Integrated-decision support system (DSS) for risk identification and mitigation in manufacturing industry for zero-defect manufacturing (ZDM): a state-of-the-art review

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Abstract
Risk management has always been a trend in manufacturing related literature in the era of zero-defect manufacturing (ZDM). However, a gap still exists to present a holistic viewpoint of the integration for a product and its related processes involved during decision-making in manufacturing industry. The (knowledge-driven) integrated-decision support system indicates the opportunity by integrating the product design and manufacturing processes related risks in a manufacturing industry to make better decisions at the shop floor. It further proposes a direction towards development of a decision support system framework for their respective risks' identification as well as mitigation to enhance the quality, while minimizing time and cost. Over the years, risk identification has been considered well but risk mitigation has mostly been overlooked in the published literature. This paper scanned over a thousand papers from renowned journals published between 2005 and 2024. Currently, the evolution involved in the advancement of decision support tools for risk management has been reviewed by utilizing systematic literature review methodology. The study also provides a design overview, highlighting its features, pros, and cons of the existing methods which can be used for risk identification, prioritization, and mitigation in the development of a dynamic decision support system to aim (data-driven) zero-defect manufacturing (ZDM). Lastly, the paper discusses the current challenges and opportunities to lessen the manufacturing recalls in the industry, followed by phases of the proposed model.

Keywords Integration of product and process · Risk identification · Risk prioritizing · Risk mitigation · Integrated-decision support system · Zero-defect manufacturing (ZDM)

1 Introduction

The transition of manufacturing industry in any developing country from conventional industrial practices to state-of-the-art systems minimizing time and cost while maximizing the quality is the primary concern and a challenge to embrace industrial evolution. In line with the Industry 4.0, developed countries are consistently optimizing their resources by offering higher quality products and services at reduced costs (as well as time) by revealing new possibilities for zero-defect manufacturing (ZDM). Knowledge-based integrated-decision support system (DSS) is very much appreciated in industrial world due to its user-friendly features to cater potential risks' identification with their respective mitigation strategies (adopting prevention rather than correction approach) with the goal to reach closer to data-driven ZDM. Moreover, integrated-DSS is basically performed by the integration (typically two-way interactions) of both product design and manufacturing processes

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for identified risks in a manufacturing environment, which are mainly based on internal and external data, data gathering solutions, data analytics, knowledge/solution management, observation/historical data management, production data, DSS communication, and user interface. Digital manufacturing technologies are just a few of the key enabling elements that can help organizations to get even closer to realize the goal of zero-defects.

Already established management tools for production such as enterprise resource planning (ERP) software are not enough to constantly monitor, control, and improve manufacturing systems. These kinds of software are no more able to have sustained competitive advantage in industrial world [1]. In comparison, DSS can significantly facilitate the decision makers to make better decisions than those made by an operator as per his/her own knowledge and experience in a real-time production scenario. It analyzes defect characteristics, creates several alternative scenarios for mitigating defects and errors, suggests viable repairing processes, and evaluates optimum alternatives [2]. However, integrated-DSS is the core objective of this research study by integrating product design and manufacturing process, obtained to examine both aspects (product and process) of manufacturing of an electric product(s) aiming ZDM. Also, it automates the decision-making procedure in the defect detection, meanwhile guiding the operator to mitigate (by applying remedial activities proposed by this decision support tool) the production wastes (in terms of time and cost) while enhancing the quality.

Generally, the concept of any process life cycle begins with a research and development stage, followed by a conceptual process design (i.e. process synthesis) and engineering design (i.e. detailed design and layout). Subsequently, the plant construction and erection stage begins. Next, the start-up and commissioning of the plant are carried out. Thereafter, the plant has an operational stage during its active lifetime with insets of relatively short maintenance/retrofitting/debottlenecking steps. Finally, the plant is decommissioned where remediation and restoration may be conducted, whenever necessary. These process life cycle stages are illustrated, although not in scale, in Fig. 1, on the horizontal axis. For products, the life cycle begins when raw materials are extracted/harvested. These materials pass through a series of processing units, until the final product is delivered to the customer. After usage of the product, it is either disposed or recycled. The main steps of this product life cycle are shown on the vertical axis [3] in Fig. 1. Therefore, the integration of product design and manufacturing process proposed in this study is likely to be formulated on the same pattern on vertical as well as horizontal axis respectively.

Risk is a combination of a probability of an event along with its consequences [4], whereas risk management is a planned and structured process to help the project team in making the right decision at the right time to identify, classify, and quantify the risks—then to manage and control them [5]. ISO-31000 defines risk management as set of coordinated activities to direct and control organization regarding risk. More particularly, the same standard considers risk assessment as a process made of risk identification, analysis, and evaluation. From functional analysis to statistical approaches, ISO-31010 is a standard for risk

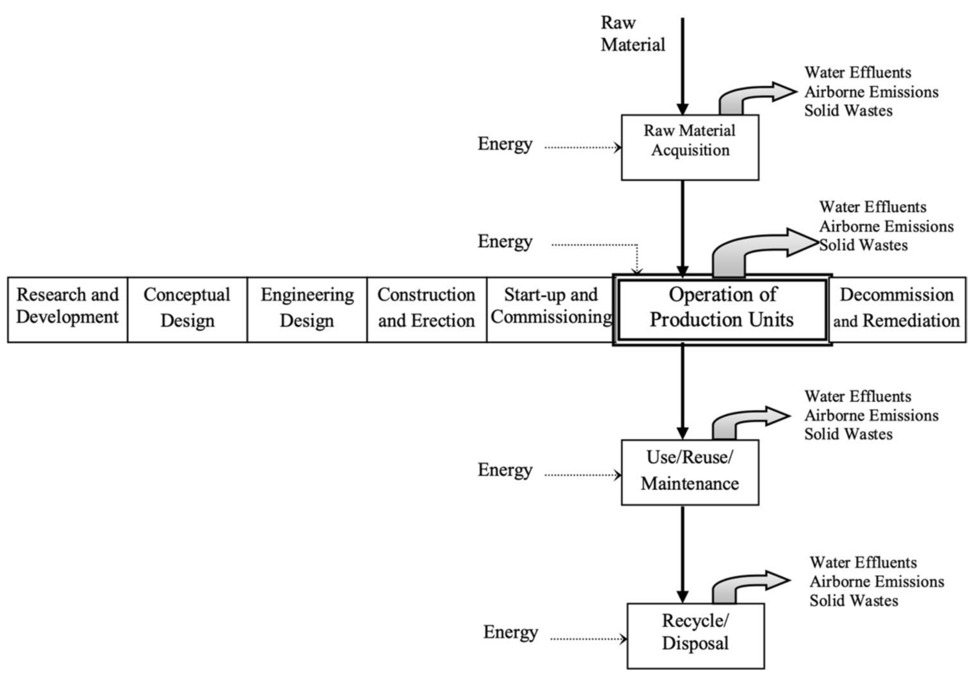

Fig. 1 Integration of process life cycle and product life cycle [3]

management which defines risk as the effect of uncertainty on objective(s) [6], which enlists different techniques for representing consequences, likelihood, dependencies, and interactions, suitable for various engineering products and processes [7]. Risk management is also represented in process related literature such as PMBOK [8]. Hence, it takes essential place in development projects and processes. Petronijevic et al pointed out this missing link between project and product risk management in manufacturing industry [9], which can further be extended to develop an integrated-DSS aiming ZDM.

The term zero-defect (ZD) was firstly introduced during the cold war by the US army regarding their defective weapon system. The US Department of Defense promoted the ZD movement and established ZD programs [11] [12] [10]. Similarly, the ZDM approach aims to reduce time and costs, while detecting defects at early stages and preventing their occurrences to assure the highest quality manufacturing outputs. It is a holistic methodology for ensuring quality of both product design and manufacturing process by reducing defects through predictive, preventive, and corrective techniques, mainly using data-driven technologies, and guaranteeing that no defective product leaves the production site and reach the customer, aiming at higher manufacturing sustainability as described in Fig. 2. There are four ZDM strategies used to decrease any form of waste: (i) detect, (ii) predict, (iii) prevent, and (iv) repair, used as pairs [10], and also it is pertinent to mention that both product design and manufacturing process equally play a critical role to achieve ZDM [13] [14]. Similarly, Bal et al introduced ZDM through five distinct strategies: (i) detection, (ii) prediction, (iii) prevention, (iv) repair, and (v) mitigation or compensation [15].

This paper aims ZDM through risk identification, risk prioritization, and risk mitigation, to seek knowledge and learn through repair data after detecting the manufacturing defects, so the prediction would possibly be made to prevent the errors in the future. Industrial world is now living in fourth industrial revolution, typically referred as Industry 4.0 which utilizes data from the past as well as the present [2], whereas Pakistani manufacturing industry does not usually recognize quality related risks, until it is identified down the shop floor or assembly line [16], and not even trying to use existing techniques, already implemented worldwide for manufacturing of electric products. Therefore, implementing Industry 4.0 technologies should always be the first measure when implementing the industrial transformation in a manufacturing setup of a country [17].

In traditional quality strategies, feedback control loops are usually implemented at single-process levels to detect and repair defects, even when the production system is complex and includes more than one stage or machines as depicted in Fig. 3a. It keeps separating the analysis of product data, which comes from inspection processes and process data, which further appears from in-situ monitoring (ISM) solutions. In this way, quality control loops are triggered only by inspection stages, which may come significantly later than the process during which the defect could have originated. On the other hand, ZDM strategies aim at proactively identifying defects or potential defects and attempt to find methods that: (i) prevent defects in the first instance, and (ii) avoid rework by compensating for defects and deviations downstream in the process chain, by means of feedforward control loops. A schematic representation of such ZDM strategies is illustrated in Fig. 3b. The ZDM paradigm grounds on the integration of product and process data coming from multi-source process chains [18], which can be achieved by two distinct methods: (i) process-oriented ZDM, and (ii) product-oriented ZDM [10]. ZDM with product orientation focuses on resolving issues within the physical components, whereas ZDM with process orientation examines flaws in the manufacturing equipment and assesses the conformity of the finished goods accordingly [19].

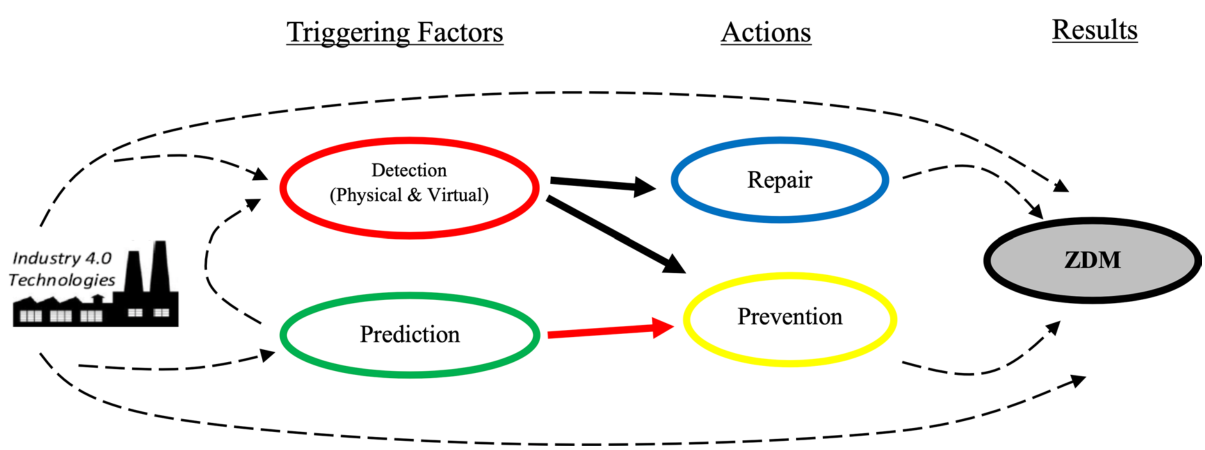

Fig. 2 ZDM under the umbrella of Industry 4.0 [10]

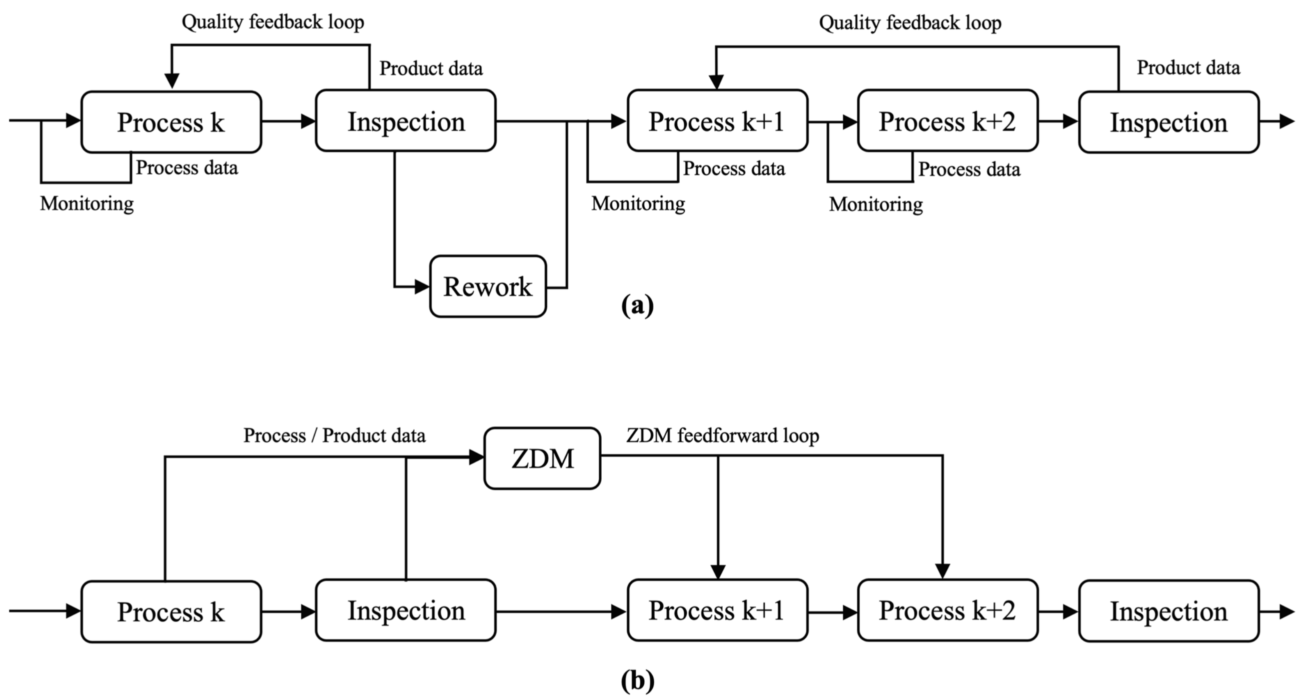

Fig. 3 Comparison of standard and ZDM approach [18] (**a**) Schematic representation of traditional quality strategies (**b**) Schematic representation of ZDM strategies

Given the advent of Industry 4.0 and the maturing of its digital technologies, the ZDM paradigm has advanced dramatically in the recent years. ZDM strategies base their operations on the collection of production and quality data from diverse sources, and the integration of that main data with data from various levels of the manufacturing plant [1]. As Industry 4.0 shown a significant move towards automation, interconnectivity, and real-time data processing, Industry 5.0 introduces the next phase of manufacturing evolution. Industry 5.0 builds upon the foundational concepts of Industry 4.0 to further enhance the implementation of ZDM by emphasizing a synergetic collaboration between humans and machines. This collaboration aims to enhance the human involvement in manufacturing processes, thereby ensuring products cater more closely to individual needs, preferences, and values [20].

This paper provides two main contributions. First, forward snowball concept is embedded in systematic literature review (SLR) methodology to search articles by their citations. Second, based on SLR methodology, identification and mitigation of interacting risks in product design as well as manufacturing process is integrated in an overview of the DSS framework. It has a potential to minimize manufacturing time and cost, while enhancing the manufacturing quality focusing towards ZDM.

The paper is structured in such a way that Section 2 shows overview of the research through an intersection diagram and existing tools and techniques for risk management which are in practice during last few decades. SLR methodology is adopted to discuss the research work based upon secondary data extraction published since 2018, followed by crux of the literature review. Synthesizing and analyzing the data for its documentation is also covered. Anticipated gaps for the guidance of this research work are endorsed in Section 3. Section 4 belongs to the statement testing to have a brief comparison between related research work performed around the globe. Tools and techniques related to risk identification are elaborated in Section 5, whereas techniques for risk prioritization and risk mitigation are covered in Section 6 and Section 7, respectively. The proposed DSS framework is explained in Section 8, followed by its co-effect with ZDM in Section 9. Challenges and opportunities of this research are discussed in Section 10, whereas phases of the proposed model are detailed in Section 11. Finally, this review article is wrapped up with conclusion and future work in Section 12.

2 Research overview

Risks can mainly be classified into different classes [21] such as macro and micro risks, natural order (for instance weather related or earthquake, etc.), or man-made (for instance political related or unrest, etc.) risks are considered macro risks, whereas micro risks include manufacturing risks occurring due to inter-relationships between entities within a firm [22], while RM consists of risk identification, its ranking/prioritizing, and mitigation [23]. Data-driven ZDM approach prevents or learns from errors/defects by evaluating the manufacturing data (with respect to the iron triangle as defined by [24] to reduce time and cost, enhancing the quality). Knowledge-driven integrated-DSS (dynamic in nature) is basically a computerized program which gathers and analyzes the data, guiding the operator to make better decisions, if defect/error occurs.

The Venn diagram in Fig. 4 shows intersection of the proposed research topic having three basic levels: (i) environment level, (ii) system level, and (iii) operator level. As discussed earlier, environmental risks cannot be controlled, but preventable with remedial strategies. System level discusses the working of the proposed DSS with the help of a preventive approach protecting the funnel. It has three core areas, i.e. risk management (RM), integrated-decision support system (DSS), and zero-defect manufacturing (ZDM). The first overlap area is RM and integrated-DSS, designs a system to identify and mitigate the risks. Second overlap area is RM and ZDM, identifies (with analysis as post-identification stage) and mitigates (with control as pre-mitigation stage) the manufacturing wastes/errors to increase the quality. Third overlap area is integrated-DSS and ZDM designs a system to streamline manufacturing of e-goods. The cumulative overlap area is RM, DSS, and ZDM, develops a system by integrating both product design and manufacturing process to identify, rank/prioritize, and mitigate the risks, aiming ZDM. A wholesome picture of a manufactured product along with its aspects for manufacturing process can be analyzed (using a DSS through its risk behaviour, probability, and severity), and evaluated (by ZDM through its manufacturing data in a DSS). Data sources (consisting internal and external source) of the organization are added inside the DSS in the funnel. At operator level, the outcome of the funnel is a knowledge-driven computerized program that gathers and analyzes data, able to learn from defects or errors as per ZDM concept. The preventive approach expects to have defect-free products, whereas in comparison with a manufacturing setup without any prevention to potential risks, recalls are likely to occur, increases manufacturing time and cost, ultimately degrading the quality.

In a nutshell, this review article would fill this challenging gap, exposing the opportunity to develop an integrated-DSS (by integration of product design and manufacturing process) for risk identification and its mitigation for manufacturing industry. It is to reach closer to ZDM approach, where the term zero-defect can be the reduction of waste in terms of time and cost to maximize the quality.

2.1 Existing methods for risk management

Literature review suggests that there are many tools for risk management, already in practise worldwide over the

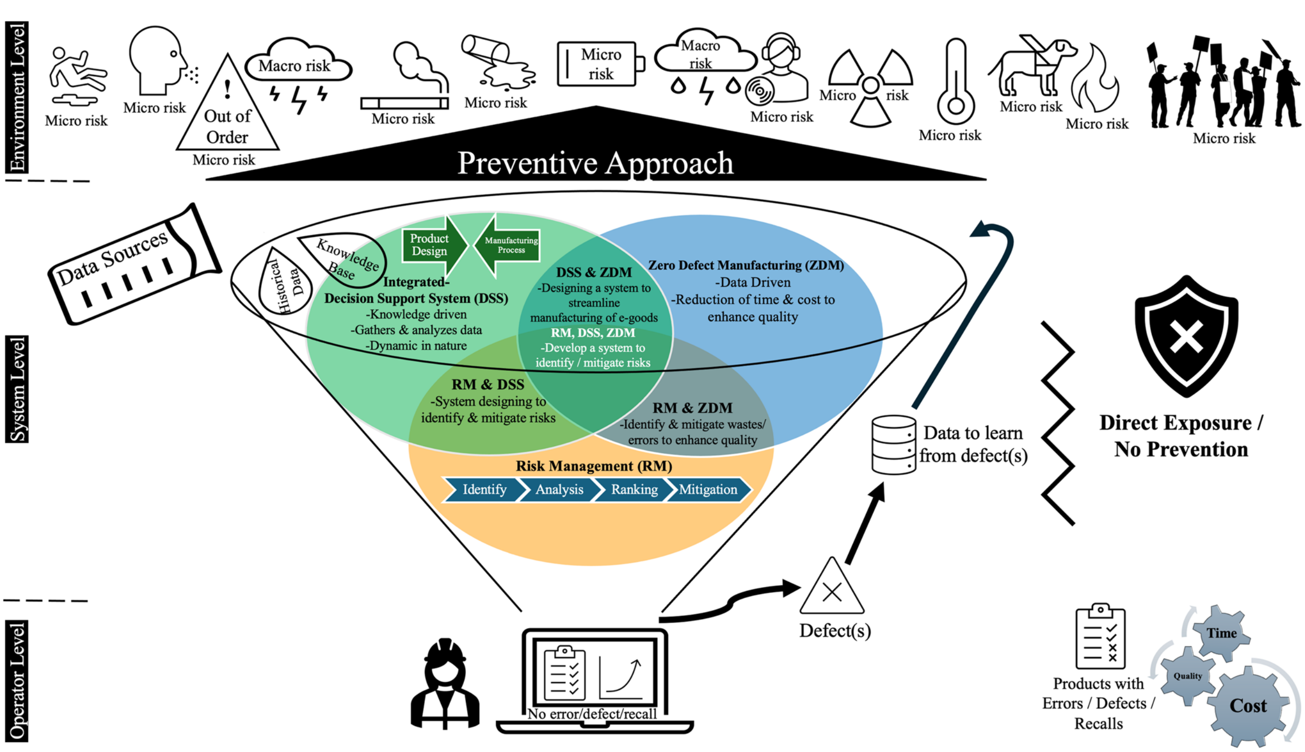

Fig. 4 Overview of the research

years. Some of the techniques are defined on a time scale since 2005 and onwards as shown in Fig. 5. This summarizes risk management tools and techniques to have a look on the trend in practise worldwide for risk management systems, in relation to different fields and scopes. Thus, development in SWOT, fuzzy-related approaches, FMEA, FMECA, Delphi method, etc. is evident since last decade, which might be considered during a case study of this research.

2.2 Systematic literature review (SLR) methodology

According to Grant and Booth, the framework of Search, Appraisal, Synthesis, and Analysis (SALSA) is an approach to determine the search procedures to be followed by the SLR methodology to ensure accuracy, systematization, exhaustiveness, and reproducibility [83]. As shown in Fig. 6, the methodology started with an advanced method for systematic and meta-analysis studies through Protocol, Search, Appraisal, Synthesis, Analysis, and Report (PSALSAR) framework. The most review works followed the literature search protocol of Preferred Reporting Items (PRI) for Systematic Reviews and Meta-Analysis [84] and the SALSA framework [85]. From those common review method types, Protocol and Reporting results with development of SALSA to PSALSAR framework [86] [87]. Therefore, this PSALSAR framework of SLR work applied in a sequence in this review paper as shown in Table 1.

Review protocol by using Population, Intervention, Comparison, Outcome, and Context (PICOC) framework is to formulate research question(s) and to identify research limitations. As described in Section 2.2.1, the refined research questions were outlined according to the objective and direction of this research study to develop an integrated-DSS for risk identification, risk prioritization, and risk mitigation in manufacturing industry. As elaborated in Section 2.2.2, these questions were answered by search for the studies using inclusion/exclusion criteria to find the suitable search string, identifying the appropriate databases. The appraisal has further two sub-sections in which those databases were assessed based on this review work objective, as explained in Section 2.2.3. Similarly, the sub-section of data extraction based on abstract and keywords of the research articles/papers was to formulate crux of the literature review accordingly. It started with a total record of 1291 research documents, whereas ended up with a total of 26 research studies by filtering out using

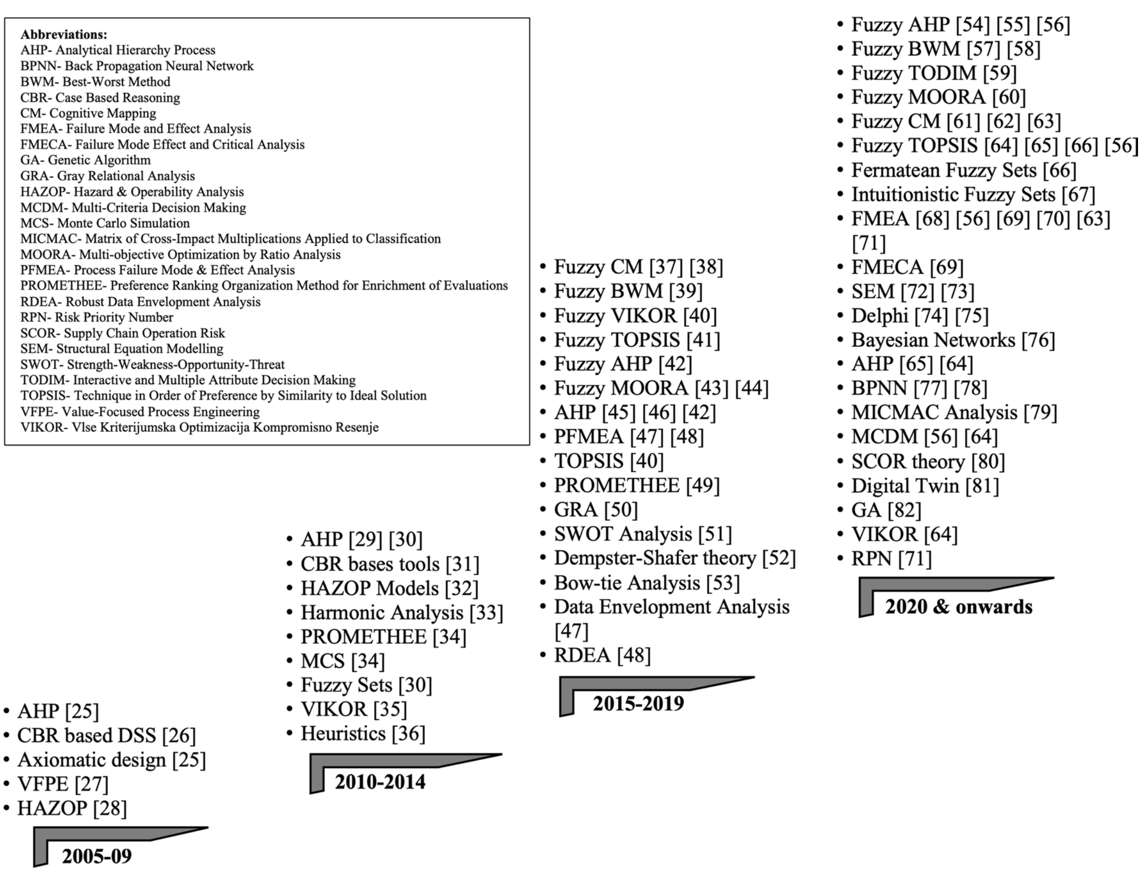

Fig. 5 Evolution and developments in the last decades

different phases, shown in Fig. 7. The finally selected papers are briefly discussed in Table 4, in terms of their model(s)/technique(s), approach(es), limitation(s), research origin, publisher/database, and author(s)/publication details, synthesizing the data to define a criterion for the extraction of useful and most relevant information for this research study from these 26 articles. As shown in Section 2.2.4, it was performed based on their criteria and categories such as data, relationships, models, qualitative and quantitative methods, methodologies, economic valuation, and model validation, although analyzed through a map-based citation network. As detailed in Section 2.2.5, the analysis was performed by using VOSviewer tool to graphically represents the network visualization, overlay visualization, and density visualization for clusters of keywords present in the title as well as abstract of the finally shortlisted papers. The last step as described in Section 2.2.6 was to have tangible research output in the form of documenting the report.

2.2.1 Review protocol

It is the first step in SLR methodology for the consideration of transparency, transferability, and replicability of the research work, general elements that make literature review a systematic one [88] and help the research to somehow lessen (as doing it manually) the biasness through exhaustive literature searches and to determine the scope of the research. This scope further guides in formulating research question followed by its limitations to identify appropriate research methods [85].

The refined objective of this SLR regarding integrated-DSS for risk identification, prioritization, and mitigation to aim ZDM is presented in the form of refined research questions as given below:

i. What is integrated-DSS (by integrating product design and manufacturing process)?
ii. What are the elements along with their workflow in integrated-DSS?
iii. What are the best possible approaches for risk identification (with analysis as post-identification stage), ranking/prioritizing and mitigation (with control as pre-mitigation stage)?
iv. What can be the optimum solutions on user interface (for the operator) in the proposed integrated-DSS to achieve ZDM?
v. What are the current challenges in developing integrated-DSS in a developing country?
vi. What will be the lessons learnt and way forward for risk management in manufacturing industry?

Above research questions are answered by following PSALSAR approach as demonstrated in this paper.

2.2.2 Search for the studies

The second step in SLR methodology is about search strategy and its delivery. The search strategy helped to define appropriate search string and identify the relevant databases to collect the relevant documentation [85].

Fig. 6 Direction of future research through PSALSAR using SLR methodology

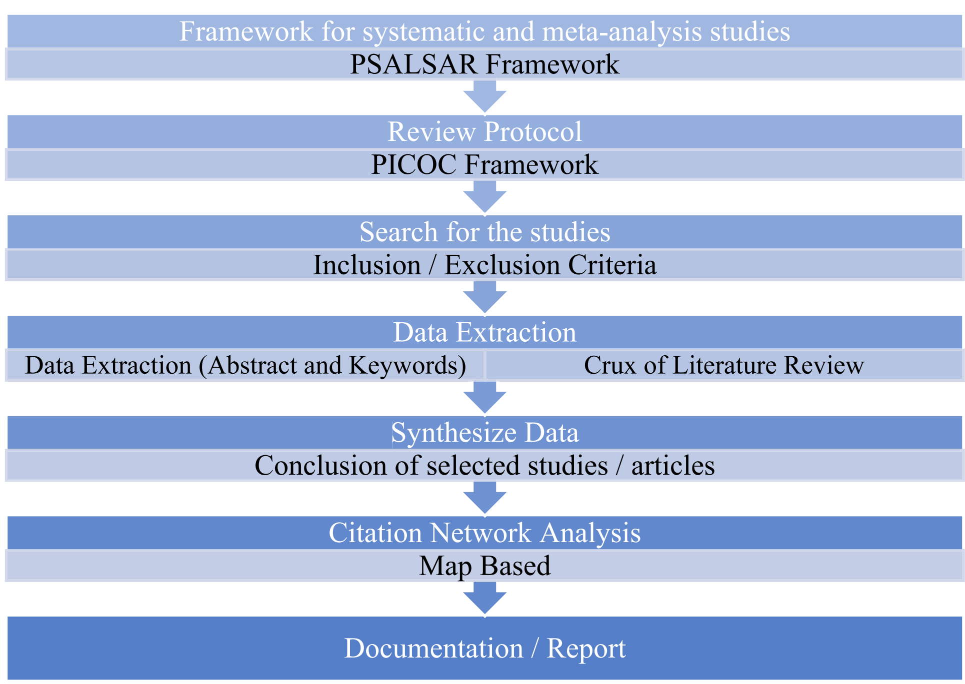

Table 1 Framework for systematic and meta-analysis studies (Modified from [85] [86] [87])

	Phase	Step(s)	Outcome(s)	Purpose/objective(s)
PSALSAR framework	Planning	Protocol	Define study scope	Risk identification, ranking/prioritization, mitigation, ZDM, Integrated-DSS (see Table 2 for details)
	Conducting	Search	Define search strategy	Searching statements and keywords (see Fig. 7)
			Search studies	Search journals / databases / libraries
		Appraisal	Selecting studies	Defining inclusion and exclusion criteria (see Table 3)
			Quality assessment of studies	Quality criteria (see Section 2.2.3.2)
		Synthesize	Extract data	Extraction template (see Section 2.2.3.1)
			Categorize the data	Categorize the data on the iterative definition and ready it for further analysis work (see Table 5)
		Analysis	Data Analysis	Quantitative and narrative analysis of the organized data (see Section 2.2.5) through citation network analysis
			Results and discussions	Trends, identify gap and results evidence
			Conclusion	Deriving conclusion and recommendations (see Section 12)
	Documentation	Report	Report writing	(See Section 2.2.6)
			Draft for publication of the review article	Summarizing the report result for the public, mostly researchers, students affiliated with academia and industry

2.2.3 Appraisal (materials and methods)

It is the third step in SLR methodology in which the selected articles/papers were evaluated on the basis of review assignment. This further includes two sub-steps such as selection of related studies and their quality assessment.

Data extraction/selection of related studies The flow diagram for the database search of publications for systematic reviews is shown in Fig. 7. A total of 1291 records were identified in the first step through keywords (i.e. Risk Management, Risk Identification, Risk Prioritization or Ranking, Risk Mitigation, DSS, and ZDM) and abstract reading in the publications published by renowned publishers like Elsevier, Emerald, IEEE, Sage, Taylor & Francis, Wiley, and Springer. To screen the second step, a total of 921 records were excluded in the initial selection, which were either PowerPoint presentations, white papers, technical reports, technical papers, competition announcements, project deliverables, magazines, and poster publications or if the studies published in other than English language. Abstract reading for the eligibility was taken place in the third step of the filtration process where 189 articles were excluded, whereas still 370 articles were included, somehow related to risk management and manufacturing engineering. The main body skim reading for the eligibility was taken place in the fourth step of this extraction process where out of 370 articles, 181 articles were shortlisted by excluding 156 studies. The fifth and last step was inclusion of finally selected articles, which came up with a total of 26 articles (published since 2018) including the one added through forward snowball method (to search articles by their citations) in the light of guidance by [90] such as a relevant paper published in 2020 by Yousefi et al. [63] was observed in the citations of an article published in 2018 by Baghery et al. [47] to get included in the crux of the literature review. As discussed in Fig. 7, out of 1291 journal papers published in this field over the years, the 26 papers (published in 2018 and onwards) were found closely related to this research study, included in the main literature review as shortlisted in Table 4.

Quality assessment Each SLR step was evaluated by using the following criteria, based on four quality assessment questions as under:

- QA1: Is the literature review's inclusion and exclusion criteria appropriately defined?
- QA2: Is the literature search likely to have covered all relevant studies on the topic?
- QA3: Did the selected publications had blind reviewers that assess the quality/validity of the study? [86] [87]
- QA4: Was the type of integrated-DSS for risk management for ZDM or its related concepts mentioned in the publications described adequately?

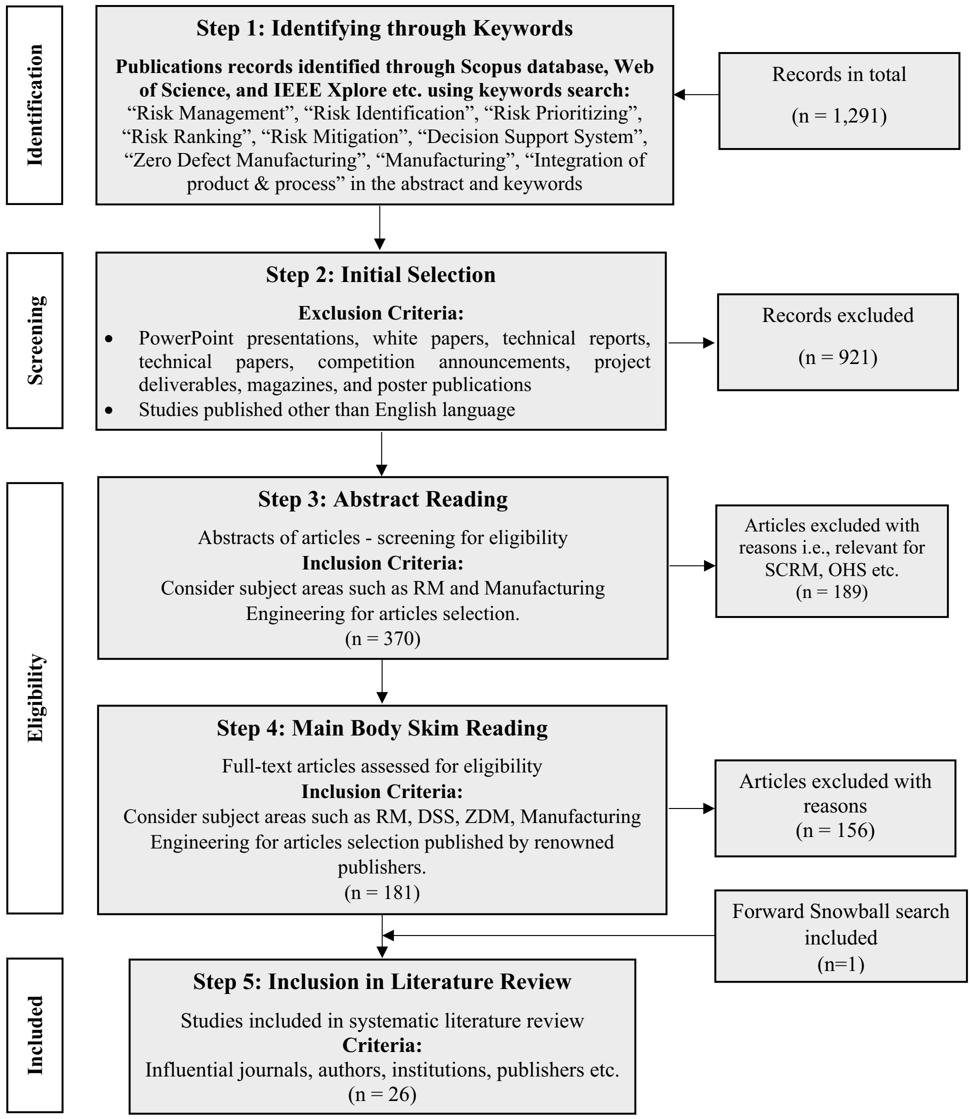

Fig. 7 Illustration of filtering processes of research methodology (concept taken from [84] [86] [87] [89])

2.2.4 Synthesize data

The fourth step in SLR methodology is about synthesization, consisted of both extraction and classification of relevant data from the selected papers to derive knowledge and conclusions. As shown in Table 5, the data extraction process involved the identification, and extraction of relevant material and data from the papers [86] [87].

2.2.5 Analysis

In this secondary data analysis (bibliometric analysis) step, SLR methodology encompassed the evaluation of synthesized data, and the extraction of meaningful information followed by conclusion of the selected papers. In this phase, the research questions would be answered covering both qualitative and quantitative explanation with narration of the results. It discussed and indicated the way forward for the future research work while inferring a conclusion [86] [87]. The analysis was mainly based upon the inter-relatedness of the articles mentioned in the literature review, during which different sources were used for the secondary data. It was therefore useful to extract the primary data, and to further observe the concentration of the theme with this research title and its keywords, published in different available sources over the years.

As already discussed in Table 3 and Fig. 7, filtering processes of research methodology through title, keywords, and their abstract in databases was performed where a total of 26 papers (mentioned in Table 4) were shortlisted. Zotero version 6.0.26 software, a tool to collect, organize, annotate, cite, and share research, was utilized to generate library files, exported in RIS (other options were BibTeX, CFF, CSV, Endnote, or RefWorks) format as bibliographic/text database file (required as a

Table 2 SLR research scope based on the application of the PICOC framework to the determined objectives (modified from [85] [86] [87])

Concept	Definition (according to [88])	SLR application
Population	The research work mainly deals with the risk management involved in manufacturing industry	Researchers affiliated with academia, industry or elsewhere focusing the risk management on manufacturing to at least come closer to ZDM
Intervention	Existing techniques will be utilized to address the problems in risks during manufacturing by developing an integrated-DSS	Indicating the gaps that need further research work: for instance, developing an integrated-DSS (by integrating product and process) for risk identification, ranking/prioritization, and mitigation approaching towards ZDM
Comparison	Techniques to contrast the intervention used to develop integrated-DSS with the existing methods/approaches in the field of risk management	Difference between the different methods applied to quantify/value/map which are evident to formulate the theoretical or conceptual framework in the field of risk management
Outcome(s)	Measure to assess the knowledge and mentioned the gaps	Development of integrated-DSS for risk management to achieve ZDM
Context	The settings or areas of the population such as labour/operators working in manufacturing setups	Trends of ZDM research, existing knowledge in ZDM studies, the challenges, and gaps in integrated-DSS, the geographical distribution of existed studies

pre-requisite for further analysis) of those articles. Similarly, VOSviewer software (Java programming language based) version 1.6.19 was utilized to create map-based analysis, which accepts library or bibliographic database files such as Web of Science, Scopus, PubMed, Microsoft academics, or reference manager files such as RIS, EndNote, or RefWorks. So, the RIS library file was imported in VOSviewer tool to visualize bibliometric information and scientific landscapes. As shown in Table 6, the terms "keywords" for "title and abstract" fields having "full counting" (instead of binary counting) method were opted as occurrences. In any cluster, items could either be included or excluded (as observed in Table 3) where terms with a low relevance score would possibly be excluded manually. As tabulated in Table 7, there were 4 clusters (for 3 occurrences per each term) with 46 items observed during VOSviewer analysis, such as the first cluster had 19 items (red coloured) with 9 major (closely related) and 10 minor (irrelevant) items, the second cluster had 12 items (green coloured) with 7 major and 5 minor related items, the third cluster had 8 items (blue coloured) with 3 major and 5 minor related items, and lastly the fourth cluster had 7 items (yellow coloured) out of which 2 were relevant, whereas the rest of the 5 as irrelevant items.

Map-based analysis Three maps (visualization of scientific landscapes) based upon bibliographic/text database file were generated by VOSviewer analysis: (i) network visualization, (ii) overlay visualization, and (iii) density visualization.

Firstly, network visualization exhibited clusters of the keywords in title and abstract with a minimum of three occurrences as shown in Fig. 8. As already discussed, VOSviewer can be used to construct bibliometric networks of scientific publications, scientific journals, keywords, or terms. Items in these networks were linked/connected with each other by co-occurrence, bibliographic coupling, and citation links, established to constitute or construct a network. In the network visualization, items displayed by their labels where the size of the label and the circle/frame of an item was determined by its weight. The higher the weight of an item, the larger the label so the circle/frame of that item. To avoid overlapping labels, the label might not be displayed for some items. As mentioned in Table 7, the colour of an item is determined by the cluster to which it belongs. Lines between items represent links, where a link defined as a connection or a relation between any two items. Each link has a strength, represented by a positive numerical value. The higher the value, the stronger the link. Hence, a network is a set of items together with the links between the items. Items might be grouped into clusters where a cluster is a set of items included in a map. The distance between two

Table 3 SLR study selection of literature using inclusion and exclusion criteria (modified from [86] [87])

Criteria	Decision
Pre-selected keywords exist as a whole or at least in title, keywords, or abstract	Inclusion
The paper published in a scientific peer-reviewed journal	Inclusion
The paper is written in English as an international language	Inclusion
Studies that present pieces of evidence on development of decision-making models for risk management	Inclusion
The articles address at least one risk identification, prioritization, or mitigation	Inclusion
Papers that are duplicated within the search documents	Exclusion
Papers that are not accessible, review papers and meta-data	Exclusion
Papers that are not primary / original research	Exclusion
Papers that are not primary / original research	Exclusion
Papers published before 2018	Exclusion

journal articles in the visualization approximately indicated the relatedness in terms of their co-citation links. In general, the closer two journal articles were located to each other, the stronger their relatedness. The strongest co-citation links between journal papers were also represented by lines but with more strength as compared to other links (guidance is taken from [102]).

Secondly, overlay visualization is identical to the network visualization, except those items coloured differently. There were two ways in which items could be coloured in the overlay visualization. If items had scores, the colour of an item could determine by the score of that item; however, default colours range from purple (for lowest score) to green to yellow (for highest score). As shown in Fig. 9, colours indicated impact factor and publication year of the journals. For example, journals coloured blue have an impact factor < 1, coloured green have an impact factor ~ 2, and coloured yellow have an impact factor of ≥ 3. Similarly, clusters of the keywords in title and abstract were also considered with a minimum of three occurrences from the oldest data (purple-coloured boxes) to the newest (yellow-coloured boxes). The keywords of the interest of this review article such as risk event and occurrences were visible in the oldest articles (published in 2020) which have purple-coloured boxes. The interested terms like model, uncertainty, and effect analysis were evident from the articles (published during mid 2020) that had blue-coloured boxes. The latest technological development in the field of DSS endorsed in the publications (having highest impact factor) during 2022 had yellow-coloured boxes (guidance is taken from [102]).

Lastly, density visualization is to showcase the cluster density based upon keywords of the title and abstract of any research idea, knowledge, or research project with a minimum of three occurrences as shown in Fig. 10. It was 100% scaled to show the weights of occurrences in accordance with their density of the clusters. As discussed earlier, there were mainly four clusters as evident in Table 7. The first cluster (having red colour) contained total 19 items where the relevant items were risk management, adoption, technology, risk event, risk behaviour, potential failure, manufacturing, and effect analysis. The second cluster (having green colour) contained a total of 12 items where the relevant items were DSS, ZDM, detection, defect, cause, action, severity, occurrence, and quality. The third cluster (having blue colour) contained a sum of 8 items including FCM, uncertainty, reliability, and competitor. Last but not at all least, cluster (having yellow colour) contained seven items in total including early warning model and sustainable innovation. The weight given to the colour of a certain cluster was determined by the number of items belonging to that cluster in the neighbourhood of the point. The larger the number of items in the neighbourhood of a point and the higher the weights of the neighbouring items, the closer the colour (red, green, blue, or yellow) of the point to its cluster. The other way around, the smaller the number of items in the neighbourhood of a point and the lower the weights of the neighbouring items, the closer the colour of the point to black (guidance is taken from [102]).

2.2.6 Documentation/report

The sixth and last step in SLR methodology is about documenting the report of the results obtained from selected literature, which includes description and methods' presentation. This report phase generally has two steps: (i) description of the main procedure followed as explained in Table 3 and (ii) public presentation of the results like a journal article [85]. In SLR methodology, a journal article production is the last step which helps to provide the research output for further academic and scientific purposes [86] [87].

Table 4 Literature review crux

S. No	Model(s)/technique(s)	Approach(es)	Limitation(s)	Research origin	Publisher/database	Reference(s)
1	Process-failure mode and effect analysis (FMEA)	-Assess the potential product or process failures from the beginning to the end of the product life cycle (PLC) -Interval data envelopment analysis (DEA) to analyze and prioritize identified failures	Impact of failures using cause and effect relation method along with imposed costs associated	-	Springer	[47]
2	Integrated robust data envelopment analysis (RDEA-FMEA)	Evaluate and prioritize Health, Safety & Environment (HSE) risks by using RPN in automotive parts industry	Causal relationships and influential effects between risks in each department or stations using FCM	Iran	Elsevier	[48]
3	Framework development using fuzzy cognitive map (FCM)	Analysis and evaluation of risks for product development projects in manufacturing industry	Integration of data mining to identify risk factors and their correlations	France	IEEE	[37]
4	Extended FMEA and TOPSIS	Prioritizing environmental risks in an intelligent manufacturing process by optical cable automatic arranging robots to improve production performance of optical cable factory	Applicability of ANP to solve correlation problems among risk factors and failure mode types	China	IEEE	[91]
5	Manufacturing execution system (MES)	A reference architecture and related software modules to achieve improved production quality performance for ZDM	Industrial implementation in ZDM-oriented architecture through a right sequence to reach a steady use and fast adaptation of ZDM strategies	Italy	Elsevier	[1]
6	Product quality loss (PQL) and work-in-process (WIP)	Verifying the superiority of method by optimal decision combination through Genetic Algorithm (GA), also the detectable deviations and potential manufacturing defects on degradation path of machine performance in engine-head-cylinder manufacturing system	-To explore appropriate mechanism model for the critical functional components to reduce continuous inspection -To improve time for decision-making by linking to productivity -Examining of possible several combinations between explicit and implicit risks to deepen the understanding	China	Taylor & Francis	[92]
7	FMEA followed by RPN	Analyzing and reducing risks involved in manufacturing of leaf-springs in vehicle manufacturing companies	Hybrid approach for FMEA and process capability analysis or GRA to reduce SOD ratings of RPN	Pakistan	Sage	[71]
8	Integration of Sequential FCM and process FMEA	Risk prioritization approach to prioritize logistics risks by using RPN and Extended Delta Rule (EDR) learning algorithm proposing risk mitigations (preventive and corrective actions) in automotive spare parts industry	Usability in assessing the risks of the logistics system of other process-oriented manufacturing systems	Iran	Taylor & Francis	[63]
9	MCDM model based on neutrosophic analytic hierarchy process (AHP), Vlse Kriterijumska Optimizacija Kompromisno Resenje (VIKOR) method, and TOPSIS method	Financial Performance evaluation and sensitivity analysis in steel manufacturing firms	Using other MCDM techniques such as Multi-Attribute Boundary Approximation Regional Comparison (MABAC) and BWM	Egypt	Springer	[64]

Table 4 (continued)

S. No	Model(s)/technique(s)	Approach(es)	Limitation(s)	Research origin	Publisher/database	Reference(s)
10	Backpropagation neural network (BPNN) method optimized by Genetic Algorithm (GA)	Early risk warning model during the process of sustainable innovation in manufacturing firms	Analyzing industrial risks like exchange rates, national economic conditions, and stock markets	China	Elsevier	[82]
11	FMEA	Review for failure mode identification, risk assessment and industrial standard application in manufacturing industry	Improvement of existing theoretical deficiencies as per industrial needs, and automation of FMEA to respond inconsistency between academia and industry	China	Springer	[93]
12	Fermatean fuzzy sets (FFSs) with Technique in Order of Preference by Similarity to Ideal Solutions (TOPSIS)	Integration of Fermatean risk assessment matrix and TOPSIS for potential hazards identification and ranking in aluminium plate manufacturing process	Calculating risk parameter weights using BWM to handle additional risk parameters such as detectability, cost, prevention, effectiveness, and sensitivity to no-application of maintenance for some comprehensive pairwise comparison-based methods	Turkey	Springer	[66]
13	Operational framework	Risk Identification in manufacturing industry of Li ion batteries for electric vehicles	Risk Mitigation to identified risks	UK	Elsevier	[94]
14	Combination of FMEA, fuzzy logic methods, and Pareto chart	FMEA with the aim of identifying the various failure modes and their causes and effects, fuzzy logic method for the factors such as occurrence, non-detection, and severity to reach Fuzzy-RPN (FRPN), whereas Pareto chart to highlight the most important causes to suggest corrective actions in manufacturing mode of solar gel batteries	Application of FMECA during operation mode and improvement of hybrid system performance by the integration of an adequate and intelligent energy management	Tunisia	Elsevier	[69]
15	Simulation based digital twin followed by sensitivity analysis	Improvement of production lead-time of discrete (compounding) processes using simulation to aid the development of a digital twin for real-time decision support in a sterile drug / pharmaceutical product manufacturing plant	Develop a continuous system for bio-processing phase in pharma manufacturing line	Germany	Elsevier	[81]
16	Interpretive structural modelling (ISM)	Classifying risks through Matrix of Cross-Impact Multiplications Applied to Classification (MICMAC) analysis in manufacturing Small-and-Medium-Enterprises (SMEs)	Identification of additional risk and sub-risk variables for assessment and prioritization using MCDM tools followed by model verification by System Dynamics Modelling (SDM) or Structural Equation Modelling (SEM)	India	Emerald	[79]
17	FMEA with fuzzy best–worst method (BWM), and fuzzy Bayesian network (BN)	Determining weights of the RPN parameters, followed by BN Structure to determine occurrence probabilities of risks in kitchen equipment manufacturing	Separate BN including main and auxiliary failure modes of each product type	Turkey	Springer	[95]

Table 4 (continued)

S. No	Model(s)/technique(s)	Approach(es)	Limitation(s)	Research origin	Publisher/database	Reference(s)
18	Z-number theory and multi-stage FCM (Z-MSFCM)	Considering the concept of uncertainty and reliability in quantities of risk factors and the weights of causal relationships in the MSFCM in an automotive manufacturing industry	Some new transfer function for FCM training to compare results with S-shaped solutions / transfer function in electronics manufacturing industry	Iran	Springer	[61]
19	Combination of fuzzy best–worst method (BWM) and analytical network process (ANP)	Identifying chemical reaction hazards, compatibility diagram to provide pair-wise interactions of hazards, and R-index/risk alternatives (RA) assessment and mitigations for highest assessment risks in a chemical industry	Mitigation plan for low assessment risks in a chemical plant	Republic of Korea	Elsevier	[96]
20	Fuzzy and R number multi-objective optimization by ratio analysis with full multiplicative form (MULTIMOORA) (fuzzy MCDM)	Considering new parameters like both negative and positive risks, negative and positive passable risks, and risk-based multi-objective optimization in an automobile manufacturing company	Effective solutions for maintaining balance between competition and collaboration in business-to-business (B2B), along with different characteristics in B2B open innovation (OI)	Iran	Emerald	[97]
21	Sequential multi-stage FCM (SMFCM)	Learning algorithm for MSFCM and finalizing the risks score/prioritizing the failures by RPN in brake-pad manufacturing industry	Adding reliability and uncertainty environment to the analysis for better risk assessment	Iran	Taylor & Francis	[98]
22	Combination of institutional theory, resource based view (RBV), technology acceptance model (TAM)	Examining the adoption of big data, artificial intelligence, cloud computing, and blockchain for risk management from operator's perspective in digital manufacturing systems	Comparison between perceived and actual use of technology after occurrence of an emergency	UK	Elsevier	[73]
23	Integration of human performance model within risk assessment process	Preventive comparison of the effects of matching worker-tasks in term of risk and consequently in terms of potential occurrences of accidents and injuries in an assembly line of heavy vehicle manufacturing plant	Risk Management tool to enhance quality and safety in heavy vehicles manufacturing plant	Italy	Elsevier	[99]
24	a model based on fuzzy-analytical hierarchy process (AHP) and fuzzy-fault tree analysis (FTA)	Fuzzy fault tree analysis (FTA) in a low-concentration gas safe combustion system	Safety assessment in the operation and maintenance in process of system in industrial coal mine	China	Wiley	[100]
25	Sustainability impact and effects analysis (SIEA)	Sustainability risk management aspects like risk assessment (scope), identification, analysis & evaluation (prioritization), and treatment & communication (remedial strategies) in aerospace engine components manufacturing firm	SIEA testing on different levels of decision-making, and combining SIEA with methods for quantitative risk modelling or scenario exploration, followed by validating the impact of SIEA on decision-making	Sweden	Elsevier	[101]

Table 4 (continued)

S. No	Model(s)/technique(s)	Approach(es)	Limitation(s)	Research origin	Publisher/database	Reference(s)
26	Hybrid DSS for ZDM	Data-driven and knowledge-based approaches to detect defects, automating necessary decision-making processes, also real-time data and past knowledge to analyze defects, identify their severity, suggesting rectifications in a manufacturing industry for ZDM	Modelling the shop floor and measuring the DSS performance when model is used for more than one product, and integration of DSS with the production system and KPIs	Switzerland	Elsevier	[2]

3 Research gaps exist in literature

Based on the report of the SLR methodology, there were six research gaps (mentioned as future work or recommendations discussed in above mentioned papers) exist to guide this research study as illustrated in Fig. 11. However, the authors were interested to work on one of the research gaps, i.e. the development of an integrated-DSS by integrating product design and manufacturing process in risk identification, its related ranking/prioritization, and mitigation strategies to reach closer to the ZDM.

4 Statement testing

The anticipated gap mentioned in Section 3 is confirmed through statement testing method as illustrated in Table 8. It draws a comparison of research studies published since 2018, closely related to this research gap in terms of availability and non-availability of the important features such as risk identification, its prioritization, and mitigation for product design, manufacturing process, and ZDM. The symbol '✔' indicates that the research work provides the feature, whereas the symbol '✖' indicates its absence.

5 Risk identification and analysis

In the existing literature, the following are the few risk identification tools and approaches already in practise since many years. As per the need and feasibility for this research work, this review article summarized all advantages and disadvantages of the methods in Table 9 to shortlist the most feasible one.

Apropos all above tools and techniques, Delphi technique might be selected for risk identification due to the relevance and scope of this research study. As mentioned on Serial 1 of Table 9, its advantages include low cost to administer and analyze, easily achievable consensus, and its adaptability to diverse data collection strategies with a decrease of peer pressure secondary to anonymity along with the ease of considering opinions of many experts into a few precise statements. However, its disadvantages such as its opinion-based consensus not considered correct answers would be addressed, similarly its unknown internal validity. It is generally difficult to define and locate its panel experts for some topics and its data collection costs and lengthy data collection time frames would be addressed by developing a concise qualitative questionnaire. Also, the opinion of the experts would then

Table 5 Criteria used for the extraction of information from the selected articles (modified from [86] [87])

S. No.	Criteria	Categories considered	Justification(s)
1	Publication Year	Since 2018	Studies before 2018 were excluded
2	Name of journals / publishers	-	To describe the distribution of the work such as Elsevier, Springer, Taylor & Francis, IEEE, Sage, Emerald, and Wiley etc.
3	Study site	Country name	Geographic sites of manufacturing firms located in Punjab, Pakistan
4	Types of data sources	Primary data	Data derived from sampling in the field (e.g. field data, surveys, or focused interviews) yet to do for this research work
		Secondary data	Data types which were derived from other readilyavailable information but not verified in the field (e.g. remote-sensed data, socioeconomic data, and mixed sources like databases like global statistics)
		Mixed data	Database (global statistics, e.g. map of carbonstorage and reports), bibliography, modelling, surveys, and field data
5	Methods	Look-up tables	Use of existing DSS models available in the literature
		Expert knowledge	Experts would be invited to rank risk identification, mitigation and ranking for development of integrated-DSS (by integrating both product and process) for ZDM
		Causal relationships	Incorporate existing knowledge to link with related risk identification, mitigation, and ranking approaches to create an integrated-DSS to achieve ZDM
		Models	Framework development
6	Mode of assessment	Qualitative	Feasible approaches for risk identification, ranking / prioritization, and mitigation
		Quantitative	Practical approaches / methods for integrated-DSS
		Economic valuation	DSS model should be economically viable such as it lowers the time and cost to enhance quality of the manufacturing line
		Mapping and modelling	Development of state-of-the-art DSS mode
7	Purpose of Publication	Expansion of knowledge	This review article may bring some new and better knowledge in the field of risk management for manufacturing
		Methodological development	This review article will be followed by a researcharticle to come up with the verification and validation of the proposed framework
		Management option	Verification of the proposed framework will be done by a simulation software as described in Section 12 of this article
		Policy	This study may guide some policy for public sector organizations of the country
		Implementation	Initially, implementation may be offered voluntarily with the aim to be a part of manufacturing policy for the country
8	Difficulties mentioned	Methodological	Uncertainties on the result due to the application ofthe unclear or less developed method
		Others	Uncertainties linked with lack of conceptual clarity
		Data	Primary and secondary data source quality and scarcity that challenges the practical work
		Lack of model validation	This research study is expected to validate the proposed integrated-DSS in the manufacturing setuprelated to electrical product / manufacturing process

be recorded and would be verified by the available literature. The internal validity of the identified risks would also be performed by some academic experts who have some industrial experience in the manufacturing sector. The drawbacks of the Delphi method such as its data collection costs and lengthy data collection time frames are somehow accepted.

6 Risk ranking/prioritizing

In a DSS, right after risk identification/mitigation step, there is a need to rank/prioritize all the optimized solutions available for all potential identified risks. The advantages and disadvantages of some available tools and techniques for risk prioritization are described in Table 10.

Table 6 Occurrences in the literature review (keywords in title and abstract) using VOSviewer tool

No. of articles/papers	Total no. of terms	Minimum no. of occurrences of a term	No. of terms meet the threshold	Maximum no. of terms to be selected	Remarks
26 (as same as Table 4)	787	1	787	472	
		2	170	102	
		3	79	47	Selected for the analysis
		4	40	24	
		5	27	16	
		6	18	11	
		7	12	7	
		8	10	6	
		9	7	4	
		10	7	4	
		11	6	4	
		12	6	4	
		13	6	4	
		14	3	3	
		15	3	3	
		16	3	3	
		17	3	3	

Table 7 Clusters and their items

Cluster No	**Total no. of items**	**Cluster colour** (except overlay visualization)	**Major related item(s)**
1	19	Red	Risk management, adoption, technology, risk event, risk behaviour, potential failure, manufacturing, effect analysis
2	12	Green	DSS, ZDM, detection, defect, cause, action, severity, occurrence, quality
3	8	Blue	FCM, uncertainty, reliability, competitor
4	7	Yellow	Early warning model, sustainable innovation

As tabulated in Serial 4 of Table 10, the DEMATEL analysis might be shortlisted for risk prioritization due to its relevance and scope in this research study. The advantages of the method such as its usefulness for causal relationships and influential behaviour among risk factors to make its integration among product design and manufacturing processes encourage its utility for this study. Consequently, its visualization of risk elements' intensity analyzes dependent factors by using graph theories and matrix computations. It also provides degrees of factor influence, appropriate for investigation of the influence structure between factors/parameters under consideration to construct a visual structure model based on data provided by the key industrial experts. However, its disadvantages will surely be catered in such a way that most relevant industrial experts would be selected to fill a quantitative questionnaire to minimize and negate the biasness which is generally expected due to its varying interpretations. The subject matters experts would then be able to provide accurate/reliable information, followed by a risk matrix questionnaire in accordance with the relationship among those risks, similarly, the expert weight criterion would be defined based on their education and relevant experience. Though the drawbacks like its complexity of data analysis for the consistency of pair-wise comparisons and its stability issues like small change in direct-relation matrix usually have a potential to make a significant difference in total-relation matrix would be discouraging but accepted for this research study.

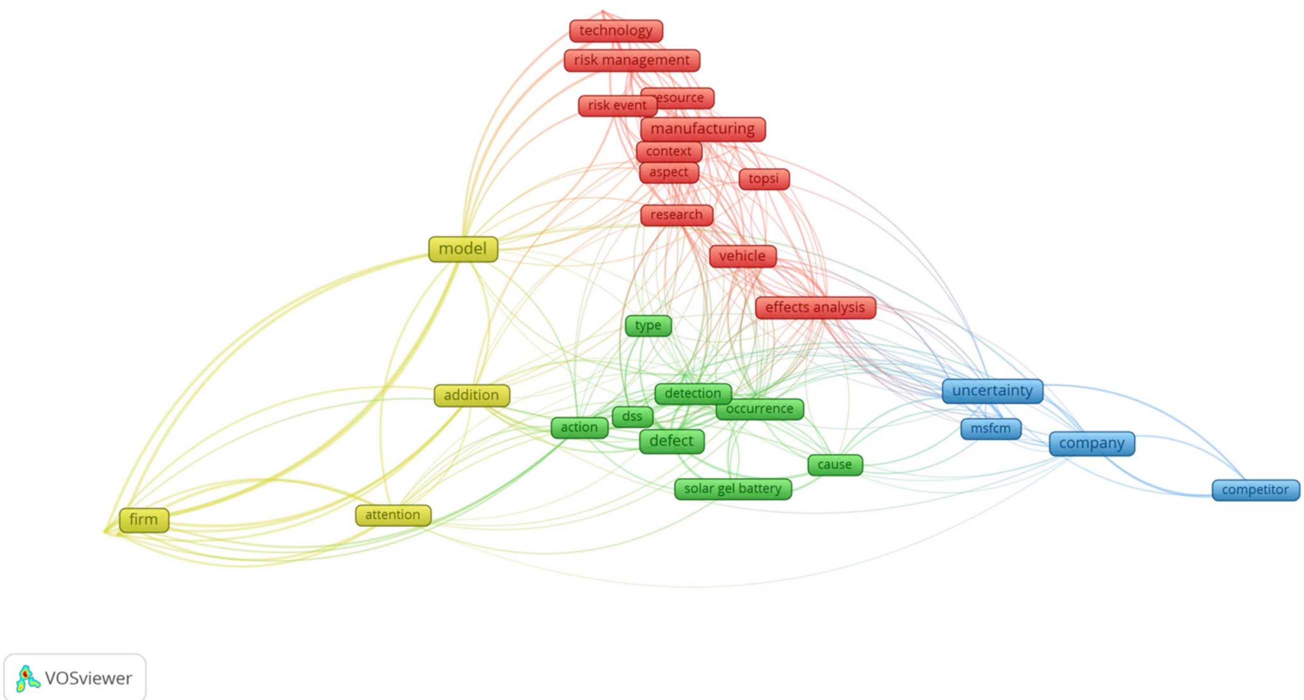

Fig. 8 Network visualization clusters of keywords in title and abstract (using VOSviewer tool)

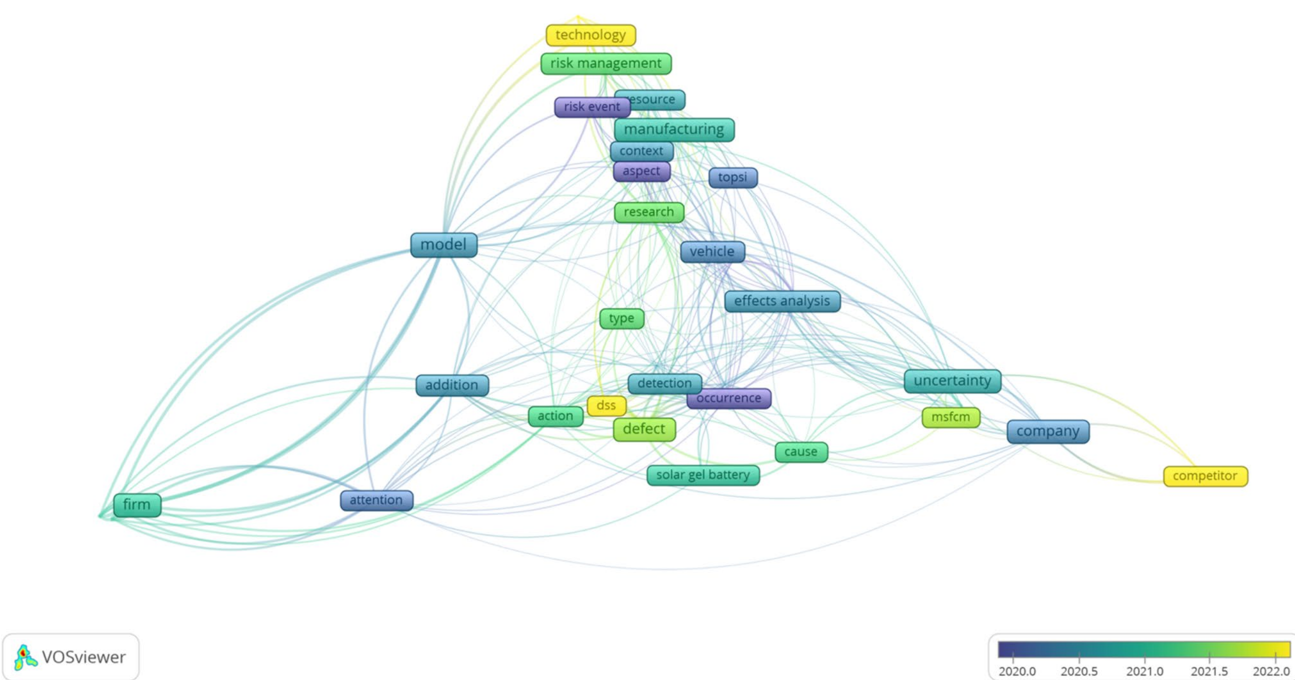

Fig. 9 Overlay visualization clusters of keywords in title and abstract (using VOSviewer tool)

7 Risk mitigation

There are very few approaches available for risk mitigation in the existing literature. Based upon advantages and disadvantages of methods shown in Table 11., the best possible tool/technique might be selected.

In other words, the suitable mitigation technique would accordingly be selected on the basis of shortlisted and

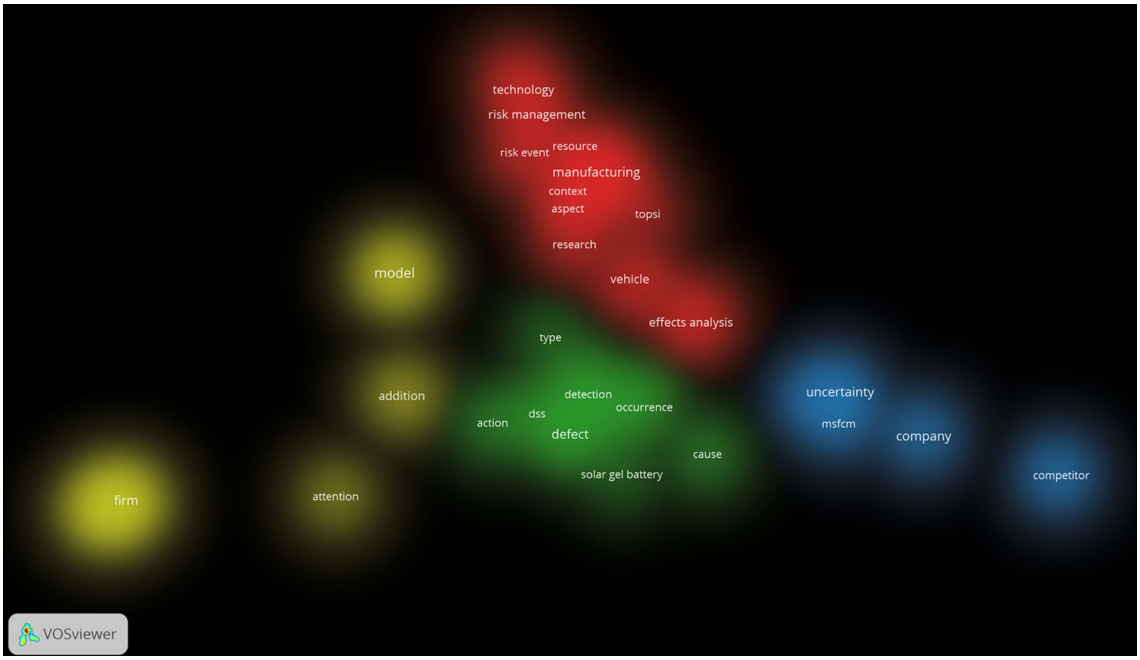

Fig. 10 Density visualization clusters of keywords in title and abstract (using VOSviewer tool)

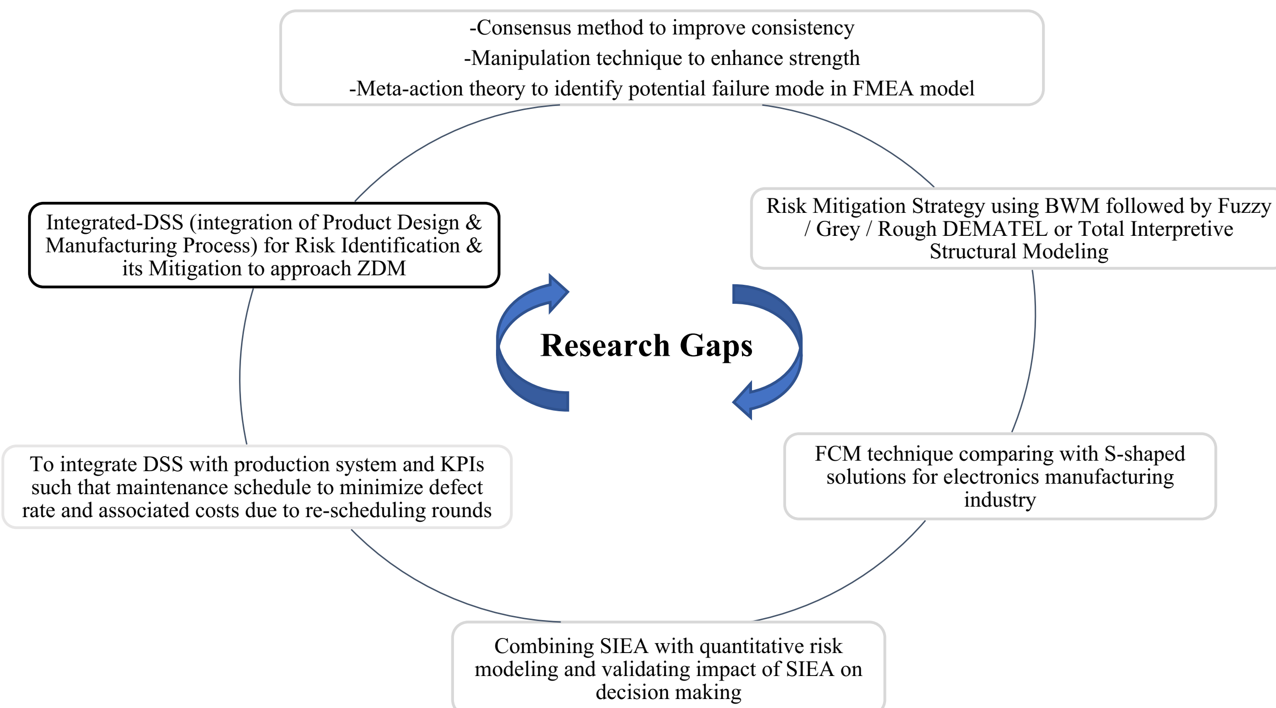

Fig. 11 Research gaps in the literature

Table 8 Anticipated gaps

S. No	Research studies	Risk identification	Risk prioritization	Risk mitigation	Product design	Manufacturing process	ZDM
1	[47]	✓	✓	✖	✖	✓	✖
2	[48]	✓	✓	✖	✖	✓	✖
3	[37]	✖	✖	✖	✖	✓	✖
4	[91]	✓	✓	✖	✖	✓	✖
5	[1]	✖	✖	✖	✖	✓	✓
6	[92]	✓	✖	✖	✓	✖	✖
7	[71]	✓	✓	✓	✓	✓	✖
8	[63]	✓	✓	✓	✖	✓	✖
9	[64]	✓	✓	✖	✖	✓	✖
10	[82]	✓	✓	✖	✖	✓	✖
11	[93]	✖	✖	✖	✖	✓	✖
12	[66]	✓	✓	✖	✖	✓	✖
13	[94]	✓	✖	✖	✓	✓	✖
14	[69]	✓	✓	✓	✖	✓	✖
15	[81]	✓	✓	✖	✖	✓	✖
16	[79]	✓	✓	✖	✖	✓	✖
17	[95]	✓	✓	✖	✖	✓	✖
18	[61]	✓	✓	✖	✖	✓	✖
19	[96]	✓	✓	✓	✖	✓	✖
20	[97]	✓	✓	✖	✖	✓	✖
21	[98]	✓	✓	✖	✖	✓	✖
22	[73]	✖	✖	✖	✖	✓	✖
23	[99]	✓	✓	✖	✖	✓	✖
24	[100]	✓	✓	✖	✖	✓	✖
25	[101]	✓	✓	✓	✖	✓	✖
26	[2]	✓ (detect defects)	✓ (evaluate defects)	✓ (mitigate defects)	✖	✓	✓
27	**This research study**	✓	✓	✓	✓	✓	✓

applied tools and techniques for risk identification and risk prioritization, i.e. most likely Delphi technique and DEMATEL analysis, respectively.

8 The proposed DSS

It is a preventive decision-making tool; altered from [2] which was basically to automate decision-making in the event of defects as corrective actions, reduce the probability of errors which allow higher repeatability on the decision quality in the era of ZDM. As presented in Fig. 12, the solid line means the connection between two elements, whereas the dotted line is actually a feedback in the overview of the proposed DSS framework. The main elements of the proposed system for a manufacturing setting are as follows:

- E1: Risk identification means identifying as well as integrating the potential risks in product design properties and manufacturing process, most likely through Delphi technique
- E2: Risk analysis is basically a risk exposure (with respect to time, cost, and quality) or risk priority number (severity, occurrence, and detection)
- E3: Risk prioritization is to rank the risks, most likely through DEMATEL technique
- E4: Risk control is considered a pre-mitigation stage to assess each identified risk along with its prioritization and mitigation
- E5: Risk mitigation is to rectify identified risks
- E6: Historical manufacturing data contains internal (previous quantifiable data of the same firm) and external (previously known data of the competitor(s), if available) data added by the shop floor manager/operator

Table 9 Risk identification tools and techniques

S. No	Tools/techniques	Pros	Cons
1	Delphi technique (experts' opinions)	-Low cost to administer and analyze -Procedure is easy so rapid consensus can be achieved -Adaptability to diverse data collection strategies, decreased peer pressure secondary to anonymity, and the ease of considering opinions of many and varied experts into a few precise statements [103]	-Based on opinion so consensus does not mean it's the correct answer -Does not have a large known internal validity -Difficulty of defining and locating panel experts for some topics, data collection costs, and lengthy data collection time frames [103]
2	Fuzzy cognitive mapping (FCM)	-Examining the causal-effect relationships between concepts (nodes) of the network -Decreasing dependence on experts' views and increasing the accuracy of the calculated weights by applying learning algorithms [104] -Dynamic [105], combinable, tuneable, expresses hidden relationships and captures more information in the relationships between concepts [106] [107]	-All concepts are grouped as one vector and every calculation of their values regarding the behaviour of the complex dynamic system is performed for every concept [108] -Final solution is local optimum rather than global optimum
3	Fuzzy C-means	-It doesn't require pre-processing of the collected data [109] -Better to predict than k-means algorithm when no. of clusters is fixed, and more homogenous regions are obtained [110] -Fast, accurate, sensitive, compatible, and easy to perform [111]	-Frequently trapped into local minima during execution [112] -Sensitive to outliers [113] -Computational time is more [110]
4	Fuzzy best–worst method (BWM) (MCDM)	-Implies more consistent pairwise comparisons so more reliable [114] [115] and precise results [116] -Better dealing with inconsistency of decision-making problem using consistency ratio [58] -Requires less decision-making (comparison data) input to calculate weights of variables and saves time [115] [117]	-It can't aggregate more than one decision maker's evaluation [118] -Static with consistency issues. Also, decisions cannot reflect the confidence level of decision, also complex decision-making problem are time dependent [58] -It ignores reciprocals so not adequate for complex problems [119]
5	Failure mode and effect analysis (FMEA)	-Follows a logical and structured method to identify areas of concern, it allows the early identification of failure points [120] -Improves the quality, simple to use, reduces time/cost [121] by treating each failure in isolation—interval flexibility for Fuzzy-FMEA [122]	-It ignores the fact that three factors (severity, occurrence, and detection) have different weights rather than equality so do not indicate which failure needs more attention [95] [123] and it is a static method which excessively depends upon the expert's knowledge so may be manipulative [124] -Some crucial parameters such as time, maintainability or cost are not integrated on failure judgement [121] -Inefficient and data uncertainty due to prioritizing risks based upon RPN [48] -Only considers single failures and displays only those system effects or top events stemming from single failures [123]
6	Decision tree analysis	-Intuitive and easy to explain by considering all available parameters [125]	-Small change in the data can cause a large change in the structure of the decision tree causing instability -Inexperience of decision maker can deter optimum decision-making process [125] -Probabilities of occurrences can be difficult to quantify in the absence of historical data [126]

Table 9 (continued)

S. No	Tools/techniques	Pros	Cons
7	Risk breakdown structure	-Assign resources and plan for the positive or negative impacts of identified risk -Offers a synthetic view on risks to group number of risk categories covering a series of risk events -Offers different pictures of the same state of knowledge, being checked that the various pictures remain consistent which is compatible with time evolutionary and dynamic nature of project risks [127]	-Lack of consensus on how to develop an RBS for a new project -Lack of clarity and inconsistencies in definition of risk categories -No consensus on how to develop RBS, so each user develops its own RBS, without following any guidelines -Difficulties in accounting for (existing) interactions between risks, because of their hierarchical structure when the underlying processes of a real project are more complex [127]
8	Fault tree analysis (FTA)	-Widely used to assess the operational performance, reliability prediction, lifetime and system safety of various complex systems involved in a nuclear reactor, aerospace, the petrochemical industry, oil and gas transmission and other complex electrical mechanical systems [128] -It can deal with uncertainties of the failure causes, due to insufficient knowledge of the relationships among basic events. Also, its model can be transformed into BN [129]	-It does not give information concerning the tolerances and variation of the probability values and the dependencies of the event, so it is not suitable where available data are insufficient for statistical inferences, or the data show a large variation [128] -Uncertainties in covering all failure modes -Inaccuracy in human error in investigation inefficiency in case of insufficient data -Entirely deterministic [129]
9	k-Means	-Simple and easy to implement/modify -An instance can change cluster (move to another cluster) when the centroids are re- computed [130] -Briefness, efficiency, clarity and has greater dependence to choose the initial focal point and another one is easy to be trapped in local minimum [131] -Able to process large data sets to minimize the sum of squared distances between all points and the cluster centre [132]	-No. of clusters 'k' must be supplied as a parameter [132] and can only detect spherical shape cluster (not arbitrary shape clusters) [133] -Sensitive to outliers [134] and scale [130] -A completely unstructured approach which proceeds in an entirely local fashion and produces an unorganized collection of clusters that is not conductive to interpretation [135]
10	Multi-objective optimization (MOO)	-Deals with optimization problems involving two or more objective function to be optimized simultaneously and provides global view of all Pareto-optimal solutions [136] -Possibility to adapt preferences during the process -Deals with optimization problems which are formulated with some or possibly all the objective functions in conflict with each other, also typically concerned with the finding a diverse set of solutions which is close to the Pareto-optimal solution set [137]	-Decision maker's influence -Difficult to generate Pareto-sets -Not all solutions are generated, moreover important solutions can be overlooked

Table 9 (continued)

S. No	Tools/techniques	Pros	Cons
11	Bayesian Network Structure/Bayes Network/Belief Network/Bayesian model/Bayesian Belief Network (BBN)	-Able to incorporate meta-regression to assess heterogeneity (e.g. for subgroups or to control for covariates), all within one model -Stable and consistently good performance to classify and small training datasets -Flexible and less restriction set in forming the good graphical structure representation datasets [138], also appears to produce valid, accurate results for star and ladder network patterns -Suitable to be used in an adaptive modelling frame—work cause of the ability to update individual causal relations independently and their explicit treatment on uncertainties [139] -Root nodes are ranked in terms of the conditional probability, which reflect the contribution to the probability of the eventual fault [129] -Probabilistic and can run in reverse -Fully defensible and accounts for interdependencies -Integrates a combination of process-based models, multivariate regressions, and expert opinion to predict probability distribution [140]	-No universally acknowledged method for constructing networks from data -Might not produce accurate results for one closed loop networks -Time consuming and stability of classification reduced when handling small training datasets [138] -Neither fast nor easy and generates heavy data -Not good for communication with all stakeholders -Tendency of experts to overload a network with pet processes related to their own research can lead to model complexity and costs in stochastic model [140] -Inability to explicitly represent feedback relationships among variables [141] and it faces model validation problems [140]
12	Bow tie analysis (a combination of fault tree & event tree analysis)	-Data is not as such heavy -Ease to understanding of risk management by upper management and operations groups -Application and understanding of the risk management process, from identification to assessment -Assessment of barrier strength to achieve the desired risk control effectiveness. Also, integration of human and organizational factors by identifying specific barriers to prevent and manage human error [142] -A valuable conception in mishap prediction and in analyzing the past accidents and signifying improvements to avoid further re-occurrence of undesired events -Able to summarize large quantities of data into a relatively small no. of common scenarios to majority of accidents [143]	-Lack of rigor -Qualitative in nature -Requirement to acquire bow-tie software to better document and visualize the resulting large bow-tie diagrams -Need to have a robust risk-assessment matrix to appropriately screen MHEs and arrive at a representative set of bow-tie diagrams per facility or business unit [142]

Table 10 Risk prioritizing tools & techniques

S. No	Tools/techniques	Pros	Cons
1	Monte Carlo simulation (MCS)	-Fuzzy-MCS considers the cognitive uncertainty in addition to the noncognitive vagueness [128] -Stochastic—easier to compute for multiple inputs, which allows a probability distribution to be used avoiding single point estimations -Provides a more representative prediction of risk, provided initial assumptions are reasonable, also relatively fast with modern computing technology, brute force approach to calculation [144]	-Probability distributions are assumed based in part on previous experience where risk profiles are often underestimated due to excluding the tails of the distributions -Most Monte Carlo packages, except for the high-end ones, do not allow for interdependence of input variables -Subjective judgement is typically used to come up with starting points which can make it too complex and unwieldy [144]
2	Risk priority number (RPN)(Severity × Occurrence × Detection)	-Relative risk for prioritizing issues in an FMEA -Sort the risks from highest to lowest	-Various sets of S, O and D ratings may produce the same RPN value -Multiplication of S, O and D in the RPN calculation makes the RPN change very sensitive -Not continuous on many lobs, e.g. 11, 43, and 901, so these kinds of values will never be the product of three factors [93] [121]
3	AHP (MCDM)	-Flexibility, instinctive interest to the decision makers and its capacity to check irregularities: for the most part, users discover pairwise comparison type of information, direct and helpful [145] -The computation process is quite simple compared with other methods. It has a comprehensible logic based on a hierarchical structure; therefore, it has a better focus on each criterion used in the calculations [146] [147] -Adaptable and doesn't involve complex mathematics. Based on hierarchical structure and thus each criterion can be better focused and transparent [148] -Better approach than RPN	-Poor stability -Removal or addition of alternatives may change final rankings -Very high computational time with complicated calculations -Decision issue is deteriorated into various subsystems, inside which and between which a considerable number of pairwise comparisons should be finished [145] -Requires data collected based on experience and additional analysis is required to verify the results. The more decision-makers that are involved, the more complex the assigning weights are [146] [147] -Interdependency between objectives and alternatives leads to hazardous results [148]
4	Decision-making and trial evaluation laboratory (DEMATEL) (MCDM)	-Typically used for causal relationships and influential behaviour among factors [149] -Visualizing the intensity of elements' relations and their importance using graph theories and matrix computations [150] -It has an advantage over AHP and ISM because it analyzes dependent factors and provides degrees of factor influence, respectively [151] -Appropriate for investigation of the influence structure between factors/parameters under consideration and to construct a visual structure model based on data provided by key experts [152] [153]	-Significantly depends on the judgments of experts, which introduces subjectivity and bias due to varying perspectives and interpretations -It can be difficult to collect accurate and reliable data on the relationships between factors, especially when data is limited, incomplete, or ambiguous [154] -More empirical research is required to determine the influencing factors of expert weight [155] -When the number of risk factors increases, comparing every two risk factors becomes a heavy workload -Additionally, the consistency of the pairwise comparison is difficult to guarantee. Similarly, a relatively small change in the direct-relation matrix can cause a more significant difference in the total-relation matrix, which reduces its stability [150]

Table 10 (continued)

S. No	Tools/techniques	Pros	Cons
5	TOPSIS (MCDM)	-Takes contribution as any number of criteria and attributes for quick results. Also, it has genuinely instinctive physical importance considering the thought of separation from perfect arrangements [145] -Simple computation process -Integrate subjective judgements with numerical data and able to immediately recognize the proper alternative [156] -Better approach than AHP and RPN	-Suitable only when the indicators of alternatives do not vary very strongly -A strong deviation of one indicator from ideal solution strongly influence the results [145] -Works based on Euclidian distance and so doesn't consider any difference between negative and positive values. Also, the attribute values should be monotonically increasing or decreasing [148] -Deterministic and does not consider uncertainty in weighting [157] -Moderately critical calculations like Preference Ranking Organisation Method (PROMETHEE)
6	VIKOR (MCDM)	-Decreases the pairwise comparisons required, and capacity limitation may not significantly control the process -An updated version of TOPSIS which calculates ration of positive and negative ideal solution thereby removing the impact [148] -Better than TOPSIS, AHP and RPN	-Difficulty when conflicting situation arises and need modification while dealing with some terse data as it become difficult to model a real time model [148] -Does not consider relative importance of distances -Lacks provision weight and check consistency of judgements
7	Information entropy weight method (EWM)	-Used in any process of weight determining -Able to do drought-risk assessment, with human factors are excluded in the calculation, thereby reducing malicious manipulation into weighting process [158]	-Used for limited problem solving
8	Risk matrix approach (RMA)	-Useful tool for qualitative risk analysis -Provide some consistency to prioritizing risks -With an extended-RMA, target can be any feasible object instead of risk and the input variables can be chosen from a range of options with diverse combinations according to the requirement of real situation [159] -Present complex risk data in a concise visual fashion, e.g. bubble charts	-Categories may not be specific enough to compare and differentiate between risk levels -Not a proper way to perform quantitative risk evaluation [159] -Sometimes mistakenly assign higher qualitative ratings to quantitatively smaller risks
9	Data envelopment analysis	-Simultaneous analysis of outputs and inputs -Need to information on prices -Ranks both efficient and inefficient decision-making units; moreover, this scale can also be validated by using non-parametric statistical tests due to which it takes advantage of human knowledge in operational contexts [160] -Relatively efficient compared to the best observation	-Ignores the effect of exogenous variables on the operations -Difficult to perform statistical tests with the results -Ignores statistical errors

Table 10 (continued)

S. No	Tools/techniques	Pros	Cons
10	MOORA	-Good level of selectivity in determining an alternative by solving problems with complex mathematical calculations [161] -Very low computational time -Very simple with good stability -Based upon quantitative information type -Simultaneous process to optimize two or more conflicting constraints on several obstacles [162]	-Uncertainty coming from erroneous mathematical calculations, so multi-objective optimization on the basis of simple ratio analysis (MOOSRA) is better
11	PROMETHEE (MCDM)	-Involves group level decision which deals with qualitative and quantitative and qualitative information -Incorporate uncertain and fuzzy information [148] [163]	-Doesn't structure the objectives properly and it depends on the decision maker to assign weight -Very much complicated so only suitable for experts [148] [163]
12	Elimination and choice translating reality (ELECTRE) (MCDM)	-Deals with both quantitative and qualitative features of criteria -Results are validated with reasons [148] [164]	-Less versatile and demands good understanding of objective specially when dealing with quantitative features [148] [164]

- E7: Knowledge base has a bi-directional link to communicate with other elements and display the decision on the user interface
- E8: Production data is to gather risk mitigation records through manufacturing
- E9: Manufacturing is to consistently assess the production data and see whether the entire loop is improving the system as aimed ZDM

The framework has a potential to get improved by employing model fine-tuning method, a technique for adapting foundation models to downstream tasks by updating model parameters using available data [183] [184] [185]. So, the proposed model is likely to deviate from this foundation version after fine-tuning of the model prior to its verification and validation. The changes can be in terms of performance metrics as well as in model behavior such as developing new input–output associations. By analyzing these behavior changes, the readers will be able to understand how generic knowledge evolves into task-specific knowledge and identify where the model does not function as expected [186].

9 The DSS and ZDM

9.1 Background

According to Psarommatis et al, "ZDM is a holistic approach for ensuring both process and product quality by reducing defects through corrective, preventive, and predictive techniques, using mainly data-driven technologies and guaranteeing that no defective products leave the production site and reach the customer, aiming at higher manufacturing sustainability". ZDM prevents or learns from defects/errors, whereas Six Sigma (6σ), lean manufacturing (LM), and total quality management (TQM) minimize or remove defects/errors [187]. The ultimate objective of ZDM is to significantly increase product yield and eventually accomplish zero-defect [188]. A ZDM strategy can also be defined as the set of tools, resources, and control rules with the aim of avoiding defects in complex manufacturing systems [18]. From a consumer perspective, ZDM enhances trust and confidence in products. As manufacturing processes become more transparent and companies emphasize their commitment to ZDM, so consumers are more likely to support product brands ensuring high-quality defect-free products. This not only fosters brand loyalty but also encourages sustainable consumer behaviour, as a smaller number of replacements and repairs are needed over product life cycle [20]. The iron triangle consists of three elements such as time, cost, and quality [24] to prevent or learn from manufacturing recalls by analyzing the potential risks with respect to their behaviour, probability, and severity, heading towards

Table 11 Risk mitigation tools and techniques

S. No	Tools/techniques	Pros	Cons
1	Manufacturing semantic ontology	-Increases quality of entity analysis -Increased use, reuse, and maintainability of information systems -Lower complexity of logic where experiment results show the effectiveness of the algorithm [165] with more precise results	-Difficult to construct a comprehensive ontology -Errors might lead to a reduced quality [166] with low precision ratio
2	GA	-Easy to understand -Searches from a population of points, not a single point -Uses payoff (objective function) information, not derivatives -Uses probabilistic transition rules, not deterministic rules -It does not require any more information than that provided by the objective function [167] -It can search the global optimization solution or the approximate optimization solution for the problems of the huge scale systems, also solves the problems of multivariable, nonlinearity, discontinuity, and multiple constraint [168] -Flexibility in modelling both time-dependent and coupling constraints and can be very easily converted to work on parallel computers [169]	-Premature convergence because the selection operator depends on the individual's quality [167] -Optimality of the solution they provide cannot be guaranteed [169] -Time-consuming so computationally expensive [170]
3	Firefly algorithm (FA)	-Efficient and an easy-to-implement -Suitable for parallel implementation -Higher convergence rate, accuracy, and robustness for chaos-based firefly algorithms [171]	-High computational complexity and low convergence accuracy, especially when solving complex problems [172] -Trapping into many local optimums due to determined parameters like step 'α' is constant which does not change over time [173] -Not memorize any history of better situation for each firefly due to which they move regardless of it and miss their situations [174]
4	Gradient descent	-Computational efficiency: it produces a stable error gradient and a stable convergence	-Weight update at a moment 't' is governed by the learning rate and gradient at that moment only -It doesn't consider the past steps taken while traversing the cost space -Slow convergence towards global minima [175]
5	Stochastic gradient descent	-Easier to fit into memory due to a single training sample being processed by the network -Computationally fast as only one sample is processed at a time -Each step only relies on a single derivative so computational cost is less than gradient descent [176]	-Frequent updates are computationally expensive due to using all resources for processing one training sample at a time -It loses the advantage of vectorized operations as it deals with only a single example at a time -Randomness introduces variance [176]
6	Adaptive learning rate method	-No manual setting of a learning rate and applicable in both local and distributed environments -Insensitive to hyperparameters, separate dynamic learning rate per-dimension with minimal computation over gradient descent, and robust to large gradients, noise, and architecture choice [177]	-Paths could lead to overjumping important learning content

Table 11 (continued)

S. No	Tools/techniques	Pros	Cons
7	Conjugate gradient method	-Comparison is relative and hence does not be dominated by a few problems for which the method requires a great deal of function evaluations and gradient functions [178] -Especially simple formula to determine the new direction vector -Simplicity makes the method only slightly more complicated than steepest descent -Restarting by searching along the steepest descent direction is that the immediate reduction in the objective function is usually less than it would be without the restart [179]	-Requires 'n' cycles to reach the minimum -Comparatively high hardware volume and pipelining delays where termination is guaranteed only if all the calculations are implemented without errors, also cannot be implemented when the single precision floating point is used [180]
8	Zeroth-order optimisation (a subset of gradient free optimization)	-Ease of implementation with only small modification of commonly used gradient-based algorithms -Comparable convergence rates to first-order algorithms -Useful for solving big data and machine learning problems when explicit expressions of the gradients are difficult or infeasible to obtain -Reduces computational time and probability to overlook the global optimum [181]	-It relies on finite-differencing for shrinking differences -Numerical cancellation can be catastrophic -It gauges invariance and enables exact energy gradients [182]

ZDM. Psarommatis et al also explained that achieving zero-defect in a real context is practically impossible; meanwhile, ZDM fulfils four missions (as illustrated in Fig. 2): the three missions such as detect, repair, and prevent are shared with current quality philosophies, while prediction is a new concept. As already discussed in Fig. 3, one major change in ZDM versus other quality concepts is the information flow. So, ZDM utilizes real-time data to prevent product from defect(s) [10] [189].

9.2 Internal mechanism with example

According to Leng et al, the manufacturing process includes concept generating, requirement capturing, collaborative designing, process planning, sustainable manufacturing, assembling and inspection, inventory and logistics, delivery and deployment, operation service, recycling and remanufacturing [190], and disposal. Product design properties can include reliability, aesthetics, size, weight, efficiency, usage, and safety. Accordingly, the potential risks of all platforms of manufacturing process and end product design in a manufacturing company are identified as illustrated in Fig. 12.

An open ended/qualitative questionnaire will be developed to note down comprehensive list of risks and their mitigation strategies at a manufacturing platform which produces sub-part of an electric motor in a firm. Firstly, a preliminary list of 'x' potential risks and their mitigations will be recorded during a field survey. Secondly, the list of 'x' risks along with remedial actions will be evaluated by a target group of industrial professionals (n_1) for the sake of initial assessment, who will either add or subtract 'y' more risks in the list. Lastly, Delphi technique will be employed to shortlist risks through Delphi experts (n_2) who fulfil eligibility criteria as guided by Hallowell and Gambatese [191]. At the end of the first round of the Delphi method, '$x \pm y \pm z$' risks will be shortlisted along with their 'm' mitigation strategies, whereas '$x \pm y \pm z \pm a$' risks will be finalized along with their '$m \pm i$' remedial actions at the end of the second round of Delphi technique. The total number of Delphi rounds would be decided accordingly based on required level of consensus, availability of the experts, and available resources etc [192]. A Likert-scaled quantitative questionnaire will be developed asking the experts to score probability and impact of those '$x \pm y \pm z \pm a$' risks. As guided by Emery et al, piloting of the survey tool for content validation should be conducted prior to its full fledge distribution which may include minor revisions to remove ambiguities in the item questions [193]. So, 'b' risks along with their 'j' mitigations would either be included or excluded during piloting stage, leaving behind a total of '$x \pm y \pm z \pm a \pm b$' risks along with '$m \pm i \pm j$' mitigations, expressed as (R_1, R_2,

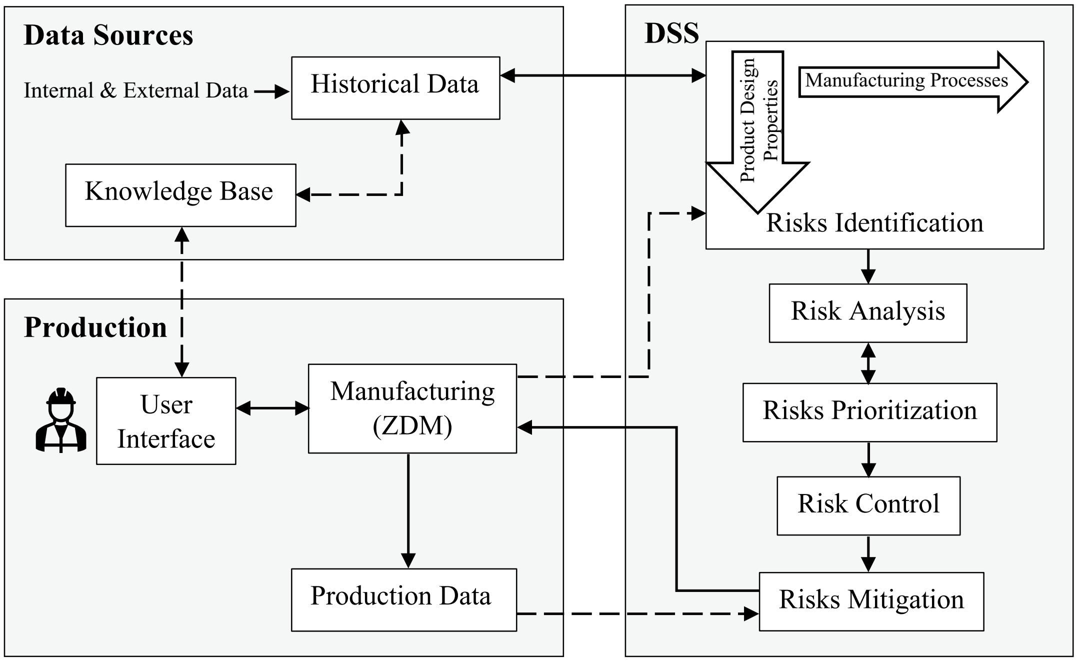

Fig. 12 Overview of the DSS framework (modified from [2])

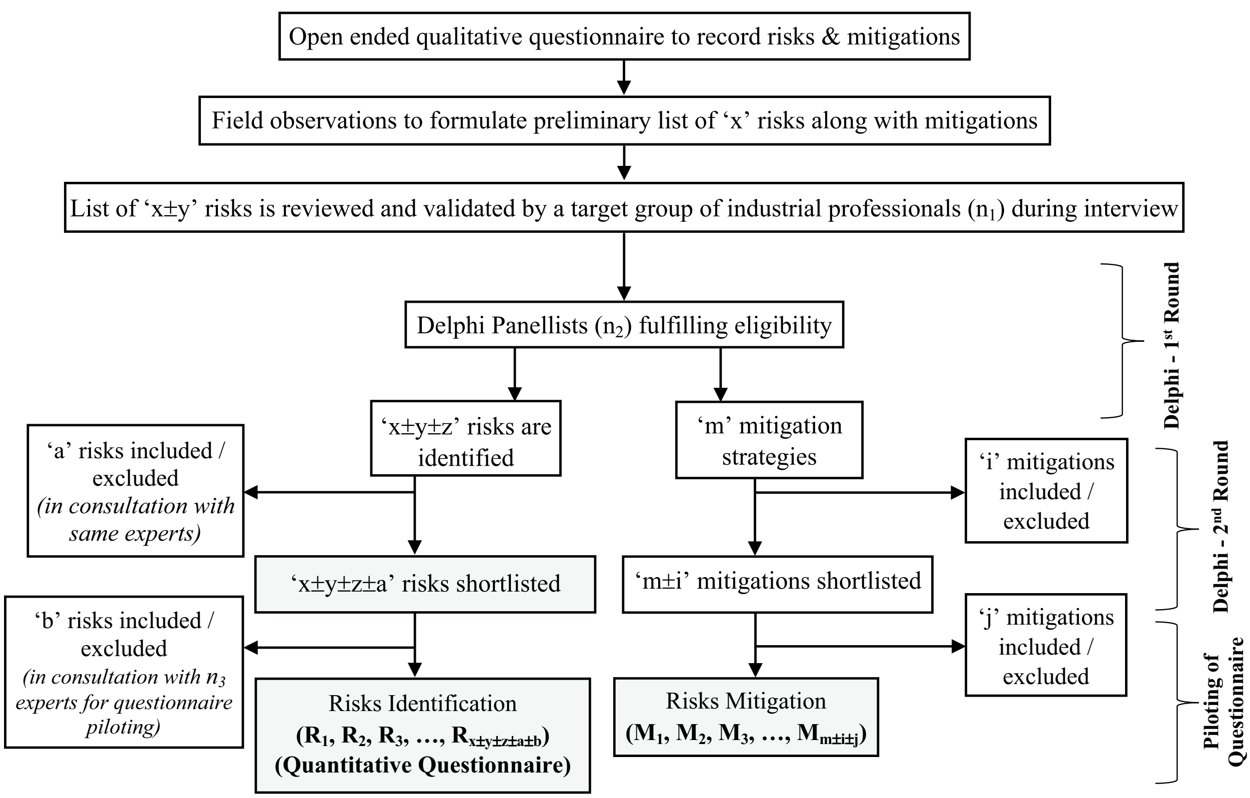

Fig. 13 Methodology for identification and mitigation of risks using Delphi technique and piloting method

R_3, …, $R_{x\pm y\pm z\pm a\pm b}$) along with ($M_1$, M_2, M_3, …, $M_{m\pm i\pm j}$) respectively as shown in Fig. 13. The final version of the survey tool will be distributed among industrial experts (n_3) requesting them to score probability and impact of '$x \pm y \pm z \pm a \pm b$' risks with respect to time, cost, and quality. The risk analysis will be performed by risk exposure technique which is a product of probability and impact of 'individual' risks as per guidance by Qazi et al [194], but in terms of three-dimensional matrix. Cronbach's alpha of the responses will also be calculated to assess the reliability of the response items [195], for instance ranges up to 0.80, so only satisfactory results would be considered. Furthermore, risk ranking will be performed by DEMATEL analysis to prioritize 'interacting' risks in such a way that manufacturing process (11 stages) and product design (7 properties) would be integrated to assess influence among all risk factors.

As discussed above, '$x \pm y \pm z \pm a \pm b$' risks will be shortlisted on a manufacturing platform which produces sub-parts of an electric motor in a company. So, integration among these risks would have been obtained by employing DEMATEL analysis as guided by Shamsadini et al. [196], during which a matrix of $x \pm y \pm z \pm a \pm b$ columns $\times$ $x \pm y \pm z \pm a \pm b$ rows $= (x \pm y \pm z \pm a \pm b)^2$ combinations (except main diagonal) will be framed to rank the risks on the basis of experts' scores given to every risk combination. For ease of understanding, it can be said that elements of the first row or column of the risk matrix will behave like concept generation–requirement capturing, concept generation–collaborative designing, concept generation–process planning, concept generation–sustainable manufacturing, concept generation–assembling and inspection, concept generation–inventory and logistics, concept generation–delivery and deployment, concept generation–operation service, concept generation–recycling and remanufacturing, concept generation–disposal, concept generation–reliability, concept generation–aesthetics, concept generation–size, concept generation–weight, concept generation–efficiency, concept generation–usage, and concept generation–safety. Furthermore, this prioritization will also provide the cause-and-effect relationship among interacting risks through a causal diagram. According to the development of the study, a separate tool/technique for risk mitigation can also be utilized in addition to Delphi technique.

9.3 Focusing ZDM

A computer code will be developed for these '$x \pm y \pm z \pm a \pm b$' risks along with their '$m \pm i \pm j$' mitigations using Python software, so its user interface would be available for the shop floor manager/operator to make better decisions, in case of risk occurs at a manufacturing platform which produces a sub-part of an electric motor. In other words, the (knowledge-driven) DSS communicates with the user through an interface which displays all identified risks along with their mitigations, arranged according to their prioritizations. Even if a manufacturing platform rapidly faces a defect/error, the complete detail of the recall will be discussed in the next round of the Delphi technique addressing the main cause of the issue. The risk and its remedial action will then be vetted / approved by Delphi experts to get it updated in the DSS code, justifying the ZDM concept which learns from errors, defects, or recalls in a manufacturing setup to prevent failures at shop floor level in the future. The operator will utilize the user interface to enter this internal data into historical data through knowledge base. Furthermore, just like any good decision-making mechanism, the proposed DSS is also dynamic and adaptable with the data change. So, any changes/improvements will be adapted in the DSS over a period of time for improved rectifications/mitigations to cater future defects. It is therefore expected that the entire loop of the proposed integrated-DSS (illustrated in Fig. 12) will continue working until positive results (i.e. lessening production time and cost while enhancing the quality) of the manufacturing block are evident on the basis of production data, so it would be concluded that the manufacturing firm has moved one-step closer to the radius of (data-driven) ZDM.

10 Challenges and opportunities

Psarommatis et al explained some potential barriers in manufacturing of quality products [189] which can be amended in the context of industry in Pakistan where every challenge provides an equal opportunity to grow as under:

10.1 Lack of training and experience

The manufacturing of a quality product needs to minimize recalls, errors, defects, and failures to save time as well as expense. For this purpose, proper training for the shop floor managers and operator is required to implement advance technologies in the field of manufacturing engineering. The famous proverb "man behind the machine" applies here referring to the operator which performs the activities in producing a product. However, trainers are even inexperienced in this field in Pakistan, who mostly train the platform operators to perform quality practices aiming to reduce manufacturing time and cost of defect-free products, not about ZDM.

10.2 Lack of commitment

The commitment of top management is the need of time to include quality arrangements in a manufacturing setting; however, a typical manufacturing firm in Pakistan does not volunteer to adopt quality practices. According to senior management of these local enterprises, they consider it as an extra cost to the quality procedures. This is the reason why they are reluctant to employ digital techniques which can help them to cater manufacturing defects, as the outcome by utilizing their full potential has never been experienced in their companies. So, all levels in manufacturing industry must feel commitment to bring innovations in their companies to enhance the reputation of locally manufactured products.

10.3 Resistance to change

Even if a manufacturing company wishes to produce quality products, most of its shop floor managers/operators are not willing to bring change in their daily routine at platforms. Majority of the workers are working on a single platform doing the same procedures since many years, as the firm does not have a concept of intra-organizational transfers of the human capital. The idea behind a famous phrase ‘jack of all trades, master of none’ can be beneficial in this regard, to make them skilled on all platforms rather than a specialist of one. Also, it will enhance the education and visibility of the operators by knowing each other’s platform operations.

10.4 Lack of resources

The innovation needs huge investments in the manufacturing industry of Pakistan, so always wishes to gain foreign direct investments (FDI) to promote localization in the country. Most of the research centres in Pakistan apply reverse engineering in the name of research and indigenous development of products due to lack of resources and funding. So, investors (foreign and local) should be given confidence to finance the technological innovations in the developing country.

10.5 Lack of employees’ involvement

The shop floor operators are not permitted to get involved during the decision-making to implement the advancements in manufacturing industry, as their valuable input and reservations are not taken seriously. Therefore, top management always faces serious retaliation during the implementation of any quality philosophies in any manufacturing firm. So, all employees (top to bottom) should be involved in developing and implementing frameworks for the betterment of their company, which ultimately contributes to the economy of the country.

10.6 Lack of framework’s implementation

Manufacturing industry in Pakistan does not welcome implementation of the technological innovations, even if few frameworks in other sub-fields were developed in the past as per the requirements by academicians and researchers which could never be implemented due to lack of interest of local industry in quality manufacturing. Hence, the frameworks developed after such extensive research studies in the field of manufacturing should be given opportunity to get adopted by the local industry to lessen manufacturing time, cost, and enhance the quality.

10.7 Need of a specialist

The manufacturing waste is one of the critical issues in Pakistan, as the local industrialists only focus on the quantity, while not considering the quality aspect. So, the researchers are required in the local industry who can practically understand the importance of such frameworks designed for quality manufacturing. It will further enhance the chances to cater industrial emergency in a growing economy of Pakistan.

10.8 Poor communication among stakeholders

The main stakeholders in manufacturing industry of Pakistan include government legislators (federal and provincial/state level), employees (top to bottom), investors (foreign or local), trainers, users, and scrappers (working to recycle and disposal). Indirect communication among all these is established in Pakistan; however, direct communication is lacking due to fear of responsibility. So, there is a need to establish strong link among all stakeholders to implement quality manufacturing in the country.

10.9 Non-availability of production data

It is impossible to get production data in a country like Pakistan, as the local industry does not share real data with the researchers due to fear of government taxes and duties. The quality research in the field of design and manufacturing engineering is always compromised due to non-availability of real-time production data. So, to minimize this suffering to quality research, a strong connection with all stakeholders in the local industry can be established to get real data prior to implement the proposed framework aiming the (data-driven) ZDM concept.

11 Phases of the proposed model

A decision statement is a set of decision-making criteria and alternatives. The decision-making system in a practical environment can be considered as a six-phased approach, namely intelligence, design, choice, implementation, monitoring [197] [198] [199], and results.

11.1 Intelligence phase

There is a need to make a top-level managerial decision to employ the integrated-DSS in a manufacturing firm with the goal to reach ZDM. The DSS in the field of risk management should have the objective to make a cost-effective solution, efficiently utilizing resources among all production platforms, and preventing product and process related manufacturing risks.

11.2 Design phase

In design phase, the integration of product and process life cycles would be performed with the help of industrial experts to design a knowledge-driven integrated-DSS which includes risk identification, ranking based on either individual (i.e. risk analysis) or interacting (i.e. risk prioritization) risks, and mitigation. This will help the shop floor manager/operator in making better decisions to achieve data-driven ZDM.

11.3 Choice phase

In this phase, alternatives are evaluated to run the proposed design in a simulation or an artificial environment to examine it as a fast, risk-free, and cost-effective way before implementation [200], so that the real-time results might be compared and analyzed accordingly with the expected ones, verifying the proposed model.

11.4 Implementation phase

One of the main challenges is to implement the proposed system for strategy/remedial actions. The rapidity and the right sequence of actions with which companies can reach a steady use and fast adaptation of the ZDM strategies to the always changing context represent a major challenge for an enterprise [1]. However, implementing Industry 4.0 technologies should always be the first measure when deploying the industrial transformation in a manufacturing setup [17]. Although its implementation may cause some extra cost for model validation, but it will be consumed once to bring remarkable improvement. Furthermore, the addition of the integration of product and process related risks in a single DSS for risk identification and mitigation is focused to achieve globally optimum and cost-effective solutions for the ZDM.

In this phase, the proposed model would be validated in a real environment producing household item (electrical or electronic product) in a manufacturing organization in Pakistan. The data sources (internal and external) will be provided to the integrated-DSS along with consistent feedback which will be provided by the operator, so that the concept of reinforcement learning will be applied to continuous quality improvement (CQI) of the model.

11.5 Monitoring phase

The decision-making process is often an iterative process [199] especially when to make critical decisions. Additionally, condition-based monitoring minimizes the risk of unexpected failures and improves system's efficiency and reliability and operator's safety [201]. In this phase, the impact of the proposed integrated-DSS will be critically observed. The main purpose is to measure either the research objectives are being met successfully as planned or otherwise.

11.6 Results phase

After industrial validation, decision-making results with and without DSS will be compared to see impact of the system, based on following three parameters: (i) production time (in labour hours), i.e. duration to manufacture a particular product before and after implementing the DSS; (ii) estimated cost (in Pak Rupees) to manufacture a product before and after applying the DSS; and (iii) quality such as number of specific defects/errors/recalls a firm still had to bear. According to Mzougui et al, manufacturing defects of an electric motor include sealing problem, improper connection, wrong electrical connections, short circuit between phases, power needed is under estimated, insular chosen is not appropriate, short circuit between coils, short circuit between phases, overload, overheating [121], dimensions, tolerances, specifications, and other electrical/mechanical issues. So, it is expected that the proposed system will generate optimum results for a manufacturing firm; it can therefore be concluded that the implementation of this proposed model will bring positive outcomes in manufacturing industry of Pakistan with the aim to come closer to ZDM.

12 Conclusion and way forward

The paper is covered with an extensive literature review to identify the gaps and the current challenges, concluding a need to formulate an integrated-DSS (by integrating product design and manufacturing process) based on risk identification, prioritization, and mitigation for the manufacturing industry aiming ZDM. There are many tools/techniques for risk identification, prioritization, and mitigation which have been discussed in the existing literature, out of which mostly renowned ones are assessed. These tools/techniques for each element of the integrated-DSS (a knowledge-driven computer system program which gathers and analyses data) are shortlisted based upon scope, requirements, resources, and applicability of the research study. The sketch of the proposed model is drawn, followed by its co-effect with ZDM between risk management parameters. Challenges and opportunities to develop and implement such system in a developing country like Pakistan are discussed to assess feasibility of the study. Lastly, administrative phases of the proposed model are elaborated, consisting of intelligence, design, choice, implementation, monitoring, and results. The structure of the proposed decision support tool is developed for manufacturing industry of a country with growing economy to approach ZDM (a data-driven approach to prevent manufacturing defects/error) to reduce production time and cost, which would ultimately enhance the quality.

Initially, a detailed framework will be developed for the proposed DSS model based on the hypothesis of this research covering aspects of risk management (risk identification, risk analysis, risk prioritization, risk control, risk mitigation), internal/external data, knowledge base, manufacturing data, and user interface (for the operator) in the upcoming research paper. The framework will be improved by employing model fine-tuning method, a technique for adapting foundation models to downstream tasks by updating model parameters using available data. A case study will be conducted, dealing with the challenges involved in implementing the proposed framework in a manufacturing setup. The model will then be verified in a simulated environment for optimization (to get the optimum solution) followed by its sensitivity analysis (to check model's robustness) and validated in AC/induction motor manufacturing setting located in fan production industrial area in Gujrat city of Punjab province of Pakistan to demonstrate the applicability and effectiveness. The theoretical and practical implications of this integrated-DSS model will be discussed in upcoming publication, making the shop floor manager/operator to have better decisions prior/during manufacturing errors/defects. The system will be able to learn from those unwanted events (as per guidance by ZDM) to further prevent the product design and its related manufacturing processes. Therefore, the model will be considered as dynamic in nature, further improves its decision-making with time on the basis of available data.

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Data availability No data used is used in this review article.

Declarations

Conflict of interest The authors declare no competing interests.

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