Repurposing production operations during COVID-19 pandemic by integrating Industry 4.0 and reconfigurable manufacturing practices: an emerging economy perspective

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Abstract

The Covid-19 pandemic has had a significant impact on manufacturing industries and supply chains. Manufacturing industries are struggling to repurpose their production activities and ramp up the supply chain to bridge the demand–supply gap. A framework that can cover Industry 4.0 technologies and reconfigurable manufacturing system (RMS) practices is desperately needed. The current study focuses primarily on the framework that could assist managers in decision-making and the step-wise adoption of RMS during repurposing. The extensive literature review was conducted to identify the prominent Industry 4.0 technologies and RMS practices. To compute the weights of selected practices, the novel Pythagorean fuzzy analytical hierarchy process (AHP) was used; while the Pythagorean fuzzy combined compromise solution (CoCoSo) method was used to prioritize the selected performance metrics. To test the robustness of the developed framework, a sensitivity analysis was carried out. According to the findings, smart factory adoption (SFA) practices were the most significant among the major criteria, followed by reconfiguration practices (RCP), soft computing practices (SCP), sustainable & circular economy practices (SCE), and quality practices (QPS). SFA's advanced technologies and SCP's computer algorithms certainly assist in the repurposing of production activities (RPO). The results of the sensitivity analysis demonstrated the robustness of the developed framework. The developed framework will be useful during RPO, and the identified practices can make a significant contribution. Advanced technologies and sustainable practices can help to improve the organization's work culture. Managers will be able to evaluate the organization's performance with the help of identified performance metrics. The work presented here may be the first attempt to develop a framework for RPO in a pandemic situation.

Keywords Reconfigurable manufacturing system · Industry 4.0 · Repurposing of production operations · Pythagorean fuzzy AHP · CoCoSo method

1 Introduction

The pandemic caused by COVID 19 has had a negative impact on a variety of industries, including manufacturing, tourism, healthcare, and many others. The spending power of a large population has been significantly reduced as a result of the lockdown and quarantine period, which has resulted in a stagnant economy in the majority of regions (Shen et al. 2020). The coronavirus outbreak has also had a significant impact on several manufacturing industries in many countries, and some researchers have developed an accounting index to assess the impact of the virus (He et al. 2020). As a result, manufacturing industries are suffering from disrupted supply chains, a shortage of manpower due to the lockdown, a shortage of raw materials, highly dynamic market needs, disrupted transportation facilities, reduced customer purchasing power, etc. The global economy's growth rate is expected to fall up to –3% in 2020, potentially leading to a global recession. Furthermore, the manufacturing industries are expected to lose around 10.7% in 2020, while the service industries are expected to lose around 16% (Gu et al. 2020). As a result, there is a need to repurpose the manufacturing

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operations to maintain the organization's financial performance. Furthermore, the repurposing of essential drugs, healthcare equipment, food and safety-related products, and many other items is a top priority. The majority of the world's supply chain has been severely impacted and must be resumed for the necessary products to reach customers. As a result, according to López-Gómez et al. (2020), a strong roadmap for rapid repurposing of manufacturing and development activities that can reflect national priorities is required to improve global manufacturing capacity. Several researchers, practitioners, and manufacturing organizations are attempting to repurpose activities, but are falling short since new product introduction necessitates the compliance of several resources as well as extensive planning. This situation necessitates the use of advanced technologies capable of meeting pandemic requirements such as customized products and rapid response. The fourth industrial revolution, also known as Industry 4.0, is made up of several advanced technologies, including information technologies used in manufacturing, which can meet such demands (Javaid et al. 2020). According to Liu and Beltagui (2021), digital technologies such as 3D printing can help to increase required flexibility, whereas collaborations with other organizations, in conjunction with digital technologies, can help to reduce product development time and thus lead time. The researchers also stated that technologies such as Computer Numerically Controlled machines can be useful for repurposing. Furthermore, advanced manufacturing systems such as Reconfigurable Manufacturing System (RMS) can help to provide the necessary flexibility during the manufacturing of products required to deal with the pandemic situation as well as to maintain individual country's economic conditions (Pansare et al. 2022a). RMS, the next generation manufacturing system, with its higher reconfigurability, flexibility, and intelligence, can assist in the rapid transition to new products required to deal with the varying needs of a pandemic situation as well as post-pandemic challenges (Khan et al. 2022; Pansare et al. 2021a).

The most important attribute in incorporating changeability in any manufacturing system in the context of Industry 4.0 is reconfigurability (Pansare et al. 2022b). Furthermore, product complexities are constantly increasing, necessitating the use of modern manufacturing systems such as RMS to manufacture them in this scenario (Bortolini et al. 2021). RMS practices and technologies such as Holonic manufacturing, Agent-based design, Cyber-Physical System (CPS), Digital Twins (DT), Industrial Internet of Things (IIoT), and many more are strengthening manufacturing systems in the Industry 4.0 era (Morgan et al. 2021). RMS, when combined with these enabling technologies and practices, can meet the aforementioned requirements and assist manufacturing systems in repurposing their manufacturing operations

during a pandemic. However, in the context of Industry 4.0, there is a need to bridge the design, theory, and practices of RMS (Liu et al. 2020).

Looking at the current situation, many manufacturing activities are hampered as a result of the pandemic, and organizations are struggling to ramp up the same using various techniques. Despite wartime efforts to address the issue, manufacturing industries are unable to meet the shortage of supply, dynamic market needs, and unexpected growth in demand for a specific type of product (López-Gómez et al. 2020). While doing so, manufacturing industries face several challenges, such as a lack of employees due to the lockdown, a lack of raw materials, etc. Furthermore, market demands are drastically changing, and products essential for Covid-19 virus protection, as well as products of basic needs, are in high demand. As a result of this shift in demand, many manufacturing industries have become desperate for survival, and they are now forced to manufacture products in response to market demands. Hence, many researchers have concentrated on developing methodologies and frameworks for repurposing manufacturing operations (López-Gómez et al. 2020). Simultaneously, Javaid et al. (2020) attempted to use several Industry 4.0 technologies to deal with a pandemic situation in which advanced manufacturing technologies are used to meet customized requirements. Similarly, many other researchers attempted to discover pathways for the recovery of various industries such as aviation (Dube et al. 2021), tourism (Škare et al. 2021), and others. However, there was a strong need to develop a framework that can use several hybrid technologies, such as RMS-Industry 4.0, to repurpose manufacturing activities while also being able to switch over products demanded by the pandemic situation. It was also necessary to identify several RMS-Industry 4.0 enabling technologies and practices that can assist practitioners during this transition as well as contribute to pandemic preparedness. Furthermore, a set of performance metrics that can reflect the overall impact of this framework and allow organizations to measure their current status must be developed. Given the current pandemic situation, the above-mentioned framework was especially important, as it may also indicate future opportunities for organizational development and market competition even during a down economic period. The following were the study's objectives:

1. To identify RMS-Industry 4.0 practices that assist in repurposing manufacturing organizations during a COVID-19 pandemic situation through a literature review.
2. Identifying and researching the challenges that manufacturing organizations face during and after a pandemic.
3. To present the role of RMS-Industry 4.0 practices in the RPO within an organization and to develop a framework for it.

4. Identifying and prioritizing performance metrics to assess an organization's ability to deal with a pandemic situation.

With the aforementioned objectives in mind, an extensive literature review was conducted to identify RMS-Industry 4.0 practices and performance metrics to assess the impact of these practices in any organization during and after a pandemic situation. This was followed by the development of a framework for these practices as well as performance metrics to assist practitioners in manufacturing organizations in dealing with the pandemic situation. To compute the weights of selected practices and then prioritize the identified performance metrics, the hybrid Pythagorean fuzzy analytical hierarchy process (PFAHP) – combined compromise solution (CoCoSo) method was used. Therefore, the current study explores the novel PFAHP and CoCoSo methods that have a ability to differentiate the alternatives. This contributes to multi-criteria decision-making (MCDM) and demonstrates how these methods can be used. The study also developed a framework for RPO during the COVID-19 pandemic situation; thus, it contributes to the field of manufacturing systems by providing a novel framework that can assist them in repurposing and bringing manufacturing operations back to normal.

The current study is divided into six sections, one of which is the current section. Section 2 presents a literature review related to RMS, Industry 4.0, and research gaps, followed by research methodology in Sect. 3. Section 4 explains the case analysis, including framework development and performance metric prioritization, while Sect. 5 discusses the study findings and their implications. Section 6 summarises the study's conclusions as well as its future scope.

2 Literature review

During the literature review, the Scopus database was used to retrieve the previous research articles that were related to RMS, Industry 4.0, COVID-19, and repurposing of manufacturing operations. Using the keyword 'Reconfigurable Manufacturing System', total 1140 research articles were retrieved that were further filtered and only 454 articles from peer-reviewed reputed journals in the English language were finally selected for further study from 1999 to 2021. Furthermore, the keyword 'Industry 4.0' was used to retrieve 281 articles published in English from 2010 to 2021 from only reputable peer-reviewed journals. Similarly, from 2019 to 2021, 151 research articles related to COVID-19, including the repurposing of several sectors, were chosen from peer-reviewed journals in English. These selected articles were later stored in a central location so that they can be

retrieved as needed. Only peer-reviewed articles from reputable publishers such as Emerald insight, Springer link, Elsevier, Taylor & Francis, and Inderscience were chosen for this study, while conference proceedings and book chapters were excluded. The selected articles were investigated further, and the results are presented below.

2.1 Repurposing Production Operations (RPO) in manufacturing industries

As previously stated, the COVID-19 pandemic has had a significant impact on manufacturing operations. As a result, many researchers began to focus on the repurposing of these operations, developing several methodologies and frameworks in the process. In addition, practitioners and managers in manufacturing organizations were working hard to recover from the current situation and restore normalcy to production operations. However, the contributions of a few researchers to RPO are summarised in Table 1 and discussed further below.

During the COVID-19 global emergency, the healthcare sectors faced a challenge due to a lack of ventilators, masks, test kits, etc. As a result, López-Gómez et al. (2020) reviewed key challenges for repurposing their manufacturing activities and proposed probable methods to mitigate the challenges. Furthermore, Deshmukh and Haleem (2020) attempted to prepare a conceptual framework for enhancing manufacturing activities from an Indian perspective, involving a variety of stakeholders. Researchers also proposed using more automation and localized skills during manufacturing activities to meet the increased demand for products. Another researcher Liu and Beltagui (2021) wanted to speed up the innovation process by repurposing; they examined case studies and concluded that exaptation can help during the crisis recovery. Saberian et al. (2021) wanted to reduce the waste generated as a result of the pandemic situation, so they proposed recycling it in civil construction. Researchers also proposed incorporating 1% shredded face masks into recycled concrete aggregate to increase compressive strength. Furthermore, Hill et al. (2020) discovered that by repurposing existing drugs for COVID-19 treatment, the mortality rate and manufacturing costs could be reduced.

2.2 Integrating Industry 4.0- RMS practices

The COVID-19 pandemic has had a significant impact on several manufacturing organizations and their production operations. The pandemic has also had an impact on the market, as the demand for certain types of products, such as sanitizer, masks, and PPE kits, has increased significantly, while the demand for other types of products has decreased significantly. Furthermore, the World Health Organization (WHO) had published a list of critical products to tackle

Table 1 Contribution of researchers for RPO

Sr. No.	Authors	Objectives	Outcomes
1.	(López-Gómez et al. 2020)	To review the challenges for repurposing the manufacturing activities and ways to mitigate them	A roadmap is prepared for rapid repurposing
2.	(Deshmukh and Haleem 2020)	To give an Indian perspective for enhancing post-COVID manufacturing activities. He also involved stakeholders during this process	The conceptual framework is prepared to assess Indian industries
3.	(Liu and Beltagui 2021)	To accelerate the process of innovation through repurposing, its application for manufacturing and design	Suggested the ability of exapt for design and manufacturing
4.	(Saberian et al. 2021)	Repurposing of single-use face masks to reduce waste	The compressive strength is enhanced
5.	(Hill et al. 2020)	To minimize the cost of manufacturing new drugs for the treatment of COVID-19 through repurposing	Repurposed drugs can be manufactured at a low cost

the COVID-19 outbreak and had advised several countries to increase the production of these products (López-Gómez et al. 2020; Qi et al. 2021). Despite the many efforts made by manufacturing organizations, there was still a demand–supply gap, and as a result, manufacturing organizations were shifting to other alternatives. Many governments around the world were encouraging manufacturers to repurpose their production lines to narrow the gap between demand and supply (López-Gómez et al. 2020). As a result, many manufacturing industries were attempting to cope with the situation by employing advanced technologies, while researchers are also contributing to this through their research into advanced technologies and practices. According to Javaid et al. (2020), advanced Industry 4.0 technologies such as information technology may assist manufacturing industries in customizing their products such as gloves, masks, and many others. Javaid et al. (2020) went on to say that the facilities available at Industry 4.0 factories, such as wireless connectivity, sensors, artificial intelligence, etc., can help with RPO. The incorporation of video surveillance and sensors into healthcare products may reduce the workload of COVID-19 doctors. Industry 4.0 information technologies may also assist doctors and staff in maintaining the necessary information to avoid misinformation.

Furthermore, due to changes in product demand, many industries are forced to transition to new products during pandemics. However, insufficient flexibility in the manufacturing system is preventing capacity adjustment and product switchover (Qi et al. 2021). Manufacturing systems, technologies, and practices that assist in this transition are becoming increasingly important at this time. Information technologies and Industry 4.0 are largely assisting in the automation of the manufacturing of healthcare-related products, whereas RMS is assisting in the adjustment of production capacity and required flexibility (Qi et al. 2021). The RMS core characteristics (Modularity, Integrability,

Customization, Convertibility, Diagnosability, and Scalability) provide the required flexibility to the manufacturing system and allow it to adjust production capacity in response to market demand (Pansare et al. 2021b). In addition, Psarommatis (2021) used several Industry 4.0 technologies for zero defect manufacturing (ZDM), including Cyber-Physical System (CPS), Artificial Intelligence (AI), Big Data, Cloud Manufacturing, etc. ZDM can be implemented in two stages using these technologies, triggering factors (detection, prediction) and actions (repair, prevention) that may result in improved quality and cost savings. Malik et al. (2020) further said that Industry 4.0 technologies like robots, IoT, etc. could help ramp up ventilator production during a pandemic. Researchesrs demonstrated a model for integrating robots and design guidelines. Morgan et al. (2021) conducted a review of RMS articles and investigated next-generation machines equipped with Industry 4.0 technologies and reconfigurable capabilities. Furthermore, many researchers in the Industry 4.0 and RMS domains attempted to investigate the impact of these technologies and practices in manufacturing in terms of cost, productivity, economy, forecasting, quality, etc. (Bortolini et al. 2018; Jaskó et al. 2020; Liu et al. 2020). Such RMS capabilities can assist in RPO and may help in dealing with pandemic situations; thus, it was necessary to identify major Industry 4.0-RMS practices. The effectiveness of these practices during RPO due to the COVID-19 pandemic must also be measured; thus, the performance metrics identified through the literature review are listed in Table 2.

The advanced technologies of Industry 4.0 and RMS practices can help on a large scale to handle the pandemic situation; meet customer needs, customize required products, and bridge the demand–supply gap. Table 3 shows how the nexus practices assist in overcoming the challenges posed by COVID-19, as well as a set of performance metrics used to assess the effectiveness of the practices.

Table 2 Industry 4.0-RMS practices

Industry 4.0 technologies	RMS practices	Reference
AI, Internet of things (IoT), Big data, Virtual reality, Holography, Cloud computing, Autonomous robots, 3D scanning, 3D printing, Biosensors	-	(Javaid et al. 2020)
CPS, IoT, Machine Learning, Big Data, Cloud Manufacturing, Smart Sensors Network	-	(Psarommatis 2021)
Human–Robot collaborative systems, IoT, Augmented Reality, Big data, additive manufacturing	Modularisation, Digital twins, Industrial Robots	(Malik et al. 2020)
Computational agents, Holonic systems, Service Oriented Architecture, IoT, CPS, Digital Twins	Reconfigurable Machine Tools (RMT), Machine control, Human–Machine interface, Horizontal & Vertical integration, Distributed & decentralized control	(Morgan et al. 2021)
-	AI, Big data, Digital Twins, Virtual models	(Qi et al. 2021)
Cybersecurity, IoT connectivity, Digital Twins, Horizontal & Vertical integration	-	(Jaskó et al. 2020)
CPS, Digital Twins	Configuration design, Optimization	(Liu et al. 2020)
Internet & Wireless Local Area Network, Robots	Reconfigurable ability, tool replacement	(Xu et al. 2021)
Advanced manufacturing solutions, Additive manufacturing, Augmented reality, Simulation, Horizontal & Vertical integration, Industrial internet, Cloud, Cyber-security, Big-data & Analytics	Configuration design, Optimization, Customized products, Quality, Testing	(Bortolini et al. 2018)
-	Prognostics & health management, Cyber-physical systems, Maintenance optimization & Scheduling	(Xia and Xi 2017)
-	CPS, 3D printing, Holonic control, Optimization, controller designs	(Kruger and Basson 2019)
-	Digital Twins, Rapid reconfiguration, Architecture design, CPS, IoT, Smart manufacturing	(Jiewu et al. 2020)
Sustainability, life standard, creativity, High quality, Customization	Reconfigurability, Optimization, waste reduction, Product & Process quality	(Massimi et al. 2020)
-	Total Quality Management (TQM), Mass customization, Concurrent Engineering, Real-time control, Human resource, Shorter lead time	(Bi et al. 2008)
-	Sustainability, Reusability, Environmental emissions,	(Kurniadi and Ryu 2020)

It is also necessary to assess the effectiveness of this nexus effect during RPO, and thus performance metrics are required (Chandak et al. 2022). The performance metrics that can evaluate the performance of the system during RPO have been identified through a literature review, as shown in Table 3. It should be noted that the important performance metrics in RMS are reconfiguration time, which represents the time required to switchover the product (Huang et al. 2019), manufacturing cost (Chen and Huang 2006), reconfiguration cost, and lead time (Puik et al. 2017), which represents the time from order placement to product delivery. Fatimah et al. (2020) considered several dimensions during his waste management study, including employee retention, manpower required, employee availability, etc., that can be used to determine its maturity level. Employee retention indicates how long an employee has been providing a service to the organization, whereas employee availability indicates the absenteeism due to illness or other reasons. These are also significant factors during RPO and must be taken into account. The authors also considered the availability of advanced technologies such as soft computing and advanced machines, as well as energy consumption, as evaluation dimensions. Yurdakul (2002) considered several factors related to product quality such as scrap rate, defectives ratio, customer complaints such as guarantee/warranty, etc. when measuring the performance of a manufacturing system. Here, the scrap rate represents manufacturing rejections, whereas the defectives ratio represents the total number of defectives that require rework or rejections. Furthermore, while evaluating RMS performance, Garbie (2014a, b) took into account machine utilization, throughput, cycle time, breakdowns, etc. The set of performance metrics identified through this literature review may enable an evaluation of the current state of RMS during RPO and the identification of development opportunities.

2.3 Literature gaps

An extensive literature review of articles on Industry 4.0, RMS, and COVID-19 is conducted, and the research gaps are identified as listed below.

Table 3 Nexus effect of Industry 4.0-RMS practices

Challenges incurred due to COVID-19	Industry 4.0-RMS practices	Nexus effect to overcome the challenges	Performance metrics
Rapid increase in demand for particular products like masks, sanitizer, etc	RMT, Scalability, CPS, Customization, Reconfigurability	RMS's scalability enables it to increase production, whereas reconfigurability enables it to switch from one product to another	• Reconfiguration time • Manufacturing cost • Lead time
Unavailability of manpower due to lockdown	Autonomous robots, IoT, Cloud Manufacturing, Smart Sensors Network, CPS, Internet & Wireless Local Area Network	Automation of manufacturing activities in RMS and Industry 4.0 may assist in operating with fewer employees. In addition, IoT, cloud manufacturing, and wireless networks allow for remote work	• Employee retention • Number of defectives per day • Reconfiguration cost • Throughput material • Number of warranty/ guarantee claims per year
Disturbed supply chain management	IoT, Internet & Wireless Local Area Network	The online services that use IoT, the internet, and wireless networks allow for the timely delivery of products. It also allows you to order the raw materials you need	• Machine utilization • Total manpower requirement • Number of soft computing technologies available
Increased requirement of customized products	Customized products, customization, creativity,	The ability of RMS and Industry 4.0 permits to satisfy these requirements	• Number of breakdowns per fortnight • Cycle time
Need of required medical standards	Product & Process Quality, Quality, Testing	The ability to manufacture quality products and testing practices enables the production of products that meet the required standards	• Overall energy consumption • Number of advanced machines available • Number of training sessions conducted
Cost expectations and financial crisis	Optimization, waste reduction	The optimization and waste minimization practices of RMS may assist to meet this challenge	• Number of customized products • Ratings received for online customer feedback • Number of accidents per month
Protect the employees/ workforce	Autonomous robots, IoT, Cloud Manufacturing, Smart Sensors Network, CPS, Internet & Wireless Local Area Network	Employees must be protected from COVID-19 infections in the workplace. IoT, CPS, cloud manufacturing, and other technologies assist organizations in maintaining a safe distance and avoiding infections	• Financial performance (profit percentage) • Number of RMT available • Employee availability • Scrap rate
Business continuity risk and its management	RMT, Scalability, CPS, Customization, Reconfigurability, creativity, Optimization	The nexus effect of Industry 4.0-RMS provides the ability to anticipate likely fluctuations in product demand and the plant's reconfigurability to respond to them. Because of this, business continuity can be ensured	
Maintaining global competitiveness	Optimization, waste reduction, Product & Process Quality, Quality, Testing, Customization	The international supply chain has been impacted by COVID-19, and manufacturing industries are struggling to supply products at the lowest possible cost to maintain competitiveness. It is assisted by the practices mentioned above	
Maintaining productivity along with social distancing	Autonomous robots, IoT, Cloud Manufacturing, Smart Sensors Network, CPS, Internet & Wireless Local Area Network	The advanced technologies and practices of Industry 4.0-RMS allow for social distance while maintaining manufacturing system productivity	

- Several RMS and Industry 4.0 researchers have contributed to this area to increase system adoption and performance. However, the overall representation of Industry 4.0 technologies was seen in very few articles, while the listing of RMS practices was quite lacking in the available literature.
- Although few researchers attempted to identify the challenges faced by manufacturing industries during the COVID-19 pandemic, the use of various technologies and practices to overcome these challenges went unnoticed in the literature.
- Almost no researchers had described the use of the nexus effect of Industry 4.0-RMS to overcome the COVID-19 pandemic and other challenges.
- The framework for overcoming COVID-19 pandemic challenges in the manufacturing sector was quite lacking in the available literature. The previous researchers also did not participate in the development of a set of performance metrics to assess the effectiveness of the prepared framework. Furthermore, the prepared framework must be tested using industrial case analysis.
- Case studies that describe the success stories of using Industry 4.0 and RMS to switchover production as well as adjust production capacity to another product to bridge the supply–demand gap were attended by almost no researchers.
- While maintaining reconfigurability and customization during production, researchers in this domain almost completely ignored the process of incorporating sustainability in the product as well as the manufacturing system.
- The use of Multi-Criteria Decision Making (MCDM) techniques to create a framework that can assist researchers and practitioners in determining the relative importance of practices and performance metrics was lacking in the existing literature. In addition, the inclusion of expert opinion in the preparation of such a framework was seen in only a few articles.
- Researchers in this domain had not yet addressed the methodology for improving and sustaining the supply chain of the manufacturing system in such a pandemic situation.

The gaps identified through the literature review demonstrated the need to prepare the framework for RPO due to the COVID-19 pandemic, which can assist researchers and practitioners in repurposing and ramping up their production activities. As discussed in Sect. 1, López-Gómez et al. (2020) highlighted the need to prepare a roadmap for repurposing manufacturing activities; thus, the identified research gaps were supported, and such a framework can assist in determining the nation's priorities. In addition, during a pandemic, this may help to bridge the demand–supply gap. As stated in the study objectives, the current study focuses on the development of a framework for the RPO and the prioritization of performance metrics that can be used to evaluate the performance of the manufacturing system. As a result, the study attempted to fill the above-mentioned research gap using expert opinion.

3 Research methodology

Initially, an extensive literature review of RMS and Industry 4.0 articles was conducted to identify the technologies and practices used during product manufacturing. For this purpose, the Scopus database was used, and the identified technologies and practices were presented to the expert panel. According to the expert panel's (please see Sect. 4.1 for more information) recommendations, they were further sorted and classified as advanced machines, scalability practices, quality practices, reconfiguration practices, and remote technologies. The expert panel was also asked to give opinion for the hybrid Pythagorean fuzzy AHP – CoCoSo approach. Based on this, the RPO framework was developed, as discussed in the following section. The Pythagorean fuzzy AHP was used to compute the weights of the major and sub-criteria, whereas the CoCoSo method was used to rank the performance metrics and compute the adoption index. Finally, the sensitivity analysis was performed, and the study's implications were listed. The sensitivity analysis was carried out to ensure that the developed framework is robust. Figure 1 depicts the research methodology used for the current study.

4 Case analysis

4.1 Industry identification and data collection

The primary goal of the presented study was to develop a framework that could assist practitioners during RPO via RMS and Industry 4.0 during the COVID-19 pandemic; thus, twenty different manufacturing industries were approached and the entire concept was explained to them. Three industries agreed to participate in the process; however, it was a difficult task for the authors to select these industries because they must be similar in terms of products manufactured, turnover, capacity, number of employees, etc. As a result, the three industries that were ultimately chosen are involved in the production of various types of plastic bottles, employing approximately 125 people, including technical and non-technical staff. All three industries have a monthly capacity of approximately 10,000 bottles and an annual turnover of 55 to 60 crore rupees. The manufactured bottles are used for a variety of applications including drinking water, sanitizer dispensing, healthcare applications, etc.
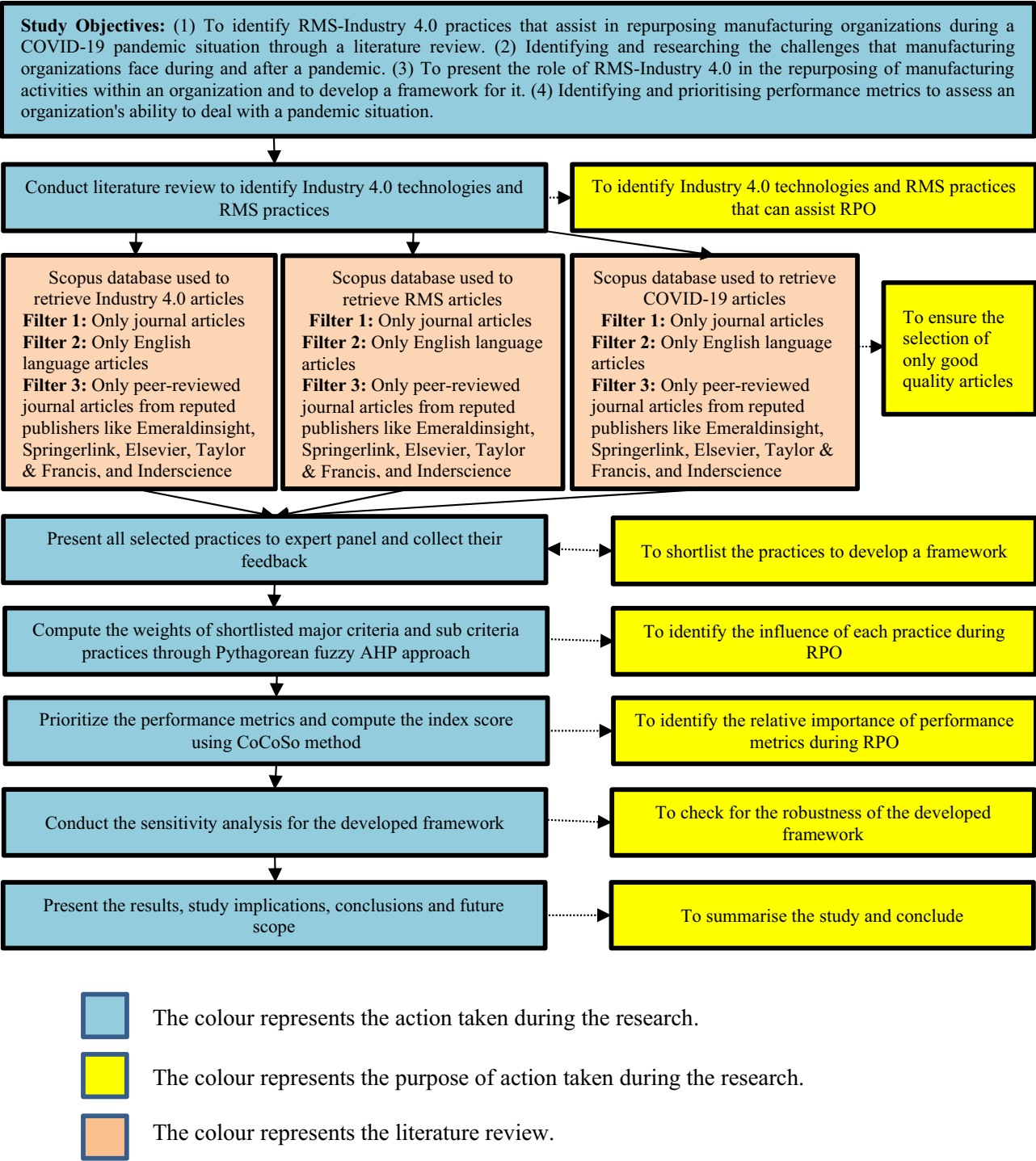
Study Objectives: (1) To identify RMS-Industry 4.0 practices that assist in repurposing manufacturing organizations during a COVID-19 pandemic situation through a literature review. (2) Identifying and researching the challenges that manufacturing organizations face during and after a pandemic. (3) To present the role of RMS-Industry 4.0 in the repurposing of manufacturing activities within an organization and to develop a framework for it. (4) Identifying and prioritising performance metrics to assess an organization's ability to deal with a pandemic situation.

Conduct literature review to identify Industry 4.0 technologies and RMS practices

To identify Industry 4.0 technologies and RMS practices that can assist RPO

Scopus database used to retrieve Industry 4.0 articles
Filter 1: Only journal articles
Filter 2: Only English language articles
Filter 3: Only peer-reviewed journal articles from reputed publishers like Emeraldinsight, Springerlink, Elsevier, Taylor & Francis, and Inderscience

Scopus database used to retrieve RMS articles
Filter 1: Only journal articles
Filter 2: Only English language articles
Filter 3: Only peer-reviewed journal articles from reputed publishers like Emeraldinsight, Springerlink, Elsevier, Taylor & Francis, and Inderscience

Scopus database used to retrieve COVID-19 articles
Filter 1: Only journal articles
Filter 2: Only English language articles
Filter 3: Only peer-reviewed journal articles from reputed publishers like Emeraldinsight, Springerlink, Elsevier, Taylor & Francis, and Inderscience

To ensure the selection of only good quality articles

Present all selected practices to expert panel and collect their feedback

To shortlist the practices to develop a framework

Compute the weights of shortlisted major criteria and sub criteria practices through Pythagorean fuzzy AHP approach

To identify the influence of each practice during RPO

Prioritize the performance metrics and compute the index score using CoCoSo method

To identify the relative importance of performance metrics during RPO

Conduct the sensitivity analysis for the developed framework

To check for the robustness of the developed framework

Present the results, study implications, conclusions and future scope

To summarise the study and conclude

The colour represents the action taken during the research.

The colour represents the purpose of action taken during the research.

The colour represents the literature review.

Fig. 1 Research methodology

The bottles produced are shipped to various parts of India as well as to countries outside of India. Following a lengthy discussion with industry officials, it was decided to form a panel of experts comprised of 15 members from various industries to ensure that the proposed framework development process is carried out effectively. As summarised in Table 4, all of the experts were highly qualified and had extensive experience in a variety of fields.

Following a series of meetings with the expert panel, the identified Industry 4.0-RMS practices were further filtered, and the ultimately selected practices were further classified, as discussed in Sect. 4.2. The expert panel was now tasked

with creating a pairwise comparison for major criteria and sub-criteria practices. For the initial pairwise comparison required by the CoCoSo approach, expert opinion was also gathered, standard weight computation and prioritization process was executed, the results were presented and discussed with the expert panel, and minor changes were made in accordance with the panel's recommendations.

4.2 Framework development

The chosen practices were then presented to an expert panel for their input, and minor changes were made based on their suggestions. The expert panel also proposed categorizing the practices into five major criteria, as depicted in Fig. 2.

The developed framework have five levels, as shown in Fig. 2. Level 1 includes the developed framework's objective as well as indications of where the framework can be applied. Level 2 displays the major criteria practices to highlight the categorization of the selected practices based on the expert panel's recommendations. The major criteria practice indicates the area of application of selected practices, which can assist practitioners to implement them. Level 3 displays the sub criteria practices according to the major criteria practices to which they belong. This is the most important level for the framework because it contains several sub-criteria practices to be used for RPO. Level 4 of the developed framework lists the selected performance metrics. This can help practitioners evaluate the effectiveness of the adopted practices in the manufacturing system, as well as identify areas for further improvement. Finally, level 3 displays the five organizations where the expert panel formation and framework case analysis was carried out. The framework

depicted in Fig. 2 demonstrates how it can be implemented in the organization in stages and evaluated using a set of performance metrics. This can help practitioners understand the chronology in which the framework must be implemented.

4.3 Framework analysis

The hybrid Pythagorean fuzzy AHP-CoCoSo method was used to compute the weights of selected Industry 4.0-RMS practices during RPO and performance metric ranking. The execution of the entire process is discussed further below.

4.3.1 Application of Pythagorean fuzzy AHP method

Many researchers have criticized the AHP process for the inaccuracy of the ranking and the need for interdependence among the criteria and alternatives, which can lead to inconsistencies (Bag et al. 2021). The intuitionistic fuzzy sets, hesitant fuzzy sets, and Pythagorean fuzzy sets all have the ability to deal with vagueness and uncertainty; however, the intuitionistic fuzzy sets are more capable of dealing with imprecision, whereas the hesitant fuzzy sets are made up of discrete values in the interval [0, 1] rather than a single number. Also, Pythagorean fuzzy sets give decision makers more flexibility when assigning values where the sum of membership and non-membership grades is greater than unity but the sum of squares is in the interval [0, 1]. To address this, Interval-valued Pythagorean fuzzy AHP was used, with the linguistic terms used listed in Table 5 (Bakioglu and Atahan 2021).

The following steps are to be executed for Pythagorean fuzzy AHP,

| Expert code	Age group (Years)	Educational qualification	Role in industry	Department of work	Work experience (Years)
E1	41–50	Post graduate	Founder/Director	Administration	23
E2	31–40	Graduate	Manager	Design	18
E3	51–60	Ph. D	Vice president	Manufacturing	28
E4	41–50	Post graduate	Senior Manager	Manufacturing	23
E5	41–50	Post graduate	Sales Manager	Marketing	19
E6	41–50	Graduate	Logistics Manager	Administration	24
E7	60+	Ph. D	Consultant	Design	40
E8	21–30	Graduate	Production Engineer	Manufacturing	06
E9	51–60	Ph. D	Senior Manager	Manufacturing	31
E10	41–50	Post graduate	Senior Manager	Design	23
E11	51–60	Post graduate	Director	Administration	32
E12	41–50	Graduate	Production Manager	Manufacturing	22
E13	51–60	Post graduate	General Manager	Manufacturing	33
E14	51–60	Post graduate	Senior Manager	R & D	32
E15	51–60	Ph. D	Senior Manager	Design	25

Table 4 Members of an expert panel
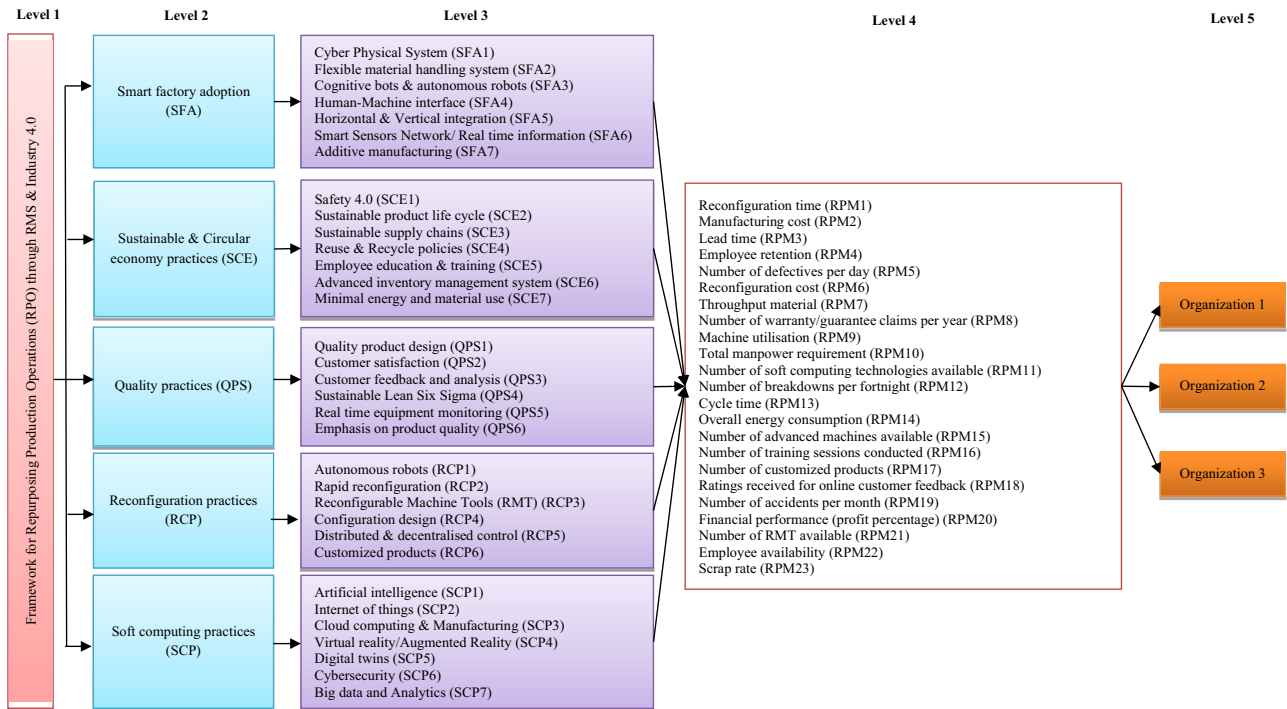
Fig. 2 A developed framework for prioritizing RPO performance metrics

Step 1: Identify the alternatives (i = 1, 2,…, m)

Step 2: Construct the pairwise comparison matrix $A = (a_{ik})_{m \times m}$

Step 3: Compute the difference matrices $D = (d_{ik})_{m \times m}$

Step 4: Compute the interval multiplicative matrix $S = (s_{ik})_{m \times m}$

Step 5: Calculate the determinacy value $\tau = (\tau_{ik})_{m \times m}$

Step 6: Compute the matrix of weights $T = (\tau_{ik})_{m \times m}$

Step 7: Compute the normalized weights w_i using the following equation,

$$w_i = \frac{\sum_{k=1}^{m} t_{ik}}{\sum_{i=1}^{m} \sum_{k=1}^{m} t_{ik}}$$

Table 5 Linguistic terms used in Pythagorean fuzzy AHP

Linguistic variables	Pythagorean fuzzy numbers			
	μ_L	μ_U	V_L	V_U
Certainly low importance (CLI)	0.00	0.00	0.90	1.00
Very low importance (VLI)	0.10	0.20	0.80	0.90
Low importance (LI)	0.20	0.35	0.65	0.80
Below average importance (BAI)	0.35	0.45	0.55	0.65
Average importance (AI)	0.45	0.55	0.45	0.55
Above average importance (AAI)	0.55	0.65	0.35	0.45
High importance (HI)	0.65	0.80	0.20	0.35
Very high importance (VHI)	0.80	0.90	0.10	0.20
Certainly high importance (CHI)	0.90	1.00	0.00	0.00
Exactly equal (EE)	0.1965	0.1965	0.1965	0.1965

The sample pairwise comparison by one of the experts is shown in Table 6.

As previously stated, the experts' opinions were gathered for pairwise comparisons of major criteria as well as sub-criteria Practices, and the weights were computed using Pythagorean fuzzy AHP. As shown in Table 7, this is followed by the computation of global weights for sub-criteria Practices.

4.3.2 Application of Pythagorean fuzzy CoCoSo approach

Yazdani et al. (2019) proposed a novel CoCoSo method, where the obtained solution is consistent with weight variation, providing stability to the decision-making process when compared to other techniques. Also, when compared to other techniques, the CoCoSo method combines the simple additive method with the exponentially weighted product method to obtain the compromise solution (Yadav et al. 2021). Reasearchers also included a Pythagorean fuzzy set in this method, which can effectively deal with uncertain issues in decision-making. Another reason for using this method was the total absence of counterintuitive phenomena, as well as the higher resolution when distinguishing between alternatives. Due to the Pythagorean fuzzy set, the approach can effectively deal with uncertainty issues and can differentiate the best alternative. The steps in the Pythagorean fuzzy CoCoSo method are as follows (Lahane and Kant 2021).

Table 6 Pairwise comparison for smart factory adoption practices

Criteria	SFA1	SFA2	SFA3	SFA4	SFA5	SFA6	SFA7
SFA1	EE	BAI	HI	BAI	AAI	AAI	LI
SFA2	AAI	EE	BAI	AAI	LI	LI	AI
SFA3	AAI	AAI	EE	HI	HI	HI	HI
SFA4	BAI	AI	AI	EE	LI	BAI	LI
SFA5	HI	AAI	AAI	AI	EE	HI	AAI
SFA6	AAI	BAI	AI	EE	AAI	EE	BAI
SFA7	HI	HI	AI	LI	EE	AAI	EE

Step 1: Initially, the decision matrix $D = (d_{ij})_{m \times n}$ where, (i = 1, 2,…m; j = 1, 2,…n) is to be constructed using the linguistic scale as shown in Table 8 and expert opinion.

Step 2: The linguistic decision matrix is then converted into Pythagorean fuzzy decision matrix as per the equation $P = (P_{ij})_{m \times n}$ where, (i = 1, 2,…m; j = 1, 2,…n)

Table 7 Global weights of major and sub-criteria practices

Major Criteria	Major criteria weights	Sub-criteria	Sub-criteria weights	Global weights
Smart factory adoption (SFA)	0.2214	Cyber Physical System (SFA1)	0.1661	0.0368
		Flexible material handling system (SFA2)	0.1307	0.0289
		Cognitive bots & autonomous robots (SFA3)	0.1457	0.0322
		Human–Machine interface (SFA4)	0.1352	0.0299
		Horizontal & Vertical integration (SFA5)	0.1399	0.0310
		Smart Sensors Network/ Real time information (SFA6)	0.1251	0.0277
		Additive manufacturing (SFA7)	0.1574	0.0348
Sustainable & Circular economy practices (SCE)	0.1905	Safety 4.0 (SCE1)	0.1624	0.0309
		Sustainable product life cycle (SCE2)	0.1327	0.0253
		Sustainable supply chains (SCE3)	0.1482	0.0282
		Reuse & Recycle policies (SCE4)	0.1331	0.0253
		Employee education & training (SCE5)	0.1407	0.0268
		Advanced inventory management system (SCE6)	0.1283	0.0244
		Minimal energy and material use (SCE7)	0.1546	0.0294
Quality practices (QPS)	0.1860	Quality product design (QPS1)	0.1739	0.0323
		Customer satisfaction (QPS2)	0.1679	0.0312
		Customer feedback and analysis (QPS3)	0.1577	0.0293
		Sustainable Lean six sigma (QPS4)	0.1652	0.0307
		Real time equipment monitoring (QPS5)	0.1535	0.0286
		Emphasis on product quality (QPS6)	0.1818	0.0338
Reconfiguration practices (RCP)	0.2068	Autonomous robots (RCP1)	0.1598	0.0330
		Rapid reconfiguration (RCP2)	0.1798	0.0372
		Reconfigurable Machine Tools (RMT) (RCP3)	0.1760	0.0364
		Configuration design (RCP4)	0.1671	0.0346
		Distributed & decentralised control (RCP5)	0.1519	0.0314
		Customized products (RCP6)	0.1654	0.0342
Soft computing practices (SCP)	0.1953	Artificial intelligence (SCP1)	0.1538	0.0300
		Internet of things (SCP2)	0.1453	0.0284
		Cloud computing & Manufacturing (SCP3)	0.1504	0.0294
		Virtual reality/Augmented Reality (SCP4)	0.1402	0.0274
		Digital twins (SCP5)	0.1338	0.0261
		Cybersecurity (SCP6)	0.1399	0.0273
		Big data and Analytics (SCP7)	0.1366	0.0267

Step 3: The score function is to be computed using $R = (r_{ij})_{m \times n}$ using the equation,

$$r_{ij} = \mu_{ij}^2 - \nu_{ij}^2 - \ln(1 + \pi_{ij}^2)$$

Step 4: The score function matrix is then to be converted into an orthogonal Pythagorean fuzzy matrix $R' = (r'_{ij})_{m \times n}$ by using the following equation,

$$r'_{ij} = \begin{cases} \frac{r_{ij} - r_j^-}{r_j^+ - r_j^-}, & \text{if } j \in B, \\ \frac{r_j^+ - r_{ij}}{r_j^+ - r_j^-}, & \text{if } j \in C \end{cases}$$

where, $r_j^- = \min r_{ij}$ and $r_j^+ = \max r_{ij}$

Step 5: Using the following equation, compute the weighted comparability sequence.

$$S_i = \sum_{j=1}^n w_j * r'_{ij}$$

Step 6: The power weight of comparability sequences is to be computed now for each alternative.

$$P_i = \sum_{j=1}^n (r'_{ij})^{w_j}$$

Step 7: For each alternative, the relative weight is determined using an equation,

$$K_{ia} = \frac{P_i + S_i}{\sum_{i=1}^m (P_i + S_i)}$$

$$K_{ib} = \frac{S_i}{\min_i S_i} + \frac{P_i}{\min_i P_i}$$

$$K_{ic} = \frac{\lambda S_i + (1 - \lambda) P_i}{\lambda_i^{max} S_i + (1 - \lambda)_i^{max} P_i} \quad 0 \le \lambda \le 1$$

Step 8: Compute the assessment value (K_i) by using an equation,

$$K_i = \sqrt[3]{K_{ia} K_{ib} K_{ic}} + \frac{K_{ia} + K_{ib} + K_{ic}}{3}$$

Step 9: The selected alternatives are ranked based on descending order of K_i

The linguistic decision matrix prepared with expert opinion for the selected performance metrics is shown in Table 9, and the ranking obtained for performance metrics after following the procedure for the Pythagorean fuzzy CoCoSo method is shown in Table 10.

4.4 Sensitivity analysis

It is critical to perform sensitivity analysis tests to ensure the suitability of the developed framework as well as its behavior under varying conditions (Yadav et al. 2020). The weights were varied by 5% and 10%, resulting in a total of 23 experiments, the details of which are shown in Table 11 and the results of which are shown in Fig. 3. Figure 3 shows that there are fewer variations in RPM 10, whereas significant variations are seen in other performance metrics. However, no significant change in ranking was observed, indicating that the developed framework is robust under varying conditions.

5 Discussion on results

The results obtained through the Pythagorean fuzzy AHP-CoCoSo method and its implications are discussed in the current section.

5.1 Study findings

During this study, an extensive literature review was conducted, and 33 Industry 4.0 technologies and RMS practices, as well as 23 performance metrics, were identified. To compute the weights of the selected practices, the Pythagorean fuzzy AHP method was used, while the Pythagorean fuzzy CoCoSo method was used to prioritize the selected performance metrics. The current section discusses the obtained results.

Among the major criteria practices, smart factory adoption received the most weight, indicating that SFA practices are extremely beneficial to RPO. Morgan et al. (2021) conducted a review of RMS and Industry 4.0 technologies

Table 8 Linguistic scale for Pythagorean fuzzy CoCoSo method

Linguistic term	Pythagorean fuzzy number	
	μ	ν
Extremely low (EL)	0	1
Very low (VL)	0.1	0.9
Low (L)	0.2	0.8
Middle low (ML)	0.3	0.7
Below middle (BM)	0.4	0.6
Middle (M)	0.5	0.5
Above middle (AM)	0.6	0.4
Middle high (MH)	0.7	0.3
High (H)	0.8	0.2
Very high (VH)	0.9	0.1
Extremely high (EH)	1	0

Table 9 Linguistic decision matrix for Pythagorean fuzzy CoCoSo method

Short code	Smart factory adoption							Sustainable & Circular economy practices							Quality practices					
	SFA1	SFA2	SFA3	SFA4	SFA5	SFA6	SFA7	SCE1	SCE2	SCE3	SCE4	SCE5	SCE6	SCE7	QPS1	QPS2	QPS3	QPS4	QPS5	QPS6
RPM1	VH	VH	MH	H	AM	AM	AM	H	AM	AM	AM	AM	AM	AM	H	H	AM	AM	H	H
RPM2	H	H	AM	MH	H	MH	H	MH	AM	AM	MH	MH	MH	ML	H	H	AM	AM	AM	AM
RPM3	VH	VH	VH	MH	VH	H	H	ML	ML	H	ML	ML	H	ML	VH	H	H	H	H	AM
RPM4	M	M	L	L	H	M	L	H	M	M	M	H	AM	AM	L	M	L	L	L	L
RPM5	MH	MH	MH	MH	MH	MH	MH	M	BM	BM	M	H	M	M	MH	MH	MH	MH	MH	MH
RPM6	H	H	MH	MH	H	H	H	ML	ML	ML	ML	AM	H	ML	H	ML	AM	AM	AM	AM
RPM7	VL	M	L	L	M	L	L	M	L	L	L	AM	AM	L	L	L	L	L	M	L
RPM8	MH	MH	MH	MH	MH	MH	MH	ML	ML	ML	M	VH	AM	AM	VH	VH	VH	AM	H	VH
RPM9	H	MH	MH	H	MH	H	MH	ML	M	H	MH	H	H	M	MH	MH	MH	MH	H	M
RPM10	AM	AM	M	AM	AM	AM	AM	M	ML	M	M	MH	M	M	AM	AM	M	AM	AM	AM
RPM11	MH	MH	MH	AM	AM	MH	MH	M	M	M	AM	M	AM	MH	AM	M	AM	MH	MH	M
RPM12	AM	AM	M	M	M	M	M	M	M	M	M	AM	M	M	ML	ML	ML	M	MH	M
RPM13	VH	VH	H	H	MH	MH	MH	L	M	H	L	H	MH	ML	AM	MH	MH	MH	H	M
RPM14	AM	AM	M	AM	AM	ML	AM	ML	AM	AM	AM	MH	ML	VH	M	AM	ML	M	M	M
RPM15	VH	H	VH	VH	VH	H	VH	M	H	M	M	MH	M	M	H	AM	ML	M	AM	H
RPM16	M	M	M	M	M	M	M	VH	H	H	VH	VH	H	H	H	M	M	H	M	H
RPM17	MH	MH	MH	MH	MH	MH	MH	ML	ML	ML	M	MH	AM	AM	MH	MH	MH	AM	M	MH
RPM18	AM	AM	AM	AM	AM	AM	AM	ML	MH	M	ML	MH	M	M	H	H	H	H	M	M
RPM19	MH	MH	MH	H	MH	H	H	VH	AM	M	AM	VH	M	AM	M	M	M	M	H	AM
RPM20	H	H	H	H	MH	H	MH	L	M	AM	ML	H	ML	M	M	AM	AM	AM	AM	MH
RPM21	H	H	H	H	H	H	H	ML	ML	ML	ML	M	M	M	MH	AM	AM	MH	MH	MH
RPM22	M	M	M	M	M	L	L	H	M	M	M	H	L	M	M	L	L	M	M	L
RPM23	AM	AM	AM	AM	AM	M	AM	L	AM	M	AM	AM	AM	L	AM	L	VL	M	M	M

Short code	Reconfiguration practices						Soft computing practices						
	RCP1	RCP2	RCP3	RCP4	RCP5	RCP6	SCP1	SCP2	SCP3	SCP4	SCP5	SCP6	SCP7
RPM1	VH	VH	VH	VH	VH	H	VH	VH	H	H	H	H	H
RPM2	VH	VH	VH	H	H	H	H	H	MH	AM	H	AM	AM
RPM3	VH	H	H	H	H	AM	MH	MH	MH	AM	AM	AM	MH
RPM4	M	M	L	M	M	L	M	L	M	L	M	L	L
RPM5	AM	AM	AM	AM	M	M	AM	AM	AM	M	AM	AM	AM
RPM6	VH	VH	VH	H	VH	H	H	VH	H	VH	VH	VH	VH
RPM7	L	M	L	L	M	L	L	M	L	L	L	L	M
RPM8	H	H	H	H	H	H	MH	MH	MH	MH	MH	MH	MH
RPM9	MH	MH	MH	MH	MH	MH	MH	MH	MH	MH	M	MH	M

Table 9 (continued)

Short code	Reconfiguration practices						Soft computing practices						
	RCP1	RCP2	RCP3	RCP4	RCP5	RCP6	SCP1	SCP2	SCP3	SCP4	SCP5	SCP6	SCP7
RPM10	MH	AM	MH	M	AM	AM	AM	AM	AM	ML	M	M	AM
RPM11	MH	MH	H	MH	MH	AM	H	H	H	H	H	H	H
RPM12	M	M	M	M	M	M	AM	AM	M	M	M	M	M
RPM13	H	H	H	MH	MH	MH	MH	MH	M	M	M	M	M
RPM14	AM	M	AM	M	AM	ML	AM	M	M	M	AM	M	M
RPM15	H	H	H	AM	M	H	H	H	H	MH	MH	MH	MH
RPM16	AM	AM	AM	AM	AM	AM	AM	AM	AM	AM	M	M	AM
RPM17	AM	AM	AM	AM	AM	MH	AM	AM	AM	MH	AM	M	AM
RPM18	M	M	M	M	M	M	AM	AM	AM	M	AM	M	M
RPM19	AM	AM	AM	AM	AM	M	M	AM	AM	AM	AM	AM	AM
RPM20	MH	MH	AM	MH	AM	MH	H	H	H	MH	H	MH	MH
RPM21	H	H	H	H	H	MH	H	H	H	AM	H	M	M
RPM22	M	M	AM	L	AM	M	AM	M	AM	AM	M	M	M
RPM23	L	L	M	L	M	M	VL	VL	VL	L	L	L	L

that were useful during COVID-19 and presented a vision of next-generation manufacturing machines that supported the current findings. Morgan et al. (2021) examined several smart technologies and smart machines that can be useful during a pandemic. Such technologies give the manufacturing system flexibility while also reducing lead time and manufacturing costs. The reconfiguration practices came in second, emphasizing the importance of reconfigurability and the technologies required for it. A similar discussion was observed in the article Prasad and Jayswal (2018), where the researchers stated that RMS is capable of adjusting its capacity and functionality as it can be upgraded to current technology. This can help manufacturing systems quickly transition to a new product in response to market demands. Also. Soft computing practices such as AI, IOT, cloud computing, BDA, etc. are extremely useful in such situations; thus, SCP was ranked third. During his literature review, Morgan et al. (2021) discussed the same and summarized the importance of such technologies in RMS and pandemic situations. The SCE and QPS ranked fourth and fifth, indicating that these practices are equally important for remaining competitive in the market.

According to global weights, rapid reconfiguration has obtained the maximum weight, implying that RMS reconfigurability is critical during pandemic to meet changing customer needs. Several researchers, including Morgan et al. (2021), had emphasized RMS's capability. According to Prasad and Jayswal (2018), the reconfigurability of the manufacturing system is assessed in terms of cost, time, and effort for product changeover, all of which are significant factors during a pandemic. The CPS and RMT have occupied the second and third positions in terms of global weight, highlighting the importance of technologies for RPO. According to Morgan et al. (2021), several technologies such as CPS and RMT that enable RMS to be capable of smart manufacturing are extremely useful during pandemic situations because they can help to increase reconfigurability and flexibility. Practices such as additive manufacturing also assist in product development; thus, during pandemic situations where demand is constantly changing, the practice is extremely beneficial for RPO. As Dantas et al. (2021) discussed, technologies such as CPS and additive manufacturing can help during product optimization and thus reduce product cost to help RPO. RMS practises such as configuration design and the ability to provide customized products were ranked fifth and sixth, respectively. These practices can help meet volatile customer demands in a pandemic situation while keeping manufacturing costs to a minimum. Among the QPS, the RMS feature, i.e. the emphasis on product quality, was the most important and ranks seventh. Because the RMS focuses on product flexibility and quality (Bortolini et al. 2018), the expert panel may gave it the most weight.

Table 10 Ranking obtained using Pythagorean fuzzy CoCoSo method

Code	Performance Metrics	K_{ia}	K_{ib}	K_{ic}	K_i	Rank obtained
RPM1	Reconfiguration time (RPM1)	0.0449	6.1364	1.0000	3.0447	1
RPM2	Manufacturing cost (RPM2)	0.0446	5.6199	0.9929	2.8483	3
RPM3	Lead time (RPM3)	0.0445	5.5857	0.9892	2.8327	4
RPM4	Employee retention (RPM4)	0.0422	3.1040	0.9381	1.8584	21
RPM5	Number of defectives per day (RPM5)	0.0439	4.5503	0.9779	2.4378	14
RPM6	Reconfiguration cost (RPM6)	0.0445	5.6710	0.9892	2.8643	2
RPM7	Throughput material (RPM7)	0.0397	2.0738	0.8835	1.4165	23
RPM8	Number of warranty/guarantee claims per year (RPM8)	0.0445	5.5470	0.9904	2.8193	6
RPM9	Machine utilisation (RPM9)	0.0444	5.2418	0.9878	2.7039	8
RPM10	Total manpower requirement (RPM10)	0.0436	4.0553	0.9696	2.2449	17
RPM11	Number of soft computing technologies available (RPM11)	0.0443	5.1062	0.9863	2.6522	9
RPM12	Number of breakdowns per fortnight (RPM12)	0.0432	3.6334	0.9615	2.0785	19
RPM13	Cycle time (RPM13)	0.0441	5.0391	0.9814	2.6235	10
RPM14	Overall energy consumption (RPM14)	0.0433	3.8016	0.9634	2.1440	18
RPM15	Number of advanced machines available (RPM15)	0.0445	5.5776	0.9913	2.8313	5
RPM16	Number of training sessions conducted (RPM16)	0.0441	4.8238	0.9810	2.5427	11
RPM17	Number of customized products (RPM17)	0.0439	4.4843	0.9758	2.4115	15
RPM18	Ratings received for online customer feedback (RPM18)	0.0436	4.0843	0.9694	2.2557	16
RPM19	Number of accidents per month (RPM19)	0.0440	4.6731	0.9793	2.4850	13
RPM20	Financial performance (profit percentage) (RPM20)	0.0440	4.8021	0.9793	2.5333	12
RPM21	Number of RMT available (RPM21)	0.0443	5.3003	0.9863	2.7245	7
RPM22	Employee availability (RPM22)	0.0427	3.3704	0.9501	1.9696	20
RPM23	Scrap rate (RPM23)	0.0372	2.7420	0.8272	1.6406	22

The selected performance metrics were then ranked using the Pythagorean fuzzy CoCoSo method, with the descending order being RPM1 > RPM6 > RPM2 > RPM3 > RPM15 > RPM8 > RPM21 > RPM9 > RPM11 > RPM13 > RPM16 > RPM20 > RPM19 > RPM5 > RPM17 > RPM18 > RPM10 > RPM14 > RPM12 > RPM22 > RPM4 > RPM23 > RPM7. The reconfiguration time was on the first position, indicating the time required to switch to another product during RPO. According to Puik et al. (2017), reconfiguration time is an important factor in determining product lead time, whereas Garbie (2014a, b) stated that when evaluating RMS, reconfiguration is an extremely important issue. During RPO, it is critical that the required products reach the customers in a timely manner, which supports the obtained results. Because lockdown has significantly reduced consumer purchasing power, manufacturing costs and thus reconfiguration costs must be kept to a minimum. Similar discussions were observed in Xia et al. (2017), where the researchers attempted to reduce manufacturing costs by reducing reconfiguration cost; thus, reconfiguration cost was ranked second and manufacturing cost was ranked third. During the Covid-19 pandemic, lockdown had a significant impact on people's financial situation. As a result, manufacturers are struggling to produce products at the lowest possible cost and with the shortest possible lead time (López-Gómez et al. 2020). The lead time was ranked fourth, while the availability of advanced machines was ranked fifth. According to Morgan et al. (2021), advanced machines, particularly those with control capabilities, are extremely beneficial to reconfiguration tasks, which support the obtained results. Furthermore, as discussed by Morgan et al. (2021), RMS focuses on product quality; thus, warranty claims have occupied the sixth position in the ranking. During their study, the researchers also emphasised the importance of RMT, which supports the seventh position for the number of RMT available. The set of performance metrics and their ranking can help practitioners evaluate manufacturing systems and make decisions.

5.2 Theoretical implications

The work presented here contributes to the theory of Industry 4.0 and RMS in three parts. First, it broadens the application of the novel Pythagorean fuzzy AHP-CoCoSo method and may assist future researchers in using it in their research. During this process, a critical review of articles on Industry 4.0, RMS, and repurposing was conducted in order to identify the prominent practices that can assist RPO. This contributes to the theoretical enrichment of the manufacturing

Table 11 Details of experiments to conduct sensitivity analysis

| Code	K_l	Exp.1	Exp.2	Exp.3	Exp.4	Exp.5	Exp.6	Exp.7	Exp.8	Exp.9	Exp.10	Exp.11	Exp.12	Exp.13	Exp.14	Exp.15	Exp.16	Exp.17	Exp.18	Exp.19	Exp.20	Exp.21	Exp.22	Exp.23
RPM1	5.5215	6.184	5.628	5.402	4.916	6.051	5.506	5.286	4.810	5.920	5.387	5.172	4.706	5.793	5.271	6.488	5.904	5.668	5.157	6.348	5.776	5.545	5.046	6.211
RPM2	5.1497	5.768	5.249	5.039	4.585	5.643	5.135	4.930	4.486	5.522	5.025	4.824	4.389	5.402	4.916	6.051	5.506	5.286	4.810	5.920	5.387	5.172	4.706	5.793
RPM3	5.1120	5.725	5.210	5.002	4.552	5.602	5.098	4.894	4.453	5.481	4.988	4.788	4.357	5.363	4.880	6.006	5.466	5.247	4.775	5.877	5.348	5.134	4.672	5.750
RPM4	2.3448	2.626	2.390	2.294	2.088	2.570	2.338	2.245	2.043	2.514	2.288	2.196	1.999	2.460	2.239	2.755	2.507	2.407	2.190	2.696	2.453	2.355	2.143	2.638
RPM5	4.2012	4.705	4.282	4.111	3.741	4.604	4.190	4.022	3.660	4.505	4.099	3.935	3.581	4.407	4.011	4.936	4.492	4.312	3.924	4.830	4.395	4.219	3.840	4.726
RPM6	5.1689	5.789	5.268	5.057	4.602	5.664	5.155	4.948	4.503	5.542	5.043	4.842	4.406	5.423	4.935	6.073	5.527	5.306	4.828	5.942	5.408	5.191	4.724	5.814
RPM7	0.9682	1.084	0.987	0.947	0.862	1.061	0.966	0.927	0.843	1.038	0.945	0.907	0.825	1.016	0.924	1.138	1.035	0.994	0.904	1.113	1.013	0.972	0.885	1.089
RPM8	5.0577	5.665	5.155	4.949	4.503	5.542	5.044	4.842	4.406	5.423	4.935	4.737	4.311	5.306	4.828	5.943	5.408	5.192	4.724	5.815	5.291	5.080	4.622	5.689
RPM9	4.8265	5.406	4.919	4.722	4.297	5.289	4.813	4.621	4.205	5.175	4.709	4.521	4.114	5.063	4.608	5.671	5.161	4.954	4.508	5.549	5.049	4.847	4.411	5.429
RPM10	3.8881	4.355	3.963	3.804	3.462	4.261	3.877	3.722	3.387	4.169	3.794	3.642	3.314	4.079	3.712	4.568	4.157	3.991	3.632	4.470	4.068	3.905	3.553	4.373
RPM11	4.6724	5.233	4.762	4.572	4.160	5.120	4.659	4.473	4.070	5.010	4.559	4.377	3.983	4.902	4.461	5.490	4.996	4.796	4.364	5.372	4.888	4.693	4.270	5.256
RPM12	3.4027	3.811	3.468	3.329	3.030	3.729	3.393	3.257	2.964	3.648	3.320	3.187	2.900	3.570	3.248	3.998	3.638	3.493	3.178	3.912	3.560	3.417	3.110	3.827
RPM13	4.6108	5.164	4.699	4.511	4.105	5.053	4.598	4.414	4.017	4.944	4.499	4.319	3.930	4.837	4.402	5.418	4.930	4.733	4.307	5.301	4.824	4.631	4.214	5.186
RPM14	3.6434	4.081	3.713	3.565	3.244	3.993	3.633	3.488	3.174	3.906	3.555	3.413	3.106	3.822	3.478	4.281	3.896	3.740	3.403	4.189	3.812	3.659	3.330	4.098
RPM15	5.0389	5.644	5.136	4.930	4.486	5.522	5.025	4.824	4.390	5.403	4.916	4.720	4.295	5.286	4.810	5.921	5.388	5.172	4.707	5.793	5.271	5.061	4.605	5.668
RPM16	4.3089	4.826	4.392	4.216	3.837	4.722	4.297	4.125	3.754	4.620	4.204	4.036	3.673	4.520	4.114	5.063	4.607	4.423	4.025	4.954	4.508	4.328	3.938	4.847
RPM17	4.2165	4.722	4.297	4.126	3.754	4.621	4.205	4.037	3.673	4.521	4.114	3.950	3.594	4.423	4.025	4.954	4.508	4.328	3.939	4.847	4.411	4.235	3.854	4.743
RPM18	3.8071	4.264	3.880	3.725	3.390	4.172	3.797	3.645	3.317	4.082	3.715	3.566	3.245	3.994	3.635	4.473	4.071	3.908	3.556	4.377	3.983	3.824	3.479	4.282
RPM19	4.3593	4.882	4.443	4.265	3.881	4.777	4.347	4.173	3.798	4.674	4.253	4.083	3.716	4.573	4.162	5.122	4.661	4.475	4.072	5.012	4.561	4.378	3.984	4.903
RPM20	4.4275	4.959	4.513	4.332	3.942	4.852	4.415	4.239	3.857	4.747	4.320	4.147	3.774	4.645	4.227	5.202	4.734	4.545	4.136	5.090	4.632	4.447	4.046	4.980
RPM21	4.9033	5.492	4.997	4.798	4.366	5.373	4.890	4.694	4.272	5.257	4.784	4.593	4.180	5.144	4.681	5.761	5.243	5.033	4.580	5.637	5.130	4.925	4.481	5.515
RPM22	2.8347	3.175	2.889	2.774	2.524	3.106	2.827	2.714	2.470	3.039	2.766	2.655	2.416	2.974	2.706	3.331	3.031	2.910	2.648	3.259	2.966	2.847	2.591	3.189
RPM23	2.0996	2.352	2.140	2.054	1.869	2.301	2.094	2.010	1.829	2.251	2.049	1.967	1.790	2.203	2.004	2.467	2.245	2.155	1.961	2.414	2.197	2.109	1.919	2.362
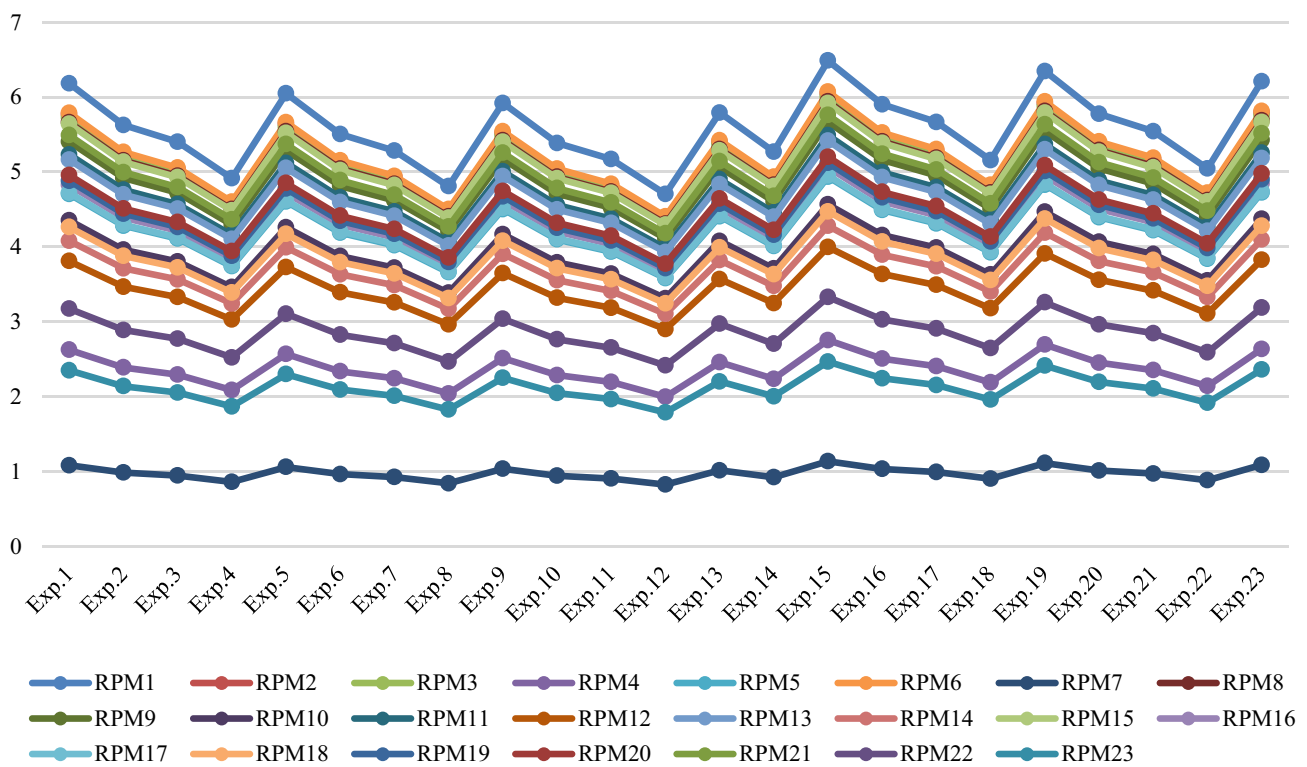
Fig. 3 Sensitivity analysis of K_i values

domain by demonstrating the useful framework development process by identifying practices and applied methods. The presented work's findings, as well as the relative importance of the practices and performance metrics, highlight the need for additional research in this domain to increase the adoption of selected practices. Researchers can use this as their future agenda and develop a detailed plan for implementing these practices in industries.

Second, as seen in a few articles, the presented research establishes a link between Industry 4.0 and RMS to assist RPO (Morgan et al. 2021). This demonstrates RMS's ability to adopt advanced Industry 4.0 technologies and provide manufacturing flexibility with the help of these technologies. As product complexity increases and customer demands become more customized, the developed framework and this connection can assist in satisfying such demands. This creates a strategy for dealing with the dynamic market demand situation as well as RPO due to a pandemic situation. This approach can be used to deal with future challenges, such as the ones we are currently facing due to COVID-19.

The importance of advanced technologies in manufacturing, as highlighted by the major criteria weights, was the third contribution. The study contributes to the proposition that important performance metrics such as lead time, flexibility, capacity, etc. are determinants of advanced technologies used in the manufacturing system. Furthermore, the

set of identified performance metrics and their prioritization provides a roadmap for evaluating the manufacturing system and assessing the efficacy of the identified practices.

5.3 Managerial implications

The presented work have managerial implications too that can improve the adoption of RMS in industries and also assist during RPO. The proposed framework can assist managers in decision-making during the pandemic situation and for RPO that can benefit society during critical situations of a pandemic. The managers may refer to the framework, selected practices, and ranking so that decisions for step-by-step RPO can be taken effectively and efficiently. The proposed framework may also assist managers to evaluate the performance of the organization which can become the basis for future improvements. This can lead to social and economic benefits for an organization. The framework can assist managers to take care of several aspects simultaneously as listed in major criteria practices. The proposed framework may motivate managers to improve the infrastructure, technologies, and work culture in an organization. This may lead to the overall growth of the organization, improved customer satisfaction, and social contributions for fighting the pandemic situations by reducing the gap between demand and supply. The framework guides and motivates the managers

to switch over the products that are in large demand in a pandemic situation and also the products that require dealing with pandemic situations.

5.4 Implications for researchers and practitioners

The presented research has a significant contribution for researchers and practitioners of the RMS and Industry 4.0 domain. During the presented work, the key Industry 4.0-RMS practices were identified that can assist during RPO during the Covid-19 pandemic. This can also help to increase the adoption of RMS in the industries. The framework developed for RPO was rarely observed in the past literature; hence, it can assist the practitioners during decision making, implementing the selected practices, evaluating the performance of the organization, etc. The prioritized performance metrics may assist practitioners to decide a suitable action plan at the initial stage of RPO that can reduce the risk of failure. This may also assist during the successful adoption of RMS in the industry. It is slightly challenging to incorporate all the practices in any manufacturing system; however, the weights computed in the presented work may assist to decide the priority of their implementation during RPO. In practice, this means that among the SFA practices first preference must be given to the cyber-physical system and additive manufacturing as compared to real-time information systems. This may result in the efficient adoption of RMS during RPO. The RMS adoption is at the initial stage in developing countries like India. Also, most of the manufacturing countries around the globe are struggling for RPO during a pandemic situation. The researchers and practitioners may use the developed framework as a ready reference to increase their organizational performance. The identified and ranked performance metrics can also assist them during the evaluation of performance. The proposed framework can also assist to reduce the difficulties during the adoption of RMS in the Covid-19 pandemic as the framework provides a structured approach of the same. This may also assist in step-by-step improvement in the performance of the organization by incorporating the practices in ranked order. The developed framework may also lead to social, economic, and sustainability including environmental benefits as several aspects related to it have been taken care of while selecting the practices. It may also assist to frame the long-term strategy of the organization during a pandemic situation and may lead to high returns for the society. The proposed framework can assist in maintaining the supply chain during a pandemic situation as the organizations in several geographical locations think of RPO and bridge the gap between demand and supply of that area. This may also assist to boost the missions of countries like 'Make in India', 'clean India', etc.

6 Conclusion and future scope

The research presented here has provided a novel framework for RPO in which advanced Industry 4.0 technologies and RMS practices can greatly assist in dealing with pandemic challenges. To find answers to the proposed research questions, 33 Industry 4.0-RMS practices and 23 performance metrics were identified. Following that, the weights of selected practices were computed using the Pythagorean fuzzy AHP method, and performance metrics were prioritized using the CoCoSo technique. It was also ensured that the selected practices would be beneficial to RPO, and the performance metrics would reflect the effectiveness of the practices selected. When selecting practices and performance metrics, manufacturing companies' challenges are taken into account.

The efforts had resulted in the development of a framework that can assist in RPO in the post pandemic situation. The obtained results show that in the manufacturing industries, the adoption of advanced technologies such as SFA, which includes CPS, the use of robots, additive manufacturing, etc., is required for RPO. This suggests that advanced technologies and computer algorithms can greatly assist RPO during pandemic situations and that practitioners and decision-makers should focus on them for effective repurposing. Furthermore, practices such as RMT adoption and rapid reconfiguration are extremely beneficial for RPO and can help to reduce manufacturing costs. During the prioritization of performance metrics, reconfiguration time was ranked first, indicating the importance of the time required to switch to another product to meet dynamic customer needs in a pandemic situation. The cost of doing so is also important; thus, reconfiguration cost has taken the second place in the ranking. The top rankings of performance metrics show that manufacturing lead time and manufacturing costs are the top priorities for any company in a pandemic situation.

However, the presented research work may have some limitations and can be attempted by future researchers. The framework was prepared based on MCDM techniques and expert opinion, but, the expert opinions are always subjective, and biasing may impact the results. Hence, the computations using the hybrid approach have to be attempted with due care. Also, the framework development process and the case organization were restricted to the three organizations in the Indian manufacturing environment. The future research work may be extended to organizations from different geographical locations with required modifications and the results can be compared. More advanced MCDM techniques may also be employed for the same and the results may be compared.

Declarations

Conflict of interest The authors declare no potential conflict of interest. The authors have no competing interests to declare that are relevant to the content of this article.

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