE International Instrumentation and Measurement Technology Conference (I2MTC)	1
134	Choi et al. [196]	Design of Automated Screw Blade Welding Defect Detection System for Image Processing-Based Zero-Defect Mass-Production	2015 International Conference on Computational Science and Computational Intelligence (CSCI)	1
135	Wang et al. [197]	Reliable screening for zero-defect quality improvement by temperature gradient testing	2013 e-Manufacturing & Design Collaboration Symposium (eMDC)	2
136	Sousa et al. [198]	Zero-Defect Manufacturing using data-driven technologies to support the natural stone industry	2021 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC)	1
137	Cheng et al. [43]	Industry 4.1 for Wheel Machining Automation	IEEE Robotics and Automation Letters	30
138	Hsieh et al. [41]	Automatic Virtual Metrology for Carbon Fiber Manufacturing	IEEE Robotics and Automation Letters	9
139	Barbosa et al. [20]	Implementation of a Multi-Agent System to Support ZDM Strategies in Multi-Stage Environments	2018 IEEE 16th International Conference on Industrial Informatics (INDIN)	10
140	Angione et al. [46]	Integration Challenges for the Deployment of a Multi-Stage Zero-Defect Manufacturing Architecture	2019 IEEE 17th International Conference on Industrial Informatics (INDIN)	6
141	Minnette and Sebastian [199]	Deep learning for zero-defect inkjet-printing of electronics	2021 IEEE International Workshop on Metrology for Industry 4.0 & IoT (MetroInd4.0&IoT)	1
142	Vali et al. [200]	Hyperspectral Image Analysis for Automatic Detection and Discrimination of Residual Manufacturing Contaminants	2021 26th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA)	0
143	Cr et al. [201]	Advanced 4S image correlation for real-time quality inspection of ceramic products using ultrasonic ToFD images	2013 International Conference on Computer Communication and Informatics	1
144	Fridman et al. [202]	ChangeChip: A Reference-Based Unsupervised Change Detection for PCB Defect Detection	2021 IEEE Physical Assurance and Inspection of Electronics (PAINE)	2
145	Bengoechea Cuadrado et al. [203]	Virtual Sensor Development Based on Reduced Order Models of CFD Data	2019 IEEE 17th International Conference on Industrial Informatics (INDIN)	1

4.2.11. Operators role in inspection, in Industry 5.0

Moving toward ZDM requires knowledge capturing from the operator's feedback [204]. The ability to identify non-conformances using digital tools in addition to the expertise and knowledge that human resources have to offer is essential for accomplishing ZDM [205]. Operators must adjust to new robot-equipped workstations. Due to their outstanding repeatability and indefatigability, robots are gradually taking over the repetitive labour [47], but operators are necessary for a task requiring a high level of dexterity [206]. In addition to being cost-effective, human–robot collaboration may also be a technical means of minimising mistakes in the industrial sector [28]. Future research should focus on closing the gap on human-centric ZDM. For instance, interdisciplinary research in hardware, software, interaction design, cognitive psychology, and system engineering is needed to integrate humans and technology in production contexts efficiently and in a sustainable manner. Future studies in the direction of human-centric ZDM should focus on both the working environment and employee wellbeing [27].

4.2.12. Information technologies used in ZDM

Automatic quality inspection is a data-intensive process, data are generated by the hardware inspection equipment and in combination with software components are analysed in order to identify, classify and take decisions depending on the inspected quality. Today's industry uses the CPS philosophy which is a subset of the Information and Communication Technology (ICT) sector. Sensors are employed to collect data from a high variety of sources. The Internet of Things (IoT) is the game changer for this digital manufacturing as well as for intelligent production and process design [207]. Systems interoperability is crucial in the era of Industry 4.0 and particularly in quality inspection, where various heterogeneous systems need to exchange data with each other. Problems with semantic and syntactic interoperability can be solved using ontologies [208]. The quality inspection could significantly benefit from the use of ontologies, as it is the mean not only for systems interoperability but also the key towards knowledge extraction and data reasoning [129]. Data modelling with ontologies enables knowledge extraction. Ontology-based modelling is a key technology for enriching industrial data with contextual information [209,210].

5. Conclusions

In this work, we have provided a systematic literature review on the current trends in the application of automation for in-line quality inspection for the ultimate purpose of achieving ZDM. Additionally, bibliometric and performance analyses have been performed to gain a full picture of the field. The data used in this study were derived from the repositories Web of Science (WoS), Scopus, and IEEE, involving a total of 368 academic papers between 2011 and 2021. Uniquely to this study, we used three research attributes for the analysis of the selected papers. Specially (i) the usage of automation has been addressed at its seven levels, (ii) inspection quality depending on its condition, and (iii) the contribution to all ZDM dimensions, i.e. 'detect', 'predict', 'prevent', and 'repair'. For each of the three attributes, we provided a detailed and concise description and examined the current state of the literature. Thus after screening and deciding upon eligibility, a total of 145 articles were included in this study.

This study indicates that interest in the topic has increased exponentially in the last 10 years, with an exponential evolution in publications from 2016. The study allows us to observe that the results are in agreement with the knowledge about the continuing growth of this technology and the opportunities generated by its adoption in the industry.

From our analysis it was found that there is almost an equal distribution between journals (41%) and conferences (47%) publications, being IEEE journals and conferences the most represented in this field. Within the field, Asian and European universities/research institutes were encountered to have the greatest expertise on this subject. More precisely, three of the most productive institutes are in Taiwan and the most researched industry is the semiconductor one, a sector in which Taiwan is globally dominant. Nevertheless, to our surprise, most of these departments with their vast experience in the sector did not work together. The lack of cross-field collaboration is reflected in different analyses of our study. For example, 1. the level of automation in terms of physical and cognition is dominant at level five i.e., static machines with only supervision of the process/product; 2. Numerical Control Machines are the decision of choice for automation; and 3. Only 1% of the selected articles focused on contributing to theoretical advancement or simulation for the field.

Based on the results of the literature analysis, it was revealed that research studies were using the principles of ZDM, but they did not explicitly mention the ZDM. Additionally, other phases of ZDM that require a holistic approach have also been mostly disregarded, and the level of flexibility of the majority of inspection systems is low as most improvements focus on making inspection systems more accurate, real-time fast for 100% inspection. An interesting observation is that 99% of the analysed papers were clearly presenting the level of integration of their quality inspection system, something that is not the case for many of the defined attributes of the current study. We hope that the standardised ZDM terminology from the [64] would be utilised and align all researchers together.

Identified trends were compared with the ZDM framework presented by Psarommatis et al. [7]. Additionally, using the learning from our previous literature review [28], we discuss and propose a new quality inspection framework for ZDM. Finally, Section 4 offers a starting point for new research ideas to be pursued in order to overcome the limitations that traditional quality inspection techniques present in changeable manufacturing.

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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Appendix A. Selected papers

See Table A.5.

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