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SURVEY

Manufacturing Systems for Unexpected Events: An Exploratory Review for Operational and Disruption Risks

ALEJANDRO VITAL-SOTO AND JESSICA OLIVARES-AGUILA
Shannon School of Business, Cape Breton University, Sydney, NS B1M 1A2, Canada
Corresponding author: Alejandro Vital-Soto (alejandro_vital@cbu.ca)

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ABSTRACT Manufacturing systems are the core of manufacturing industries that have evolved to adapt to the ever-changing landscape. Nowadays, manufacturing systems are more frequently exposed to disturbances and risks that affect their everyday operations. Hence, it is imperative to analyze and design proactive and reactive strategies to respond to those disruptive events. While there has been an increasing interest in tackling risks from the supply chain perspective, an analysis of risks from the manufacturing system view has been neglected. Risks are broadly classified into operational risks and disruption risks. This study presents a literature review of different manufacturing paradigms and what operational risk considerations have been discussed for each stage of the manufacturing life cycle. The review further analyzes how manufacturing systems are trying to handle disruption risks. Additionally, the article maps the different manufacturing systems and the strategies implemented to the different adaptability facets. Finally, the paper discusses managerial insights and possible research avenues.

INDEX TERMS Disruption risks, flexible manufacturing systems, manufacturing systems paradigms, operational risks, reconfigurable manufacturing systems, smart manufacturing systems.

I. INTRODUCTION

Manufacturing systems (MSs) (or production systems) are comprehensive systems that involve equipment, people, and procedures organized to accomplish the manufacturing operations of an organization [1]. The different manufacturing system paradigms have evolved, influenced by new production, machines, information, materials, and product technologies, as well as the evolution of organizational strategies [2]. Therefore, the manufacturing landscape has evolved to become leaner, more flexible, and smarter, impacting factory design, operation, and control [3].

The COVID-19 pandemic has changed the manufacturing panorama. On one side, industries have been exacerbated by the increased demand and the nervousness created in the supply chains (SCs). On the other hand, industries have halted their production to adjust to the new needs [4]. Therefore, several initiatives have been proposed worldwide to tackle the arising risk factors.

The manufacturing organizations and systems are exposed to different risks or disruptive events that interrupt production operations and conditions. Although the production system is the core section of the industry, including the entire product value chain from product design to services [5], the analysis of risks in the MSs context is scattered. While there is a growing body of literature on supply chain resilience [6], manufacturing systems' capabilities and ability to handle different risks require further study.

Table 1 provides a sample of previous review papers focused on MSs. From the table, the scope of prior reviews is limited to a specific manufacturing paradigm for a particular topic or aspects of the evolution of MSs (e.g., characteristics, drivers, enablers, use cases, future perspectives, etc.). However, there has been limited concentration on risks and disruptions and how different manufacturing paradigms can handle them. Further research in this area is needed. Hence,

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this research presents a literature review on the state of the art of manufacturing paradigms (i.e., flexible manufacturing systems, reconfigurable manufacturing systems, and smart manufacturing systems) and how they plan, react, and cope with different risks. Therefore, the following research questions were defined:

TABLE 1. Sample of recent reviews on manufacturing systems.

Author	Scope
Leng *et al.* [7]	Digital twins for SMS
Mullet *et al.* [8]	Cybersecurity for SMS
ElMaraghy *et al.* [2]	Evolution and future of manufacturing systems
Yelles-Chaouche *et al.* [9]	Optimization perspectives for RMS
Lu *et al.* [10]	SM process and system automation
Menghi *et al.* [11]	Energy efficiency of manufacturing systems
Bortolini *et al.* [12]	RMS applications, methodologies, and tools
Yadav and Jayswal [13]	Modeling of FMS
Esmaeilian *et al.* [14]	Evolution and future of manufacturing

RQ1. What type of operational or disruption risks could each manufacturing paradigm handle?

RQ2. What mitigation strategies does each manufacturing paradigm implement when facing risks?

RQ3. What characteristics allow MSs to deal with operational and/or disruption risks?

RQ4. How can the different manufacturing paradigms be mapped to the adaptability facets?

The main contributions of this study are: (1) to present a literature review covering from 2000 to 2021 to assess manufacturing paradigms and their capabilities to deal with various risks, (2) to map manufacturing systems characteristics to different adaptability facets, and (3) to discuss managerial insights and future research directions.

The remainder of this paper is organized as follows. Section II provides several definitions significant to the article. Section III discusses the research methodology implemented. Section IV to VII classifies the state-of-the-art related operational risk considerations in each MS's lifecycle stage. Section VIII reviews the literature on MSs dealing with disruption risks. Section IX discusses the findings and the answers to the research questions. The paper concludes by summarizing and outlining future research opportunities in section X.

II. RESEARCH BACKGROUND

A. MANUFACTURING PARADIGMS

Several manufacturing paradigms have been proposed throughout history, influenced by product changes, production technology, processes, production volume, varying degrees of automation, intelligence, and adaptation [2]. Moreover, through industrial revolutions, prominent manufacturing paradigm systems have been introduced. The first industrial revolution was characterized by mechanization. During the second industrial revolution, the mass production strategy was enabled by dedicated manufacturing systems to achieve economies of scale. The third industrial revolution featured computers and automation, allowing flexible and reconfigurable manufacturing systems to be designed. In recent years, the fourth industrial revolution has been developing based on integrating information and communication technologies, such as cyber-physical systems and cloud computing, to enable smart manufacturing systems [15].

Flexible manufacturing systems (FMSs) consist of automated numerically controlled workstations connected through handling systems under computer control for automatic processing. The main advantage of FMSs is their flexibility in managing resources to manufacture a large variety of parts of a single family, also known as generalized flexibility. However, FMSs often contain excessive capability, resulting in unnecessary costs [16]. Flexibility could include several categories, such as machine, production, product, routing, volume, and expansion flexibility. The FMS's key characteristics are:

- Adaptability that allows changes and adaptation of processes and production volumes within the pre-defined limits without physically modifying the MS.
- Responsiveness to changes in products, production technology, and markets.
- Agility to launch new products for new markets and react to change, which is achieved with the help of computer-integrated control and operation of system modules and production schedules.

Reconfigurable manufacturing systems (RMSs) were introduced in the mid-1990s as a cost-effective reaction to market demands for responsiveness and customization by allowing a rapid change in structure (hardware and software components) to quickly adjust production capacity and functionality within a part family [9]. They can be improved, upgraded, reconfigured, and extended rather than replaced. RMSs have six distinguished characteristics [2], [10], which include:

- Modularity of physical and logical modules
- Scalability to modify the production capacity by adding or removing resources
- Convertibility to quickly transform the system's functionality
- Diagnosability to identify the sources of quality and reliability problems requiring repair or maintenance
- Customization to allow flexibility around a product family
- Integrability of system modules through standardized hardware and software

Smart manufacturing systems (SMSs) are fully integrated, collaborative MSs that respond in real-time to meet changing demands and conditions in the factory, supply network, and customer needs. It includes the manufacturing equipment and the cyber layers linked by the interface.

The manufacturing equipment has its own intelligence, while the cyber layer provides system-wide intelligence [17]. This concept shares many characteristics with the Cyber-Physical Production Systems (CPPS) and Industry 4.0 (I4). Therefore, they are used interchangeably in the literature [2]. SMSs employ the concepts of CPPS, the Internet of Things (IoT) (and everything), cloud computing, service-oriented computing, artificial intelligence (AI), and data science [17]. The key features of SMSs are:

- Data connectivity and transparency to establish connections and gather information, among other systems
- Virtualization to represent the physical systems
- Predictability, which analyzes the gathered data and executes data-driven decisions
- Sustainability for products and processes development
- Interoperability for resource sharing and networking

B. OPERATIONAL VS DISRUPTION RISKS

Risks in the manufacturing environment and the SCs can be classified into two broad categories: operational and disruptive risks [18], [19]. Operational risks are recurrent and are related to inherent uncertainties that arise from the coordination of demand and supply. Common operational disruptions are machine breakdowns, transportation delays, forecast errors, demand fluctuations, and those that can be identified using historical data to quantify the level of risk [20]. On the other hand, the externally rising events considered major disruptions would last longer, and their impacts could be propagated to different SC echelons [21]. Disruptive risks arise from significant disruptions caused by natural and man-made disasters.

III. RESEARCH METHODOLOGY

A systematic review was performed using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines proposed by Moher et al. [22]. The literature search covered 2000 to 2021 using the SCOPUS database. The initial investigation was conducted on January 21, 2022.

The search was performed in two stages. The first stage corresponds to the general analysis of MSs and risk integration. Therefore, the bibliographic search on the articles' title, abstract, and keywords was carried out using the following search terms: ("manufacturing system" OR "production system") AND ("disruption" OR "risk). This search was intended to gather relevant works discussing different risks and their implications for general manufacturing systems (GMSs).

The second stage of the search corresponds to specific manufacturing paradigms: FMSs, RMSs, and SMSs. These three paradigms were chosen as they are the flagship systems of the third and fourth industrial revolutions. Therefore, the article's title, abstract, and keywords were searched using the following terms ("flexible manufacturing system" OR "reconfigurable manufacturing system" OR "smart manufacturing") AND ("disruption" OR "risk"). It is important to note that this study does not pretend to document all the available literature but instead analyzes the most representative studies.

A. ELIGIBILITY CRITERIA AND ARTICLES SELECTION

The articles included in this study are articles published in a journal, original contributions, full-text available, and written in English. After implementing the search strategy mentioned in the section before, a total of 218 articles were identified. Moreover, other sources identified additional records to add 71 extra papers. After removing duplicates, a total of 247 articles were screened.

Review articles and articles that did not explicitly tackle risks or disruptions were excluded. Additionally, articles focusing on SCs, inventory strategies (e.g., [23] [24]), energy systems, and agricultural systems were removed. A total of 96 articles were included in this review. Fig. 1 summarizes the selection process and states the reasons for the exclusion.

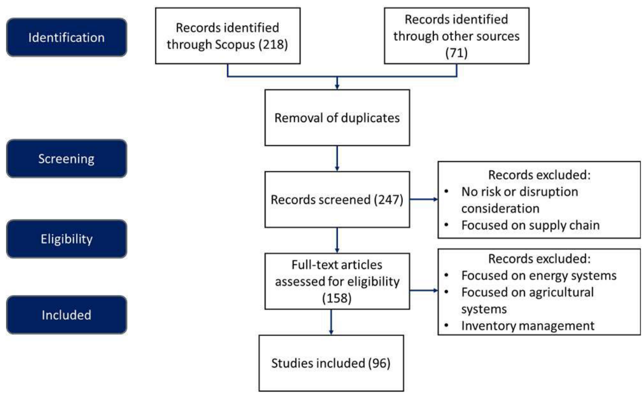

FIGURE 1. Literature selection.

B. DATA ANALYSIS

The articles were classified using two main categories: those covering operational risks and those discussing disruptive risks. The papers were further categorized for operational risks according to the manufacturing system life cycle stages in which the risk is considered.

The manufacturing systems life cycle includes the initial system design and synthesis, modeling, analysis and simulation, realization and implementation, operation, and redesign/reconfiguration phases [25]. The resource life cycle was classified by .von Euler-Chelpin [26] into the design, production planning, production, use, and disposal stages. Therefore, the following four stages for the manufacturing system life cycle are used to classify the literature: design, development/implementation phase, operation phase, and dismantle and/or redesign. Not all the paradigms have considered risks in all the lifecycle stages (i.e., disposal), as presented in Fig. 2. Therefore, sections for each lifecycle and paradigm will be introduced if there is available literature. Otherwise, they will be omitted.

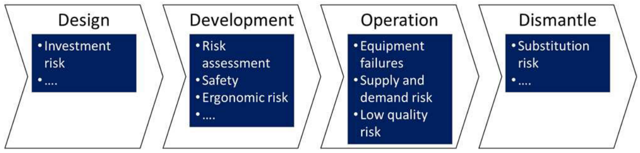

FIGURE 2. **Studied manufacturing lifecycle stages and operational risks.**

IV. OPERATIONAL RISKS IN THE DESIGN STAGE OF MANUFACTURING SYSTEMS

The manufacturing environment has evolved to adapt to market conditions and customer demands. Hence, the design of MSs is a challenging activity. The design stage starts with a stakeholder analysis to identify the design's constraints and degrees of freedom [27].

A. FMSS CONSIDERING RISK IN THE DESIGN STAGE

In the initial FMS conceptual design, evaluating the flexibility required and the investment feasibility is critical. Considering investment risks, Karsak [28] introduced a distance-based fuzzy multicriteria decision-making method based on the concepts of ideal and anti-ideal solutions for selecting an FMS alternative. This framework combined economic and strategic performance variables represented with linguistic variables, fuzzy triangular numbers, and crisp numbers in the evaluation process.

B. RMSS CONSIDERING RISK IN THE DESIGN STAGE

To consider the possible investment risk and demand uncertainties, Andersen et al. [29] established a decision-support tool for assessing the investment feasibility of changeable and reconfigurable manufacturing design concepts based on future demand predictions and their uncertainties. The tool analyzed the discounted value of capital and operating costs of the design concepts and the changeability extent. Sanderson et al. [30] proposed a Function-Behaviour-Structure methodology for Evolvable Assembly Systems to allow the self-adaptiveness of operational parameters and reconfiguration behavior. The method encompasses an ontology model and design process, which can be beneficial in addressing challenging environments such as I4.

C. SMSS CONSIDERING RISK IN THE DESIGN STAGE

One of the main features of SMSs is the usage of information technologies (IT) to streamline the manufacturing process more efficiently. However, IT systems are vulnerable to different threats. Therefore, Häckel et al. [31] developed a risk assessment model that helps companies in the investment decision-making process regarding IT security measures by identifying and assessing the most critical areas of the information network. They implemented graph theory, matrix notation, and value-at-risk to quantify IT availability risks.

V. OPERATIONAL RISKS IN THE DEVELOPMENT STAGE OF MANUFACTURING SYSTEMS

During the process development phase, the rough solutions from the design phase are refined to a level that allows investigation with analysis tools. This phase refers to the system definition, where one solution is refined to a detail that will enable starting system implementation. This stage is characterized by system integration, where previously defined subsystems are composed into a complete system [32], [33].

A. GMSS CONSIDERING RISK IN THE DEVELOPMENT STAGE

Different authors have considered the design of risk assessment frameworks and methods to evaluate and overcome various risk factors. For instance, Lazov [34] introduced a risk-based analysis of a single workstation facility using system information and entropy. The system information represents a loss function; the system entropy (uncertainty associated with the system) means the risk function. They determined the system parameters to control the system risk in a unified way. On a narrower view, risk assessment of tool failure has also been considered. For instance, Khalaj et al. [35] employed the Dempster-Shafer method and risk assessment diagram to calculate tool failure risk when the correct data is lacking or incomplete. Their method defines an interval for the consequence impact and determines the likelihood of failure relative to risk and reliability. Similarly, He et al. [36] proposed the functional risk concept of a MS, which includes explicit (product dimension variations caused by geometric machine errors) and implicit (infant product failure during the usage phase) risks. Additionally, they introduced a method for fault detection of high-quality manufacturing processes.

1) SAFETY RISK

The development stage allows the identification of possible risks and failure modes that could arise during the operation stage. For instance, Silvestri et al. [37] incorporated the failure, mode, effects, and criticality analysis with economic variables to consider the risk and minimize the total safety costs. They defined a total risk priority number index. The index is established using the improved risk priority number in combination with the analytic network process.

2) ERGONOMIC RISK

Automation for MSs has achieved a high production rate. However, system flexibility is often provided by human dexterity and the cognitive capabilities of the workforce. Therefore, workers are exposed to ergonomic risk due to repetitive manual tasks. To find the optimal job rotation schedules in assembly lines, Mossa et al. [38] introduced a mixed-integer programming model that maximizes the production rate, minimizes the ergonomic risk, and balances human workloads. Similarly, Moatari-Kazerouni et al. [39] developed an occupational health and safety risk estimation tool for MSs by integrating occupational health and safety (OHS) matters into facility design models.

B. FMSS CONSIDERING RISK IN THE DEVELOPMENT STAGE

Researchers have also tried to identify possible risks in the development of FMSs. Therefore, risk assessment methods have been proposed in the literature. For instance, Zhang et al. [40] suggested the combination of Fault Tree Analysis and Fault Mode and Effect Analysis (FMEA) to establish functional fault modes by criticality analysis. They used the TOPSIS method to assess the priority ranking of fault modes/causes.

1) ERGONOMIC RISK

Research has been conducted to prevent human factor-related disruptions and ergonomic risk in FMSs. Arocena et al. [41] investigated the impact of risk prevention practices and organizational factors on occupational injuries, which consist of occupational safety measures (intensity and the orientation of risk prevention), the implementation of quality management tools, the enhancement of workers empowerment, and the use of flexible production technologies. They found that firms with more flexible production technologies are significantly affected by higher accident levels. Likewise, Bautista et al. [42] developed optimization models to solve the assembly line balancing problem by considering temporal, spatial, and ergonomic attributes. They suggested a risk category classification that merges various evaluation methods of risk factors (postural loads, repetitive movements, and manual handling).

C. RMSS CONSIDERING RISK IN THE DEVELOPMENT STAGE

To define the detailed design, Abdi and Labib [43] analyzed RMS key-design attributes such as capacity value, functionality degree, and reconfiguration time and described them with fuzzy sets to consider the uncertain demands of product families. They proposed an integrated structure of the analytical hierarchical process (AHP) and fuzzy set theory, providing insights into a RMS design feasibility by contemplating technical and economic aspects.

1) RESOURCE FAILURE

To determine the probability of human errors in RMSs, Elmaraghy et al. [44] developed a model centered on task characteristics, work environment, and workers' capabilities by applying a multi-attribute utility analysis based on a collaborative negotiation approach. The model is intended to be employed to evaluate the level of acceptable human error.

2) SAFETY RISK

RMSs offer high versatility thanks to critical characteristics (e.g., modularity, integrability, etc.), which allow the systems to "plug and produce." Although RMSs offer significant functional improvement, the issue of safety guarantee during runtime is still an issue. Koo et al. [45] analyzed the requirements for machinery safety demanded by established standards in the European Union. They discussed the challenges of implementing an automated solution for assessing the safety of plug-and-produce systems. Similarly, Berger et al. [46] addressed the safety issue of humans cooperating with RMSs and proposed to design a safety bubble. Hence, they devised a methodology of deployment with offline/online systems to validate the safety of the cooperation of safe robotized units and to detect any intrusion of the operators in the robotized areas.

D. SMSS CONSIDERING RISK IN THE DEVELOPMENT STAGE

Several researchers have carried out risk assessments for the implementation of SMSs. For instance, Helu et al. [47] defined an Implementation Risk Assessment Framework for smart manufacturing (SM) to identify higher risks and weaknesses. The framework classifies manufacturing technology implementation barriers and ranks them using community-developed standards and tools. Sarwar et al. [48] introduced a FMEA, which integrates rough set theory and ELimination and Choice Translating Reality (ELECTRE) II method to consider subjectivity and uncertainty in decision makers' assessments. The rough numbers are considered to recognize the risk priority of technical failures, eliminate them, and evaluate the risks from design, system, and process.

Riddick et al. [49] studied the SM concept for a food production network. They introduced a Smart Manufacturing Platform, a software and services platform designed to decrease the risks of ingredient variability and improve efficiency.

1) SAFETY RISK

OHS in SM is a challenging factor to address. For instance, Dombrowski et al. [50] employed real-time physics simulation using a virtual factory model to understand better the risks involved in human-robot collaboration. Users can interact with components and tools and perform tasks, including collaborative steps. Similarly, Dombrowski et al. [51] studied risk assessment and safety certification for planning human-robot collaboration. They investigated the requirements to avoid direct collision between humans and robots employing power and force limiting and proposed parameters for the simulation of human-robot cooperation. In another study, Mengoni et al. [52] developed a spatial augmented reality system to support manual work in intelligent factories. The system delivers instructions and alerts in case of risks to human safety and ergonomic issues. The system was tested in two factories and is more efficient than an LED monitor-based system.

With the advent of new technologies, OHS needs to be linked with Human-Computer Interaction (HCI) and cybersecurity for functional safety, as it can lead to a potential risk for humans. Therefore, Korfmacher [53] emphasized that standards are an appropriate resource for considering functional safety and cybersecurity. This view is supported by Ehrlich et al. [54]. They examined the alignment of safety and security risk assessment processes and the possibility of automation for MSs in the I4 context. They mentioned that current risk assessments are not adaptive and undermine the I4 flexibility. Therefore, they highlighted the need for a common taxonomy of both domains.

Etz et al. [55] envisioned designing a self-organizing safety system to discover all safety-related devices and automatically produce a proper safety configuration. The configuration is deployed to the system automatically after adaptation and validation, which minimizes engineering efforts and machine downtime.

VI. OPERATIONAL RISKS IN THE OPERATION STAGE OF MANUFACTURING SYSTEMS

The operational phase of the MS refers to the use phase of the resources, which includes production activities such as maintenance and improvements [26].

A. GMSS CONSIDERING RISK IN THE OPERATION STAGE

Different risks could arise during the operation phase, such as material unavailability, resource failures, unavailability of operators, and rush orders. Therefore, researchers have proposed different methods to cope with those disturbances. For instance, Darmoul et al. [56] proposed an immune-based framework to monitor and control MSs that effectively deal with unexpected events. Based on analogies from the biological immune system to face threats (viruses, cancers, etc.), they implemented the prototype using a multiagent approach to show the feasibility of the framework. Likewise, Bayar et al. [57] proposed a biological immunity to guide the design of a knowledge-based approach to handling disruptions and risks (detection, identification of consequences, and reaction to disturbances). They developed and implemented a prototype using ontologies and multi-agent systems to highlight the importance of the approach.

Scheduling and rescheduling approaches have been proposed to react to a possible disturbance in the MS. For instance, Vieira et al. [58] highlighted the importance of rescheduling when facing different operational disruptions and provided a framework to classify the various rescheduling strategies, policies, and methods. Similarly, Tanimizu et al. [59] considered the rescheduling problem when facing disturbances such as manufacturing operations delays and adding new jobs. Therefore, they proposed a reactive scheduling method activated only when unscheduled disruptions occur during manufacturing.

1) LOW-QUALITY RISK

Due to different circumstances, the output from the MS could have low quality. To avoid this risk, Tannock and Saelem [60] studied the cost of poor-quality performance. They defined the concept of disruption cost as a separate category of quality cost. They simulated a manufacturing cell incorporating inspection and rework and quantified the disruption cost. However, validation with empirical data was not performed. Comparably, Zhao et al. [61] analyzed the functional risk using the correlation between product quality decline and machine performance degradation. They proposed a risk-oriented optimization method of integrated maintenance considering the quality loss of work-in-process from the production system. Likewise, quality rework loops and random machine failures were analyzed by Zhu et al. [62]. They developed a mathematical program based on real-time events and data to estimate the machine production rate. They defined the concept of permanent production loss as a system's real-time performance indicator.

2) MACHINE-RELATED DISRUPTIONS

Equipment failure is a common risk faced by MS. Hence, Park and Tran [63] proposed a cognitive agent-based MS in which the shop floor overcomes the disruptions by agent cooperation without upper-level aids (enterprise resource planning or manufacturing execution system). The agents use the ant colony technique for handling equipment failures. They implemented cognitive agent technology in a machining shop at Hyundai Company, demonstrating the autonomous adaptability to internal disturbances. Comparably, swarm-based cognitive agents were developed by Park and Tran [64] to cope autonomously with disturbances on the shop floor.

To assess the effects of resilience on lean practices, Zarrin and Azadeh [65] developed a simulation model and tested scenarios considering resource breakdown. The results revealed that redundancy improves efficiency compared to other resilience engineering principles (velocity, reporting culture, and top management commitment).

MSs downtime can be related to reactive or preventive maintenance. Thus, critical components and a decision-support tool for managing maintenance activities were provided by Erozan [66]. The tool utilizes the duty cycle, the utilization rate of capacity, the safety stock effect, and the redundancy effect. The results were compared with the traditional reliability function, showing that the tool provides a more realistic impact. Similarly, Paprocka [67] simulated predictive-reactive and proactive-reactive maintenance to select a better method of production organization that decreases costs and waste due to equipment failure. In the predictive-reactive approach, a stable schedule is constructed. In comparison, a schedule is developed for the best sequence of idle times between jobs for the proactive-reactive method. Then, robustness measures are analyzed to compute the operational efficiency of the disrupted system.

Sobaszek et al. [68] presented the time-based machine failure prediction algorithm, which analyzes historical data to define the failure rate of the equipment. Likewise, Paprocka et al. [69] studied the maintenance and production task scheduling to enable the production system to be indifferent to disruptions by developing the best predictive schedule.

B. FMSS CONSIDERING RISK IN THE OPERATION STAGE

1) SUPPLY AND DEMAND DISRUPTIONS AND RUSH ORDERS

Flexible resources have been adapted to mitigate demand-supply mismatch risks. This is exemplified by Tomino et al. [70], in which Toyota, Nissan, and Mitsubishi were surveyed regarding integrating changing market demand information into their production plans and collaborative practices. They also studied the evolution from ‘‘operation-specific’’ to a ‘‘value chain-involving’’ flexible customizing system.

Mak and Shen [71] introduced an integer stochastic programming formulation to optimize the process flexibility and the network structure given various resources, production costs, and demand uncertainty. Considering rush orders and machine breakdowns, Zhang and Wong [72] suggested a genetic algorithm to solve the integrated process planning and scheduling in an FMS, which uses operation sequences directly as chromosomes.

2) MACHINE-RELATED DISRUPTIONS

Machine disturbances are frequent occurrences for FMS. Inherent to FMS, deadlocks can occur in the system caused by the competition and indefinite waits for the shared limited resources among parts processed concurrently in the same sets. The three most popular strategies to handle deadlock are detection and recovery, prevention, and avoidance [73]. Chew and Lawley [74] and Chew et al. [75] studied FMSs where deadlocks could occur. They proposed supervisory controllers to allow parts to continue the manufacturing process if they are not required to use the failed resource. Therefore, the system is not entirely shut down.

Several authors have studied the strategies to handle machine breakdowns. Among the most popular solutions is the consideration of scheduling/rescheduling solutions. For instance, Piramuthu et al. [76] introduced an adaptive framework for dynamic MS scheduling with a knowledge base to decide the dispatching rules. Its relative performance is enhanced further when the introduction of tight job due dates and machine breakdowns causes frequent disruptions. Similarly, Yazgan [77] proposed an analytical network process model based on benefit, opportunity, cost, and risk to select FMS dispatching rules using a multiple-criteria decision-making process. They considered risks such as tool and software failure and machine breakdown. In another study, Gaula and Sharma [78] suggested a hybrid framework by implementing qualitative techniques (i.e., FMEA) and quantitative techniques (i.e., Generalized Stochastic Petri Net and simulation experiments) to model and analyze the failure aspects in cells. They proposed a combination of scheduling and maintenance policies to tackle the failures. In the same vein, Alotaibi et al. [79] studied scheduling in dynamic FMSs and introduced an energy and time-aware job-shop using agent-based dynamic bi-objective robustness. They considered dynamic job arrival and machine breakdown and examined how different combinations of decision-making policies affect the system's resilience.

Jimenez et al. [80] proposed a switching mechanism framework in dynamic hybrid control architectures (i.e., hierarchical scheduling and heterarchical execution systems) that searches for optimal coupling of predictive scheduling and reactive control. It monitors the system dynamics online and adapts between operating modes to obtain the most suitable production control strategy. The switching mechanism implementation demonstrated an improved response to disruptions in a global performance indicator.

Regarding scheduling/rescheduling strategies, the consideration of routing flexibility allows for tackling uncertainties such as machine breakdown. For instance, Chen and Chen [81] suggested an adaptive scheduling approach for the integrated decisions of part/machine scheduling and operation/tool routing on a dynamic horizon. They used a two-state continuous-time Markov process to analyze this problem. Altumi et al. [82] considered tool failure's impact on the performance of FMSs for system reliability requirements. They suggested a mathematical model for determining the spare requirements of the tooling system in an FMS to obtain the desired system reliability and minimize the cost. In another research, Wang et al. [83] developed a robust scheduling model for an FMS with replenishment considering uncertain machine failure disruptions. They showed that solving a mixed-integer linear program is similar to the optimal solution obtained by the multi-stage dynamic scheduling problem. Mejía and Lefebvre [84] studied an FMS with an uncertain environment (i.e., operation interruptions and unreliable resources) using Petri nets and a graph search algorithm. The author aimed to represent the risk of operation disturbances and inaccessible resources and achieve robust scheduling for FMS.

Nouiri et al. [85] introduced the Green Rescheduling Method to study an energy-efficient scheduling/rescheduling problem with routing flexibility to cope with machine breakdowns. They devised a mixed integer programming model for a flexible job-shop (FJ) to compare the method's performance.

Industrial production is increasingly becoming flexible, diversified, customized, and dynamic. Therefore, scheduling research needs to alter its focus from traditional static, centralized decision-making to smart, dynamic, and distributed models and methods since many assumptions of traditional job-shop problem models become no longer valid [86]. The introduction of Industry 4.0 has called for the implementation of SM technologies. For instance, Yao et al. [87] introduced a decision-support system to assist decision-making when facing manufacturing disruptions. The system employed a database, a discrete-event simulation model, optimization models, and a manufacturing execution system integrated by IoT. The system enables the scheduling and re-scheduling of machines and autonomous guided vehicles while finding near-optimal production schedules, prioritizing just-in-time material delivery performance and energy efficiency of the material transportation. Zhang et al. [86] studied a dynamic FJ environment with the integration of SM. They considered the integrated processing planning and assembling scheduling with shop floor disruptions. They included an exact solution method into a metaheuristic, finding good results for optimizing makespan, maximum machine workload, and total tardiness.

Meza et al. [88] presented a dynamic hybrid control architecture to minimize myopic and nervous behavior in the presence of perturbations for a dynamic FJ scheduling problem. The authors started by executing a metaheuristic to establish a predictive schedule. After that, when perturbations occur, the system uses a reactive model to update the schedule with a heuristic algorithm. The researchers suggested strategies in the system to minimize nervousness and myopic conduct.

C. RMSS CONSIDERING RISK IN THE OPERATION STAGE

1) MACHINE-RELATED DISRUPTIONS

To design resilient RMS, Gu et al. [89] studied machine failure and developed three resilience measures (i.e., production loss, throughput settling time, and total underproduction time), which are analyzed using a Bernoulli reliability model. The measures are intended to be used for the optimal design for the resilience of RMS configurations, investment decisions, and control strategies for risk mitigation. Similarly, Qin et al. [90] proposed using reconfigurable machines and movable buffers to increase the resilience of a production system. They used a customized Markov chain model to mimic the production system. They evaluated the production system resilience by combining production loss, steady production rate with threshold, work-in-process in idle-area, process time of work-in-process in idle-area, and investment returns.

Khan et al. [91] considered an imperfect RMS prone to defects and quality-related concerns caused by machine disruption and tolerance-related problems. Therefore, they analyzed the process planning, introduced a multi-objective model to optimize the process plan's total cost and quality decay index, and implemented a multi-objective particle swarm optimization. The results can aid in understanding the effect of quality on process plan selection.

2) SUPPLY AND DEMAND DISRUPTIONS

RMSs have been designed to meet unexpected operational disturbances such as fluctuation/uncertainty of demand and/or availability of resources. One of the most critical decisions for RMSs is the definition of their configuration. Rehman and Babu [92] studied the importance of several RMS configurations utilizing an AHP-based procedure. They considered changes in the customer arrival patterns, the number of orders per customer, and order priority rules. This procedure helped to select the system configuration based on several customer/system performance metrics.

Inspired by the flexibility inherent in FMS and RMS, Copani and Urgo [93] considered two flexibility-oriented manufacturing models, the ''reconfiguration guarantee'' and the ''capacity guarantee,'' which are invoked throughout the RMS lifecycle based on customer requirements. They proposed stochastic configuration methods to design focused-flexibility production systems as a promising methodological enabler of new flexibility-oriented business models.

Zheng et al. [94] studied the configuration design for robotic MSs in small and medium-sized enterprises (SMEs). They developed a template model for defining the basic architecture of robotic MSs, allowing rapid change from one MS to another according to changing customer requirements. To reconfigure a system, different criteria can be evaluated. However, the literature tends to neglect the criteria' definition and importance. To assess the reconfiguration of a RMS during the operation, Mabkhot et al. [95] suggested a broad set of quantitative indicators and provided a framework to set up the weights. Therefore, they introduced three weighting methods according to the decision maker's expertise and the reconfiguration process' participation. To react to changing orders and the need for frequent reconfiguration, Koo et al. [96] proposed a dynamic meta-model that executes a risk assessment and FMEA process during the runtime, considering safety and production quality.

D. SMSS CONSIDERING RISK IN THE OPERATION STAGE

To prepare for disturbances and become resilient, Tomiyama and Moyen [97] developed a design method for a resilient architecture of a CPPS that can deal with disturbances and failures in a discrete-event process. The design is based on three principles: (1) different kinds of redundancy helpful for reconfiguration, (2) a mesh topology for controllers, sensors, and actuators, and (3) subsystems must be apart from additional subsystems to the greatest extent.

SMSs structures have been analyzed to find insights that can boost resiliency. For instance, Moghaddam and Deshmukh [98] studied how control structures in CPPS affect the resilience of manufacturing control. They considered operational disruptions (e.g., computing errors, dysfunctional/compromised controllers), which could cascade in the control structure. They found that more heterarchical structures are more resilient against non-cascade disruptions and less resilient against cascade disruptions. In contrast, hierarchical structures show the opposite behavior.

To prevent disruptions during the operation phase, Lee et al. [99] performed risk identification and assessment in distributed manufacturing networks. They adopted Petri nets to make decision-makers aware of the multiplicative effect of distributed risk. Additionally, Monte Carlo simulation assessed how quality risk affects the cost and customer lead time. With the intention of developing real-time production control, Zou et al. [100] and Zou et al. [101] employed sensor data of random disruptions to suggest an event-based data-driven mathematical formulation to define the real-time dynamic behavior of MSs performance and complex networked structures.

Zhao et al. [102] proposed an operational risk modeling and evaluation framework for discrete MSs in the SM context. They use the operational data to quantify the risk-oriented operational performance systematically. They transform mission-reliability-centered indexes into levels of whole system health conditions. Eirinakis et al. [103] designed a situation-aware MS that detects and forecasts operational disruptions (e.g., machine failures, quality issues, inventory shortages, transportation delays), assesses their effect, and reacts promptly to restore the impacted processes. The framework considers a complex event processing and predictive analytics module, a cyber-physical system to monitor and gather data, an optimization module, and a simulation module.

1) MACHINE-RELATED DISRUPTIONS

To provide a self-diagnosis/prognosis system, Zou et al. [104] designed a data-driven stochastic MS. They focused on studying disruptions to the system, such as equipment failure, prolonged cycles in a manual station, and subassembly starvation. The model describes the production dynamics and identifies the reasons for permanent production loss in deterministic and stochastic settings. They use sensor data with the knowledge of the production system's physical properties to enable real-time production control and decision-making.

Moussa and ElMaraghy [105] developed a method for generating a master assembly network with multiple alternative assembly sequences. The master assembly network is constructed based on legacy data of assembly sequences for the set of variants of a product family. Therefore, the assembly sequences can change routes to cope with real-time workshop disturbances (i.e., change orders, machine breakdowns, and tool failures) in I4 assembly systems.

For predicting production line disruption, Iftikhar et al. [106] utilized sensor data analysis through descriptive statistics analysis and machine learning (ML) models such as logistic regression. The accuracy of the models was tested on a real-world data set, and the results' effectiveness was validated. However, near real-time anomaly detection mechanisms are still missing.

To assess perturbations in a system-of-systems approach, Weichhart et al. [107] proposed an adaptive production system to achieve resilient manufacturing. They concentrated on operational disturbances such as machine breakdown. The authors focused on scheduling and reconfiguration by simulating the production plans.

To automatically discover MSs and create suitable digital twins (DTs), Lugaresi and Matta [108] introduced a method where a production system's relevant characteristics (logical system structure and parameters) are automatically retrieved from the event logs. Then, they proposed an automated generation and tuning method that can contribute to real-time simulation applications. It guarantees that an updated and reasonably digital model can be generated within one minute and with marginal manual involvement.

Preventive maintenance. Focusing on preventive maintenance, Kiangala and Wang [109] presented an experimental predictive maintenance framework for conveyor motors that detects a conveyor system's impairments and reduces the risk of incorrect faults diagnosis. They used an ML model that identifies if an anomaly could affect the production, and to improve its accuracy, the authors employed time-series imaging and a convolutional neural network. Similarly, Alemayehu et al. [110] calculated the optimum time of the constant interval of preventive replacement strategy to minimize maintenance costs and prevent risks that may cause damage to resources (human and equipment) in the CPS.

2) CYBERSECURITY RISK

SM will allow connected networks where the Industrial Internet of Things (IIoT) sensors monitor the conditions of industrial devices and machines. Therefore, devices can be vulnerable to many viruses, threats, and attacks. Zarreh et al. [111] used game theory to study the risk of cyberattacks in the SM paradigm. They evaluate the probability of attacks from different attackers' profiles and the quantal response equilibrium method to find the best strategy for system protection.

Zhu et al. [112] designed a multilevel flow model-based dynamic risk assessment approach for cyberattacks in MSs. They developed a Bayesian network to quantitatively analyze the effects of cyberattacks in the production process and their propagation. Abuhasel and Khan [113] proposed a framework to schedule resources effectively and provide data security in the IIoT.

Pinto et al. [114] presented an intrusion detection system approach for CPPS using the deterministic dendritic cell algorithm. The algorithm was assessed using a crafted dataset and by introducing different attacks. The results indicated that attacks were effectively identified with the algorithm. Similarly, Leander et al. [115] derived requirements and implications for access control between devices and services within SMSs. They introduced an Attribute-Based Access Control model and assessed it against the prerequisites in a particular setting. In the same vein, John et al. [116] proposed using a middleware platform and Domain-Specific Languages to allow the safe integration of systems and interoperability in the SM context. They analyzed a use case for a predictive maintenance system (i.e., machine failure scenarios).

VII. OPERATIONAL RISKS IN THE DISMANTLE STAGE OF MANUFACTURING SYSTEMS

Once the system is in the operation stage, according to future market demands, it might be needed to retrofit it; otherwise, substitute it. The consideration of substitution risk has received little attention. Only one work for GMSs has been found. In the literature, Stauder et al. [117] provided a systematic approach to evaluate the substitution risk of production systems regarding current and possible future product demands. Their approach carries out a static evaluation based on an analytical cost model. Then, a scenario analysis is performed to derive possible future product programs. Suitable scenarios are defined and analyzed with a Monte Carlo simulation based on the described scenarios. Therefore, the user can optimize a production system at different points in time.

VIII. MANUFACTURING SYSTEMS AGAINST DISRUPTION RISKS

Disruption risks can highly deteriorate MSs' performance. To overcome unexpected events, Ocampo et al. [118] provided a systems approach for studying risks caused by disturbances in their supply due to natural disasters, economic conditions, and government policies. They implemented a supply-driven inoperability input-output model to establish the total impact of a given supply shift on the price rise. Therefore, mitigation strategies can be planned to improve the resilience of manufacturing systems.

Anarchic manufacturing was introduced by Ma et al. [119], aiming to employ a highly distributed planning and control philosophy. They compared hierarchical systems with anarchic MSs, showing that anarchic systems are as robust and flexible as the simple hierarchical system under unanticipated disruption. Also, these systems showed adaptability and self-optimizing traits, providing a platform to potentially enable the emerging digital manufacturing paradigm through the free market structure.

A method for quantifying resilience in MSs based on calculating the penalty of possible changes was introduced by Alexopoulos et al. [120]. Practitioners can utilize the resilience metric to evaluate, compare, and improve their production systems' resilience and determine strategic investments. They measured the resilience of additive MSs and injection molding systems when COVID-19 disturbed their production.

A. RMSS AGAINST DISRUPTION RISKS

Epureanu et al. [121] introduced a method to coordinate reconfigurable manufacturing resources from multiple enterprises to structure production networks for critical products (e.g., ventilators) required in emergencies (i.e., pandemics). They proposed synchronous machine- and network-level reconfiguration optimization models and data-driven interaction algorithms.

B. SMSS AGAINST DISRUPTION RISKS

SM as a service-oriented model enables cloud manufacturing (CM), allowing a new product development model in which users can configure, select, and utilize customized manufacturing services on demand. Zhu et al. [122] designed a manufacturing risk evaluation for a CM platform to search for an alternative resource when original manufacturing nodes failed unexpectedly. Therefore, the platform enables CM to be reliable, robust, and flexible with self-repair capability.

A distributed modeling, a simulation framework, and an interoperability platform that considers the environment to evaluate sustainability and risk were developed by Gorecki et al. [123]. The risk management tool assumes disruption risks (weather constraints, delivery issues, or emergencies) and operational risks (uncertainty of human and machine resources), allowing the planning of SM components and services.

Li et al. [124] proposed utilizing automated manufacturing assets supervised by networked sensors and monitored by intelligent decision-making algorithms to mitigate production disruptions caused by a pandemic. They devised an optimization model to allocate intelligent manufacturing (IM) assets according to market demands and the severity of the pandemic. The decision-making model is intended to define the optimal distribution of IM resources that enhances an existing industrial network.

Leng et al. [125] considered commissioning a new MS under a pandemic scenario. Therefore, they proposed a DT-based remote semi-physical commissioning to enable remote semi-physical commissioning to allow the design of new MSs. Similarly, Vrabič et al. [126] suggested an intelligent agent-based architecture to enhance the robustness (accuracy of representativeness) and resilience (timely update) of a DT. The architecture can detect disruptions in the DT and establish a response (self-adapt). The architecture includes a learning agent that learns on operational data and can reduce resilience loss when the same disturbance happens.

IX. DISCUSSION

From our study, it is essential to note that most of the literature is dedicated to operational risks, representing approximately 91% of the articles. Moreover, according to the manufacturing stages, most literature provides risk considerations for the operation stage, with 69% of the papers, followed by the development stage with 25%, the design stage with 5%, and the dismantle stage with only 1%.

To draw insights from the data, a keyword co-occurrence analysis was performed using VOSviewer (www.vosviewer.com), as shown in Fig. 3. The circle size represents the weight of each keyword. The proximity of the circle position in the network means the relatedness strength. Moreover, the color bar displays the years the articles were published and indicates how the years are mapped to colors [127]. For instance, journals published around 2020 are yellow, while articles published before 2012 are purple. From the network, the evolution of the manufacturing systems can be observed, starting from FMSs and passing to RMSs and SMSs.

From the reviewed articles, it is essential to highlight that SMS articles address more risk considerations than other paradigms. Although FMS and RMS have been in the market for longer, considering risks have not been explicitly accounted for or thoroughly tackled. This phenomenon can be observed in Fig. 3. Also, it can be noted that FMSs and RMSs have become aware of the need for risk assessment lately. Additionally, simulation and optimization methods are closer to those paradigms. On the other hand, SMSs deal with risk assessment and disruption management, and methods such as AI and DTs are employed. However, new challenges are considered, such as cybersecurity and human factors.

Moreover, it can be highlighted that the term risk assessment has been used more than the term resilience (turquoise bubble between simulation and flexibility bubbles). However, with the current pandemic, this trend is expected to change.

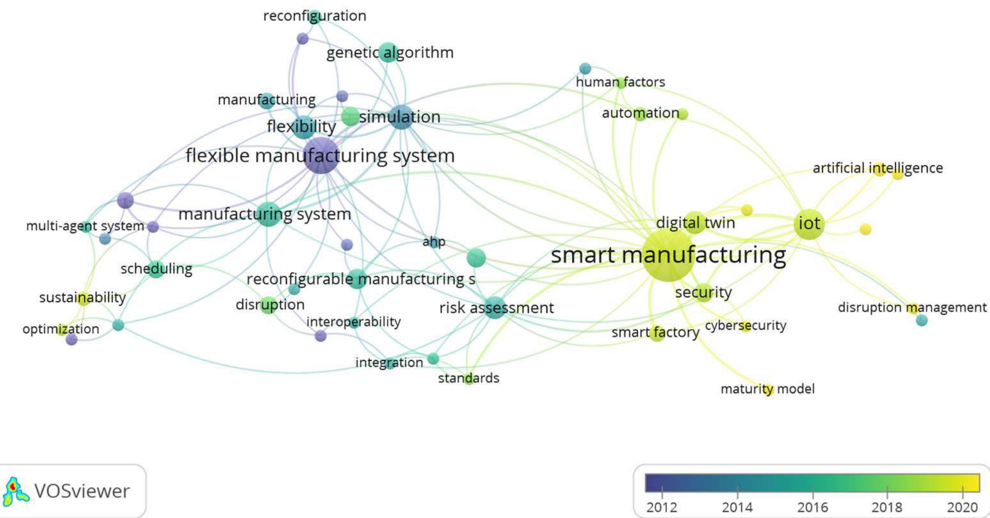

FIGURE 3. Keyword co-occurrence network.

TABLE 2. Risks and strategies considered for GMSs.

	Risks										Strategies								
Authors	Investment risk	Risk assessment	Ergonomic risk	Safety risk	Demand uncertainty	Resource failures	Low-quality risk	Substitution risk	Cybersecurity risk	Disruption risks	Planning and control	Scheduling	Routing	Redundancy	Reactive maintenance	Capacity adjustment	Reconfiguration	Preventive Maintenance	Monitoring and prediction
Lazov [34]		✓									✓								
Khalaj *et al.* [35]		✓				✓					✓								
He *et al.* [36]		✓				✓					✓								
Silvestri *et al.* [37]				✓							✓								
Mossa *et al.* [38]			✓									✓							
Moatari-Kazerouni *et al.* [39]			✓								✓								
Darmoul *et al.* [56]		✓			✓	✓					✓								
Bayar *et al.* [57]		✓									✓								
Vieira *et al.* [58]					✓	✓						✓							
Tanimizu *et al.* [59]					✓							✓							
Tannock and Saelem [60]							✓				✓								
Zhao *et al.* [61]						✓	✓											✓	
Zhu *et al.* [62]						✓	✓				✓								
Park and Tran [63]						✓					✓								
Park and Tran [64]						✓					✓								
Zarrin and Azadeh [65]						✓					✓			✓	✓			✓	
Erozan [66]						✓					✓			✓				✓	✓
Paprocka [67]						✓						✓						✓	✓
Sobaszek *et al.* [68]						✓													✓
Paprocka *et al.* [69]						✓						✓			✓			✓	✓
Stauder *et al.* [117]								✓			✓								

Unexpected events (i.e., operational and disruption risks) will always exist in the manufacturing environment. Therefore, a proactive perspective is needed to improve the manufacturing systems' performance. More emphasis is required on designing manufacturing systems capable of coping with a variety of risks in an integral manner. However, a strong collaboration among the different stakeholders in the various life cycle stages is needed as there could be conflicting objectives.

TABLE 3. Risks and Strategies Considered For FMSs.

	Risks										Strategies								
Authors	Investment risk	Risk assessment	Ergonomic risk	Safety risk	Demand uncertainty	Resource failures	Low-quality risk	Substitution risk	Cybersecurity risk	Disruption risks	Planning and control	Scheduling	Routing	Redundancy	Reactive maintenance	Capacity adjustment	Reconfiguration	Preventive Maintenance	Monitoring and prediction
Karsak [28]		✓									✓								
Zhang *et al.* [40]		✓									✓								
Arocena *et al.* [41]			✓								✓								
Bautista *et al.* [42]			✓										✓						
Tomino *et al.* [70]					✓						✓								
Mak and Shen [71]					✓								✓						
Zhang and Wong [72]					✓	✓						✓	✓						
Chew and Lawley [74]						✓							✓						
Chew *et al.* [75]						✓							✓						
Piramuthu *et al.* [76]						✓						✓							
Yazgan [77]						✓						✓							
Gaula and Sharma [78]						✓						✓			✓			✓	
Alotaibi *et al.* [79]					✓	✓						✓							
Jimenez *et al.* [80]						✓						✓							✓
Chen and Chen [81]						✓						✓	✓						
Altumi *et al.* [82]						✓						✓	✓	✓					
Wang *et al.* [83]						✓						✓	✓						
Mejía and Lefebvre [84]						✓						✓	✓						
Nouiri *et al.* [85]						✓						✓	✓						
Yao *et al.* [87]						✓					✓	✓	✓						
Zhang *et al.* [86]					✓	✓						✓	✓						
Meza *et al.* [88]						✓						✓	✓						

TABLE 4. Risks and strategies considered for RMSs.

	Risks										Strategies								
Authors	Investment risk	Risk assessment	Ergonomic risk	Safety risk	Demand uncertainty	Resource failures	Low-quality risk	Substitution risk	Cybersecurity risk	Disruption risks	Planning and control	Scheduling	Routing	Redundancy	Reactive maintenance	Capacity adjustment	Reconfiguration	Preventive Maintenance	Monitoring and prediction
Andersen *et al.* [29]	✓				✓						✓								
Sanderson *et al.* [30]						✓					✓						✓		
Abdi and Labib [43]					✓						✓								
Elmaraghy *et al.* [44]						✓	✓				✓								
Koo *et al.* [45]				✓							✓								
Berger *et al.* [46]				✓							✓								
Gu *et al.* [89]						✓					✓			✓			✓		
Qin *et al.* [90]	✓					✓											✓		
Khan *et al.* [91]							✓						✓				✓		
Rehman and Babu [92]					✓												✓		
Copani and Urgo [93]					✓											✓	✓		
Zheng *et al.* [94]					✓												✓		
Mabkhot *et al.* [95]						✓					✓						✓		
Koo *et al.* [96]		✓		✓			✓				✓						✓		

A. RQ1. OPERATIONAL AND DISRUPTION RISKS HANDLED BY EACH MANUFACTURING PARADIGM

Risk consideration in the design stage for FMS is related to the flexibility level and decision-maker evaluation process. For RMSs, the risk is considered for the demand uncertainties and the investment risk in the design stage. While FMSs and RMSs risk considerations are more limited, for SMSs, the risk consideration is more integral, as the analysis of different

TABLE 5. Risks and strategies considered for SMSs.

	Risks										Strategies								
Authors	Investment risk	Risk assessment	Ergonomic risk	Safety risk	Demand uncertainty	Resource failures	Low-quality risk	Substitution risk	Cybersecurity risk	Disruption risks	Planning and control	Scheduling	Routing	Redundancy	Reactive maintenance	Capacity adjustment	Reconfiguration	Preventive Maintenance	Monitoring and prediction
Häckel *et al.* [31]	✓	✓							✓		✓			✓					
Helu *et al.* [47]		✓									✓								
Sarwar *et al.* [48]		✓									✓								
Riddick *et al.* [49]		✓									✓								
Dombrowski *et al.* [51]				✓							✓								
Dombrowski *et al.* [50]				✓															✓
Mengoni *et al.* [52]			✓	✓															✓
Korfmacher [53]				✓					✓		✓								
Etz *et al.* [55]				✓													✓		
Ehrlich *et al.* [54]				✓							✓								
Tomiyama and Moyen [97]						✓					✓			✓			✓		
Moghaddam and Deshmukh [98]						✓					✓								
Lee *et al.* [99]		✓					✓				✓								
Zou *et al.* [100]					✓	✓					✓								
Zou *et al.* [101]					✓	✓					✓								
Zhao *et al.* [102]					✓	✓	✓												✓
Eirinakis *et al.* [103]					✓	✓	✓				✓	✓	✓						✓
Zou *et al.* [104]					✓	✓					✓								✓
Moussa and ElMaraghy [105]					✓	✓					✓	✓							
Iftikhar *et al.* [106]						✓					✓								✓
Weichhart *et al.* [107]						✓						✓					✓		
Lugaresi and Matta [108]						✓							✓						✓
Kiangala and Wang [109]						✓												✓	✓
Alemayehu *et al.* [110]				✓		✓												✓	
Zarreh *et al.* [111]									✓		✓								
Zhu *et al.* [112]		✓							✓										✓
Abuhasel and Khan [113]									✓			✓							
Pinto *et al.* [114]									✓		✓								
Leander *et al.* [115]									✓		✓								
John *et al.* [116]						✓			✓									✓	✓

data streams allows the study of additional risks such as machine failures, product or process quality issues, inventory shortages, transportation delay, and investment risk.

Several authors have designed models to prevent various risks at the development and implementation stages. GMSs have been focused on risk assessment, safety, and ergonomic hazards. FMSs have concentrated on risk assessment and ergonomic risk, while RMSs tackle resource failure and safety concerns. SMS models target risk assessments and focus on safety, especially for human-robot collaboration. However, as Ehrlich et al. [54] highlighted, current risk assessments are not adaptive and contradict I4 flexibility.

Resource/machine failure is the most studied risk for the operation stage, followed by analyzing demand uncertainties or supply/demand mismatch. GMSs are focused on low-quality risks and machine-related disturbances. FMS and RMS are also considering supply and demand disruptions. GMSs and FMSs tend to handle those disruptions by (re)scheduling the resources. On the other hand, demand uncertainty is well managed by RMSs as they are designed to change their configuration by adding or removing modules to allow scalability. For operational risks, GMSs, FMSs, and RMSs try to establish planning and control, maintenance, and scheduling strategies. In contrast, due to the possibility of gathering data, SMSs look to develop monitoring and provide prediction before such events happen. Additionally, since one of the main foundations of SMSs is the usage of IT, cybersecurity risk has also been addressed.

MSs are capital assets that usually require a high amount of investment. While the investment risk has been studied, the substitution risk has received little attention. Also, it is relevant to consider that MSs can be retrofitted to allow the integration of more capabilities. For instance, lately, FMSs and RMSs are being adapted to use more advanced IT, enabling them to boost their management capabilities.

Disruption risks are scarcely considered for MSs. While some managers would argue that the responsibility of risk consideration should lay on the SC analysis, MSs, the core of

TABLE 6. Disruption risks and strategies considered for MSs.

		Risks										Strategies								
Authors	**Paradigm**	Investment risk	Risk assessment	Ergonomic risk	Safety risk	Demand uncertainty	Resource failures	Low-quality risk	Substitution risk	Cybersecurity risk	Disruption risks	Planning and control	Scheduling	Routing	Redundancy	Reactive maintenance	Capacity adjustment	Reconfiguration	Preventive Maintenance	Monitoring and prediction
Ocampo *et al.* [118]	GMS		✓			✓					✓	✓								
Ma *et al.* [119]	GMS										✓	✓	✓					✓		
Alexopoulos *et al.* [120]	GMS										✓	✓								
Epureanu *et al.* [121]	RMS										✓	✓						✓		
Zhu *et al.* [122]	SMS		✓								✓	✓								
Gorecki *et al.* [123]	SMS						✓				✓	✓								✓
Li *et al.* [124]	SMS										✓	✓	✓							✓
Leng *et al.* [125]	SMS										✓	✓								
Vrabič *et al.* [126]	SMS										✓	✓								✓

TABLE 7. Mapping between manufacturing paradigm characteristics and risks handled.

		Handled risks					
		Operational risks					
Paradigm	Characteristics	Demand uncertainty	Equipment failures	Low quality risk	Ergonomic risk	Safety risk	Disruption risks
FMS	Adaptability	◑	◑	◕	⊗	◔	◔
	Responsiveness	◑	◔	⊗	⊗	⊗	◔
	Agility	◔	⊗	⊗	⊗	⊗	◔
RMS	Modularity	●	◕	⊗	⊗	⊗	◔
	Scalability	●	◑	⊗	⊗	⊗	◔
	Convertibility	●	◑	⊗	⊗	⊗	◑
	Diagnosability	⊗	●	●	◔	◑	⊗
	Customized flexibility	◕	⊗	⊗	⊗	⊗	◔
	Integrability	●	◕	⊗	⊗	◔	◔
SMS	Data connectivity and transparency	●	●	●	◔	●	◑
	Virtualization	●	●	●	◑	●	◑
	Predictability	●	●	●	◔	●	◔
	Sustainability	◑	⊗	◔	⊗	⊗	⊗
	Interoperability	◕	◕	⊗	⊗	◔	◕

⊗ ◔ ◑ ◕ ●

Not Applicable → Highly Applicable

the production, could offer more adaptability and resilience. RMSs and SMSs have been considered to tackle disruptive risks, and the possibility of connecting resources through IT systems allows for this alternative. While enabling communication among resources scattered in different locations can allow flexibility and resilience to handle disruptive risks, considerations of connectivity and cybersecurity need to be addressed to permit MS networks to interact, communicate, and adapt to the manufacturing landscape.

Surprisingly, the role of DTs and CPPs in predicting, managing, and recovering MSs from risks and disruptions has not been explicitly explored. While the strings used to perform the search could disregard important works, more detailed literature is needed to avoid such events.

B. RQ2. MITIGATION STRATEGIES WHEN FACING RISKS

Several strategies have been implemented to tackle different risks that are pursued to obtain redundancy and flexibility. Flexibility strategies encompass scheduling, routing, and capacity adjustment. For redundancy, usually, there is a backup of resources to utilize when there are failures in the primary resources. The redundancy strategy is one of the most effective ways to continue working and delivering products.

However, it is expensive and inefficient. Therefore, redundancy is not usually considered unless the resource is highly critical. Also, it has been observed that most of the analyzed studies focus on reactive strategies to overcome the different operational risks. For all the paradigms, planning and controlling is the most used strategy.

Planning and controlling (e.g., scheduling, maintenance, etc.) as a general strategy encompassing the analysis of foreseeable risks through risk management/assessments (e.g., FMEA, decision trees, etc.) and developing possible solutions. However, the controlling part follows already defined strategies to optimize established objectives, leaving aside the possibility of providing strategies that could improve the performance system. Moreover, the controlling activities react to the risks instead of preventing them. However, the recognition of having some plans after the risks occur needs to be acknowledged.

Resource/machine failure is the most studied risk for the operation stage combined with re/scheduling strategy. Reactive or adaptive scheduling was widely studied for FMS. Another technique used to tackle machine breakdown in FMS is re/routing. The maintenance of the resources in a proactive-reactive way is also a strategy that can improve the system's performance.

In the operation stage of RMSs, the available literature evaluates operational resilience related to machine disruptions. Usually, a reconfiguration strategy is followed to adapt the system to resource failures. Also, capacity adjustment (i.e., scalability) is possible when demand changes occur.

Nowadays, with the possibility of harnessing data from different sensors and systems, proactive/predictive strategies are gaining more interest. The traditional strategies (e.g., scheduling, maintenance) have been enhanced to leverage data and provide insights that could not be obtained in the past. However, the full potential is still to be unveiled.

The literature shows that different risks can be handled according to the manufacturing paradigm. Tables 2 to 5 offer the most studied risk factors and the various strategies implemented to alleviate the system's performance by each paradigm. While there is no one-size-fits-all solution, the researchers pay more attention to this relevant topic.

Additionally, the literature is homogeneous about organizations implementing different strategies to handle risks; however, SME roles and MSs have received little attention.

Regarding disruption risks, similar strategies as utilized for operational risks have been proposed (e.g., planning and controlling, scheduling, and reconfiguration), as observed in Table 6. However, monitoring and prediction have been suggested lately, which is possible thanks to IoT and the implementation of AI and ML algorithms. It is relevant to highlight that those disruptive risks are difficult to predict; therefore, awareness and preparedness must be considered.

C. RQ3. SYSTEMS' CHARACTERISTICS TO DEAL WITH RISKS

Each manufacturing paradigm has been designed to accomplish particular objectives. Therefore, they possess specific features that help them address specific challenges. However, the manufacturing landscape is evolving, and new opportunities and challenges arise. Thus, MSs must adapt and evolve to catch up with the challenges ahead.

MSs can handle risks at various degree levels thanks to different system characteristics. In Table 7, key features that characterize each paradigm are listed and mapped to risks that can be addressed. Also, the level at which each specific characteristic contributes to managing certain risks is represented with bubbles, as described in the table footnote.

Some features can directly be related to lessening the impacts of specific risks. For instance, the scalability feature of RMSs allows for adjusting the system capacity to address the demand uncertainty. Another example is the predictability feature of SMSs, which permits anticipate failures in the system. However, there are other characteristics that the contribution is not as evident. For example, SMSs interoperability could help to decrease safety risks. That is, the availability of different software, devices and their interconnection could aid in discovering issues not noted with tools working independently. Other features might not be applicable. For instance, scalability and low-quality risk or interoperability and low-quality risk might not be related.

Disruption risks consider a broad spectrum of catastrophic situations that are not foreseeable; therefore, the manufacturing system's characteristics could, at some point, alleviate the effects of such conditions.

Nevertheless, complete protection cannot be provided. From Table 7, it can be observed that there is not a single characteristic that will help to tackle all the risks. However, combining several factors can enhance the overall manufacturing system's resilience. While RMSs and SMSs are designed to deal with certain risks, upgrading and retrofitting FMSs with IIoT technologies could improve performance.

D. RQ4. MANUFACTURING SYSTEMS AND THEIR ADAPTABILITY

While recovering from disruptions and springing back into the designed system state (i.e., resilience) is critical to

TABLE 8. Mapping between manufacturing paradigms, adaptability facets, and adaptation strategies.

	Adaptability facets			
Paradigms	Static	Dynamic	Cognitive	Extreme
FMS	++	++		
RMS	+++	+++	++	++
SMS	+++	+++	+++	+++
	Scalability	Repurposing	Substitution	Intertwining
	Adaptation strategies			

continue operations, the ability to adjust to new conditions and be modified for a new goal, use, or purpose is required (i.e., adaptability). ElMaraghy et al. [2] introduced a new classification for adaptability - static, dynamic, cognitive, and extreme.

- Static adaptability refers to built-in preplanned flexibility by design, allowing flexible, resilient, and robust behavior within the pre-defined parameters and boundaries (i.e., product family, scope, and scale).
- Dynamic adaptability involves physical hardware and soft logical adaptation by reprogramming devices, changing controls of machines and/or systems, and revising operating and sequencing rules.
- Cognitive adaptability utilizes built-in changeability enablers to allow agile and optimal changes in function (scope) and capacity (scale) beyond previously anticipated and planned total.
- Extreme adaptability relies on the MS's resilience and capacity to recover (partially or fully) from major unexpected multi-dimensional extreme disruptions.

In the same vein, Ivanov [128] proposed four major SC adaptation strategies – scalability (capacity expansion), repurposing (process flexibility), substitution (structural reconfiguration), and intertwining (collaboration). These SC strategies are aligned with the manufacturing systems' adaptability facets to cope and survive in the uncertain environment. As can be observed from Table 8, depending on manufacturing paradigms, different levels of adaptability and adaptation can be reached (+ signs symbolize the degree that each paradigm could achieve for each facet). Although FMSs have been in the market longer than RMS and SMS, their characteristics enable only static and dynamic adaptability to a certain degree. To a certain extent, RMS and SMS could allow cognitive and extreme adaptabilities, permitting the substitution and intertwining when facing challenging times such as the current pandemic. However, to fully boost their resiliency, new capabilities need to be considered (e.g., adaptiveness, agility, changeability, self-optimizing, etc.).

X. CONCLUSION AND FUTURE RESEARCH AVENUES

While manufacturing systems risks have been discussed in the literature in a segmented manner, a wide panorama was lacking. Therefore, this paper examined the different risk perspectives (i.e., operational and disruption risks) for several manufacturing paradigms. The article mainly concentrated on MSs, which are the flagships of the third and fourth industrial revolutions (i.e., FMSs, RMSs, SMSs). As most of the articles are focused on operational risks, the works are further classified according to the lifecycle stage in which the risk is considered.

The literature shows that FMSs are more concentrated on adding capabilities to deal with disruptions by implementing reactive strategies. On the other hand, RMSs are designed with capabilities that allow them to adapt to uncertain demand and machine failures. Moreover, with the advent of new technologies, SMSs target proactive strategies to predict and prevent disruptions.

These technologies can retrofit brownfield systems and boost their capabilities to handle unexpected disruptions. Although operational risks have been widely studied, the consideration of disruption risks is still in the infancy stages for MSs. While manufacturing environments have been planned to be efficient and lean for just-in-time environments, MSs will be envisioned for just-in-case situations. Therefore, it is critical to analyze the possible risks and trade-offs to establish proactive and reactive strategies to balance resiliency and efficiency.

While substantial progress has been made in dealing with disruptions, many challenges and opportunities remain to be addressed. Future research avenues include:

- The exploration of other risks, such as accidents, noncompliance, process/machine obsolescence, and intentional disruptions
- The investigation of the layout redesign and process planning for RMSs to tackle and efficiently reconfigure the system when facing different risks
- The development of retrofitting paths for MSs and FMSs to consider different risks
- The possibility of the predict-then-optimize paradigm could boost the performance, as it could guide the execution of unscheduled activities (e.g., reconfiguration, rescheduling, maintenance) and fully optimize the system even before the risk occurs
- The use of AI and ML to design strategies to cope with unexpected disturbances in a dynamic environment system
- The study of implications of implementing DTs to provide process and environment visibility and transparency
- The participation of SMEs as a part of the manufacturing systems network
- The design of dynamic and robust risk assessments for SMSs to evaluate real-time hazards related to safety and ergonomic risk to enable real-time strategies' implementation
- The possibility of automatic repurposing, substitution, and intertwining to enable self-adaptation and self-organization aid by data-driven technologies such as blockchain
- The analysis of the evolution of IIoT to allow self-optimization and the development of new manufacturing characteristics to prepare for various risks
- The creation of new business models rooted in MSs that allow handling disturbances

- The interconnection of different paradigms to boost their capabilities
- The consideration of humans and their expertise as a central part of the systems
- The design of systems that learn from humans and execute self-learning to implement strategies to tackle the various risks
- The development of algorithms to enable cognitive and adaptive systems
- The possibility of self-commissioning systems
- The development of resilience metrics applicable to different manufacturing systems to benchmark alternatives
- The simultaneous assessment of multiple risks in different scenarios to holistically determine the best alternative
- The analysis of MS's resilience in parallel with sustainability
- The design of MS mechanisms inspired by nature to mimic their ability to balance the environment when facing disruptions

Limitations of this research are related to the literature search process, as it is based upon the definition of a set of keywords, years, and sources. However, the authors strived to be objective in selecting articles; the literature selection process is subjected to bias and the subjective view of the researchers.

Future extensions of this work consider reviewing conference articles and exploring the capabilities of other manufacturing paradigms, such as cloud manufacturing. Moreover, bibliometric and text analytics tools can be used to provide a different perspective of the analysis.

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ALEJANDRO VITAL-SOTO received the Ph.D. degree in industrial and manufacturing systems engineering from the University of Windsor, Windsor, ON, Canada, in 2019. Since 2019, he has been an Assistant Professor of operations research and management science with the Shannon School of Business, Cape Breton University. His research interests include manufacturing systems design, optimization, scheduling, and Industry 4.0.

JESSICA OLIVARES-AGUILA received the Ph.D. degree in industrial and manufacturing systems engineering from the University of Windsor, Windsor, ON, Canada, in 2018. She has been an Assistant Professor of supply chain management with Cape Breton University, since 2019. Her main research interests include supply chain design, supply chain risk management, disruption risks, product design, digital twins, and Industry 4.0.