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Resilience in closed-loop supply chain: a systematic literature review

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Abstract

Purpose – As global supply chains shift from linear to circular models, resilience in reverse logistics and closed-loop supply chains (RL and CLSC) remains underexplored and fragmented, despite its critical role in mitigating disruptions. This study addresses this gap by systematically reviewing and synthesising the existing literature.

Design/methodology/approach – A review of 194 studies published between 2005 and 2024 was conducted, reflecting the earliest study returned by the search. Through thematic analysis and synthesis, a three-component conceptual framework was developed, comprising: (1) risk types, (2) mitigation strategies for different risk types and (3) mitigation development approaches.

Findings – The review identifies 16 risk types specific to RL and CLSC, with waste management, collection processes and natural resource scarcity risks being particularly distinctive. Proactive mitigation strategies dominate the field, but there is a need for greater emphasis on real-time and reactive approaches to enhance adaptability. Quantitative, especially model-based techniques, prevail in mitigation development, while data-driven methods remain largely underutilised, signalling an opportunity for future research.

Originality/value – This study consolidates fragmented RL and CLSC resilience literature into a comprehensive framework, mapping key interactions across risk types, mitigation strategies and development approaches. It also highlights seven research directions: (1) developing risk identification and classification systems; (2) investigating risk interdependencies using complex systems and network analysis; (3) focusing on concurrent mitigation strategies; (4) integrating real-time, concurrent and reactive resilience strategies; (5) exploring new data sources for resilience enhancement; (6) applying and developing data-driven methods; and (7) conducting cross-sectoral comparative studies to generate both generalisable and contextual insights.

Keywords Resilience, Reverse logistics, Closed-loop supply chain, Risk management, Literature review, Conceptual framework

Paper type Literature review

1. Introduction

Modern economies are evolving from traditional linear models to circular ones, incorporating both forward and reverse flows, resulting in closed-loop supply chains (CLSC). The added reverse logistics (RL) presents significant environmental and economic opportunities but also introduces additional layers of uncertainty and complexity. Any disruptions in RL or CLSC networks can lead to delays and operational breakdowns, requiring time and effort to recover. For instance, when China, the world's largest importer of waste, banned nearly all solid waste imports, it disrupted the material supply for local remanufacturers (Yang *et al.*, 2022). This leads to production delays, factory relocations and the search for alternative material sources – all of which came with extra costs (Song *et al.*, 2023). Similarly, the ship recycling industry faced a crisis during COVID-19 due to labour shortages and transportation difficulties, with approximately 300 million Gross Tonnage of end-of-life (EOL) ships at risk

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of non-recycling. This situation could result in a potential loss of 20 billion dollars and reduced economic and employment opportunities for recycling nations in South Asia (Rahman *et al*., 2021). These examples highlight the need to strengthen RL and CLSC networks to better withstand adverse events and adapt to unexpected challenges.

To achieve such adaptability, resilience needs to be designed into these networks, enabling them to shift toward desirable states in which failure modes could be minimised (Christopher and Peck, 2004; Irfan *et al*., 2022). Supply chain resilience (SCRES) has gained significant attention in recent years for its potential to maintain business continuity and competitive advantage under uncertainty. However, most SCRES research still focuses on classical forms of the SC (Ali *et al*., 2017; Kochan and Nowicki, 2018), which only take into account the one-way movement of materials and products. Studies about resilience that do consider RL or CLSC often treat it as an emerging subtopic with little attention to its details (Hosseini *et al*., 2019; Rha, 2020). This lack of focused investigation has left a critical gap in the literature, as the resilience mechanisms needed to support RL and CLSC networks may differ substantially from those applied to traditional linear systems. Hence, addressing this gap becomes essential to establish a foundation for future research and provide actionable insights for designing more robust RL and CLSC.

Moreover, the conceptualisation of SCRES still remains rather fragmented, with considerable variation in how its constructs are identified and defined (Chowdhury and Quaddus, 2017; Hosseini *et al*., 2020). Some studies portray resilience as a dynamic competence in risk situations since it enables the SC to address various risk types across multiple stages of the risk management process (Um and Han, 2020), thereby positioning risk as the central element. Meanwhile, others focus on the operational capabilities that firms must build and align with SC partners to adapt to both anticipated and unforeseen disruptions (Cheng and Lu, 2017; Tan *et al*., 2020). This leads to a lack of consensus on what constitutes resilience and how its components interact. The need for conceptual clarity becomes even more pronounced in the context of RL and CLSC, where resilience must account for complex processes such as product remanufacturing, recycling and resource recovery. These networks also require collaboration among a more diverse set of stakeholders, particularly those managing the reverse flow (Lin and Chu, 2025). Accordingly, theoretical advancements are needed to map the relationships among SCRES constructs and to understand how they collectively contribute to resilience within RL and CLSC contexts.

In light of these gaps, this paper seeks to consolidate what has been studied about resilience in RL and CLSC through a conceptual framework guided by a systematic literature review. Grounded in the theory of complex systems, this framework organises and synthesises relevant knowledge at the intersection of resilience in RL and CLSC networks to identify key constructs considered in the literature. These constructs would then be analysed, both individually and in relation to one another, to provide greater conceptual clarity on the topic. This approach aligns with calls in the literature to transition SCRES research from basic exploration to theory development and relationship-building, which are essential for advancing the field and supporting the development of resilient networks (Macdonald *et al*., 2018). Ultimately, the study aims to offer a structured and comprehensive understanding of resilience in RL and CLSC, facilitating both theoretical advancements and managerial applications by addressing the following research questions:

RQ1. What are the key risks and related mitigation strategies discussed in the RL and CLSC literature, and how should stakeholders prioritise them to strengthen resilience?

RQ2. How can a resilience framework for RL and CLSC be developed to clarify the main constructs and their interrelationships?

RQ3. What future research and strategic pathways are needed to support the development of more resilient RL and CLSC systems?

This review makes several significant contributions to the field of SCRES. It develops a conceptual framework that systematically integrates resilience into RL and CLSC networks, providing a structured approach to understanding how resilience can be designed into these systems. Through this framework, the study organises and synthesises existing knowledge, identifies key SCRES constructs and elucidates the relationships between them. From a theoretical perspective, the review advances understanding by laying a foundation for future research to explore the underlying theories and practices that support resilience in RL and CLSC. Practically, the review enhances managerial awareness of the interconnectedness of SCRES constructs, providing actionable insights for building resilient SC capabilities. By clarifying the dynamic interplay between these constructs, the study offers guidance for designing more robust and adaptable RL and CLSC networks. These contributions address critical gaps in SCRES research and provide value both to academia and practitioners in the field.

This literature review will focus on highlighting the key findings. Meanwhile, the rigorous content analysis conducted will be detailed in the Supplementary Materials. The structure of this paper is as follows: Section 2 presents the conceptual development, providing the rationale for including risk identification and mitigation within resilience, which forms the basis for the proposed conceptual framework. Section 3 outlines the methodology employed to guide the systematic analysis of the literature. Section 4 discusses the findings and highlights the critical relationships between resilience constructs, derived from the content analysis. Section 5 identifies potential avenues for future research to advance the field further. Section 6 highlights the practical relevance of the review by detailing its managerial, policy and theoretical implications. Finally, Section 7 concludes the paper by summarising the key insights and contributions of the review.

2. Theoretical background

2.1 RL and CLSC as complex systems and the need for resilience

The interconnectedness within extended chains in RL and CLSC networks significantly amplifies their complexity, making them increasingly vulnerable to disruptions (Sadeghi *et al.*, 2025). Unlike traditional forward logistics, RL and CLSC networks face unique challenges, such as managing the uncertain quality of returned products, low standardisation and the coordination of multiple stakeholders. These characteristics align with the principles of Complex Systems Theory (CST), which provides a valuable lens for understanding and managing RL and CLSC networks.

Complex systems are characterised by interdependent components, dynamic interactions and emergent behaviours that cannot be fully understood by examining individual parts in isolation (Thurner *et al*., 2018). These systems are highly sensitive to initial conditions and continuously evolve in response to both internal and external influences, which also makes them inherently vulnerable to adverse situations. Within RL and CLSC networks, complexity manifests in forms such as sequential, reciprocal and pooled interdependencies (Thompson, 2017). Such multidimensional nonlinear interactions within these networks often give rise to emergent patterns, unexpected outcomes and counterintuitive behaviours. Identifying and analysing these patterns are essential for enhancing decision-making processes and adapting RL or CLSC networks to achieve desired performance goals (Coenen *et al*., 2018). Consequently, research has increasingly relied on CST as a foundational framework for understanding RL and CLSC dynamics. Applications of this theory range from analysing waste management challenges in the petroleum industry (Engelseth, 2017) to facilitating the digitalisation of CLSC networks through the adaptation of Industry 4.0 technologies (Simonetto *et al.*, 2022).

The heightened complexity of RL and CLSC networks necessitates resilience as a system-wide characteristic – one that ensures these networks can maintain functionality and adapt despite disturbances. Resilience, as a concept, often appears in interdisciplinary areas concerned with complex systems, such as enterprises, critical infrastructure and ecosystems.

From these perspectives, resilience is usually regarded as an inherent attribute of complex systems, enabling them to survive, adapt and thrive in the face of change (Holling, 1973; Dalziell and McManus, 2004; Gibbs, 2009). Accordingly, in the context of RL and CLSC networks, resilience must also be approached holistically, focusing on the interactions and interdependencies between system components rather than isolating individual elements (Dalziell and McManus, 2004; Fiksel, 2006). This perspective recognises that resilience is not static but evolves as the system interacts with its environment.

Viewing resilience through the lens of CST provides valuable insights into how RL or CLSC networks can adapt, evolve and withstand disruptions. By understanding the sources and effects of complexity, as well as employing strategies to manage uncertainty, RL and CLSC networks can develop the systemic resilience needed to operate effectively under adverse conditions.

2.2 Resilience in RL and CLSC through risk identification and mitigation

To build a foundation for understanding resilience in RL and CLSC networks, it is crucial to explore the core definition of SCRES. SCRES is commonly defined as the ability of an SC to prepare for, adapt to and recover from disruptions while maintaining its core functionality or even enhancing its performance (Blackhurst *et al*., 2011; Jüttner and Maklan, 2011). In other words, resilience directly reduces the impact of risks by enabling SCs to respond effectively to challenges, ensuring both continuity and long-term success.

Central to such definitions is the interdependent relationship between risks and the firms' abilities demonstrated through their mitigation strategies. Resilience cannot exist without first understanding risks. Giannakis and Papadopoulos (2016) also highlighted how essential it is to identify and understand risks before applying any mitigation strategies. Risks define the problems (i.e., understanding what we are dealing with), and mitigation strategies provide the solutions (i.e., understanding how we can deal with it). Together, they form the backbone of resilience, making risk identification and mitigation inseparable and equally vital in building robust SCs.

This interdependence is particularly critical in RL and CLSC networks, where new risks constantly emerge, and existing risks evolve. Risk identification, therefore, needs to extend beyond recognising potential disruptions to involve evaluating their characteristics to prioritise actions. Mitigation strategies then complement this by addressing risks at different stages of the risk management process, enabling networks to anticipate, respond to and recover from disruptions effectively. Linking specific risks to targeted mitigation strategies ensures a focused and efficient approach to resilience.

3. Review methodology

A literature review is a systematic approach to identifying, evaluating and interpreting existing research, helping to uncover gaps, synthesising scattered findings, and, therefore, serving as an essential foundation for theory development (Seuring and Gold, 2012). Accordingly, to gain a thorough understanding of SCRES in RL and CLSC, a comprehensive literature review is conducted using the systematic research approach proposed by Mayring (2010). This method has been widely employed in a number of review papers in the SC field, such as Seuring (2013), Nguyen *et al*. (2018) and Duong *et al*. (2022), as it provides a reasonable examination of the decisions taken and ensures the quality of the review process. Specifically, the review is carried out through an iterative process with four steps: material collection, descriptive analysis, category selection and material evaluation. This structured approach acts as a backbone supporting the analysis of relationships between the key constructs in the conceptual framework outlined above, as well as their interconnections.

3.1 Material collection

Publications presented and analysed here were collected across three well-known academic databases, i.e., Scopus, Web of Science and EBSCOhost until October 2024 to ensure the

coverage of relevant sources and minimise the impact of subjective bias. In particular, the search focused on articles written in English and published in peer-reviewed journals, with no limit set on the date range.

Two groups of keywords, as listed below, were combined to capture the synthesis of existing literature related to our research topic.

(1) Group 1: Words related to RL and CLSC: "reverse logistics"; "reverse supply chain"; "closed-loop supply chain".

(2) Group 2: Words related to resilience: resilien*; risk*; disrupt*; vulnerab*; robust*.

Note that in Group 1, a double quotation mark was applied to each term to obtain more relevant papers. As for Group 2, keywords were chosen in line with other systematic reviews on SCRES (Ali *et al*., 2017; Ali and Gölgeci, 2019). Further, an asterisk (*) sign was placed on each term to broaden the coverage by retrieving articles that used variations of the keywords (e.g., resilien* would find "resilience", "resilient" or "resiliency"). The search was then set up to look for these combinations within the titles, abstracts and articles' listed keywords. On that account, we collected a total of 2,209 papers. These papers then went through the process of duplication removal, title and abstract review, full-text analysis and cross-referencing as summarised in Figure 1, forming a sample of 194 studies for the full review. Although the search did not apply any time restrictions, the earliest relevant study retrieved from the databases was published in 2005. Therefore, the 2005–2024 span reflects the natural range of studies returned by the search rather than a predefined temporal cut-off.

3.2 Descriptive analysis

In this section, a descriptive analysis is conducted to provide preliminary insights into the collected articles through a descriptive lens. This analysis focused on (1) the distribution of publications over time and (2) the number of articles published across various journals.

As illustrated in Figure 2, these articles were published between 2005 and 2024. Yet the topic of resilience in RL and CLSC has not gained much attention until the early 2010s and has only become popular in recent years. On the other hand, this research area still appears to be understudied when compared with the development of research about resilience in the forward flow. A quick search within a more limited range (i.e., a search within articles' titles on Scopus only) using keywords related to SC and resilience, whilst excluding terms about RL and CLSC, returns around 1,600 papers.

Regarding the journal-wise distribution, the selected papers are spread across 102 academic journals, among which only 14 have published more than 2 papers. Table 1 provides the list of these 14 journals, which comprise 90 articles (around 46% of the total publications). This indicates that our considered topic is covered in a great variety of journals. Furthermore, the diversity of journals' research themes (e.g., production research, engineering, mathematical modelling, operations management) also proves the multidisciplinary nature of the topic and the increasing attention it is attracting from various research communities.

3.3 Category selection

Each of the 194 articles was initially summarised and broken down into a number of themes based on their content. These themes served as the foundation for identifying key constructs across the studies. The synthesis was then conducted by consolidating the papers to identify associations and common constructs that are consistently discussed in the literature. In systematic literature reviews, various approaches to synthesis are available, including aggregation, integration, interpretation and explanation (Rousseau *et al*., 2008). For this review, the integration approach was chosen due to the heterogeneous nature of the articles and the objective of synthesising insights from multiple studies and methods to address the research question.

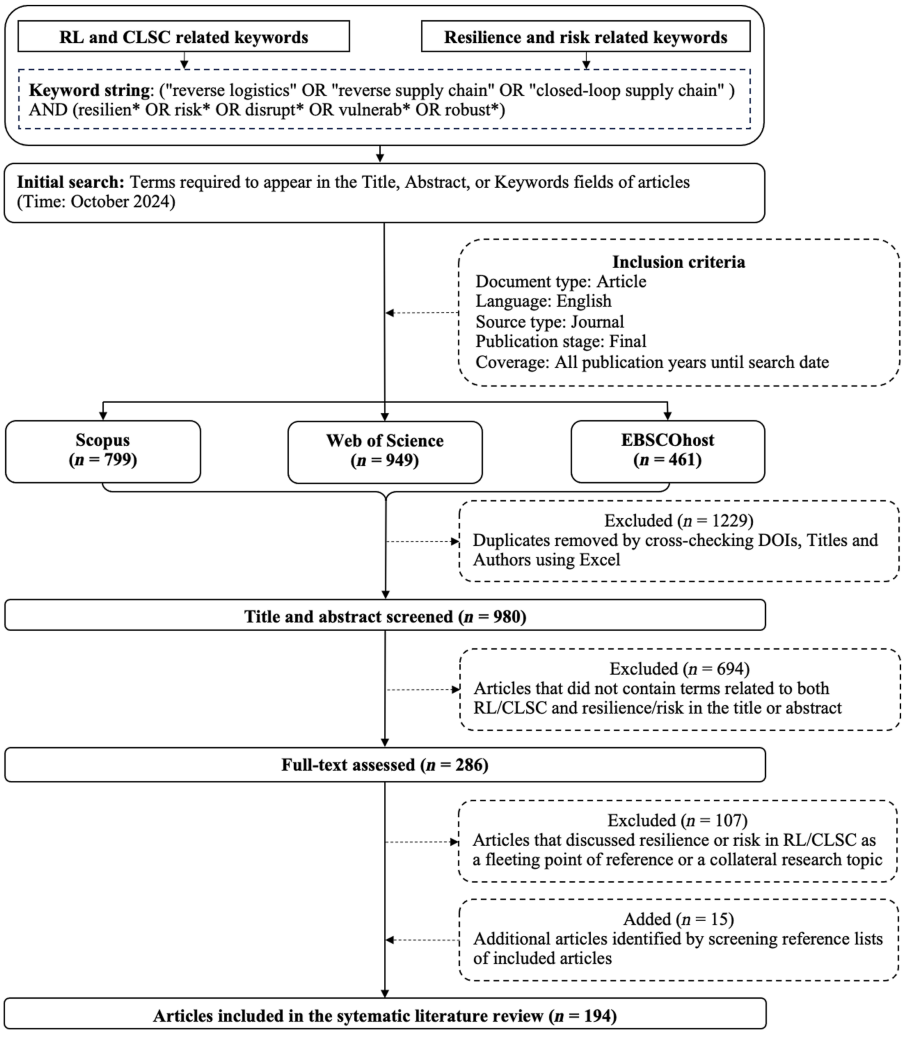

Figure 1. Literature selection process. **Source(s):** Authors' own work

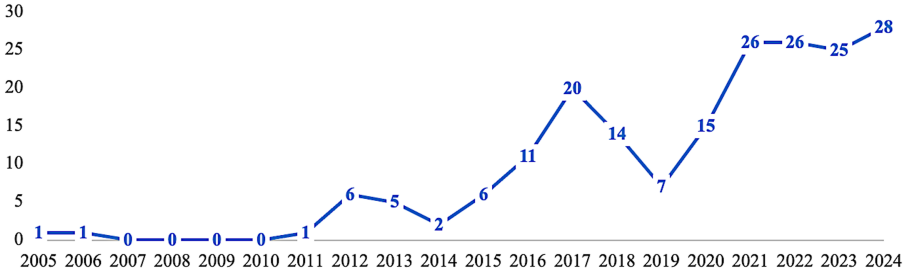

Figure 2. Number of publications by year. **Source(s):** Authors' own work

Table 1. Top 14 journals representing resilience in RL/CLSC

Journal title	Number of papers (N = 194)
Journal of Cleaner Production	13
International Journal of Production Economics	12
Computers and Chemical Engineering	11
Annals of Operations Research	9
Applied Soft Computing	7
Sustainability	7
International Journal of Production Research	5
Environment, Development and Sustainability	5
Environmental Science and Pollution Research	4
International Journal of Engineering	4
Applied Mathematical Modelling	4
International Journal of Physical Distribution and Logistics Management	3
Mathematical Problems in Engineering	3
Scientia Iranica	3

Source(s): Authors' own work

To clarify further, some categories within the identified constructs were pre-selected based on existing frameworks, reflecting a deductive approach, while others emerged inductively from insights gained during the review process. This iterative process involved continuously refining these categories throughout the analysis to formulate the conceptual framework presented in this paper.

3.4 Material evaluation

After the key constructs along with their categories were identified, each paper was analysed and coded according to the relevant categories within each construct. A frequency count of the categories was performed, and the results were interpreted accordingly. Additionally, the constructs were cross-checked with one another to provide more insights and reveal interconnections. The subsequent synthesis is an informed interpretation of the scientific evidence relating to the research question and the gaps found in the review process.

4. Findings and discussion from the content analysis

The findings from the literature review are presented in four sub-sections. Firstly, the risk types identified in the literature are analysed to uncover the events and conditions that drive risks in RL and CLSC networks. Secondly, the mitigation strategies employed at various stages of the risk management process are examined to ensure their alignment with the specific risks they are designed to address. Thirdly, the approaches used to develop and implement these mitigation strategies are explored, focusing on how the proposed mitigation strategies can be operationalised in real-world settings. Finally, a holistic framework is proposed to enhance conceptual clarity by integrating the key constructs that emerged from the literature review.

4.1 Risk types in RL and CLSC resilience

4.1.1 Risk identification. In this first construct, based on their terminologies and definitions, the considered risks were categorised into 16 types as presented in Figure 3. A large part of the sample (150 papers) refers exclusively to one risk type, while most of the remaining papers cover 2–3 types simultaneously. This results in a total frequency of 244 mentions of risks across the reviewed literature.

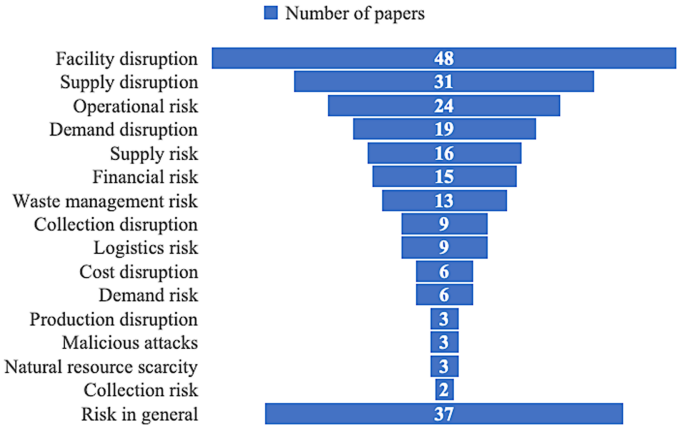

Figure 3. Identification of risk types. **Source(s):** Authors' own work

A conceptual distinction is drawn between the terms "risk" and "disruption" used in these categories to enhance analytical clarity. "Risk" refers to *ex ante* vulnerabilities – latent conditions or uncertainties that may lead to adverse outcomes – whereas disruption denotes ex-post realised events or, in the reviewed papers, simulated disturbances used to test network resilience. Accordingly, disruptions such as "supply disruption" or "demand disruption" are treated as extensions of their parent categories ("supply risk", "demand risk"), reflecting how potential vulnerabilities can escalate into system shocks. Additionally, the category termed "risk in general" captures papers that mention risk or disruption without providing a clear definition of the specific risks considered. Detailed references of these risk types are provided in Table S1 of the Supplementary Materials.

Here, we highlight the risk types that are specific and unique to RL and CLSC. Among the 16 identified risk types, those related to waste management, the collection process and natural resource scarcity are considered distinct to RL and CLSC. These risks arise from the specialised characteristics of RL and CLSC networks, which can help to address inherent challenges of certain industries. For instance, sectors like healthcare, hospital furniture and explosive waste management require safe and efficient waste handling to prevent the spread of infectious diseases or hazardous chemicals (De Oliveira *et al.*, 2021; Lotfi *et al.*, 2021a; Hrouga *et al.*, 2022). Meanwhile, industries such as lead-acid battery manufacturing, electronic appliances and used engine oil heavily depend on the collection process in RL and CLSC, which ensures that used products are retrieved either to meet legal targets defined by environmental regulations or to recover valuable materials essential for reuse and recycling (Subulan *et al.*, 2015; Safaei *et al.*, 2017). Furthermore, the growing emphasis on conserving natural resources has led to the increased adoption of CLSC, raising critical concerns about how these networks can minimise uncertainties surrounding strategic resource availability (Asif *et al.*, 2012; Bell *et al.*, 2013).

Additionally, risks typically associated with forward SCs, such as facility disruptions, supply/demand challenges and logistic risks, were also identified. However, in the RL and CLSC context, these risks are considered from a broader spectrum, introducing unique challenges. For instance, facility disruptions in RL and CLSC often involve hybrid production–reproduction, production–recovery or distribution–collection facilities (Hatefi and Jolai, 2014, 2015; Ziari and Sajadieh, 2022). Disruptions in these multi-purpose facilities can impact several processes at once, resulting in more significant consequences compared to disruptions in single-purpose facilities.

Supply risks or disruptions in RL and CLSC frequently involve the timing, quality and quantity of returned, remanufactured, recycled or EOL products (Chen *et al.*, 2018; Huang and Wang, 2018;

Bakhshi and Heydari, 2021), which are more uncertain compared to the relatively stable supply of newly produced products in the forward flow. On the demand side, challenges include fluctuations in consumer interest in green products or sudden demand surges that disrupt recycling networks (Cheramin *et al.*, 2021; Dev *et al.*, 2021). Logistical risks are also further amplified in RL and CLSC due to delays, breakdowns or accidents during the transportation of used products, components and hazardous materials (Doan *et al.*, 2018; Meybodi *et al.*, 2022). Due to these additional dimensions, RL and CLSC introduce a broader and more nuanced range of risks, necessitating tailored strategies and approaches for effective management.

4.1.2 Risk evaluation and grouping. Once the main types of risks were identified, a classification mechanism was applied to further group these risks together, facilitating a more structured comparison of risks and enabling their alignment with mitigation strategies in the subsequent discussion. Traditional risk classification methods typically categorise risks based on their level of expectancy (i.e., operational/disruption risks) (Tang, 2006) or the nature of their causes (i.e., internal/external risks) (Rao and Goldsby, 2009; Rangel *et al.*, 2015). However, for this study, the probability–impact–manageability (P-I-M) matrix was chosen as it is proven to be a more nuanced and actionable tool.

The P-I-M matrix classifies risks based on three critical dimensions: the *probability* (*P*) of a risk occurring, its potential *impact* (*I*) and the organisation's *manageability* (*M*) when that risk event happens. While the first two dimensions are commonly paired in risk analysis (Lee *et al.*, 2012; Kırılmaz and Erol, 2017), the third dimension – manageability – is integrated into this matrix to account for the influence of the surrounding environment and the organisation's capacity to mitigate risks (Charkhakan and Heravi, 2018). This makes the matrix particularly well-suited to the complex and multifaceted risks inherent in RL and CLSC networks. This approach, therefore, provides a clearer understanding of the risks faced by RL and CLSC networks and enables a fine-grained yet practical classification system. By balancing detail with simplicity, the P-I-M matrix enhances the effectiveness of risk assessment and management.

Next, for each dimension in the matrix, the risk types identified above are evaluated at three levels: low, medium and high. Following the same approach used by Thun and Hoenig (2011), this paper presumed that internal risks, such as supplier problems or demand changes, have a higher probability of happening than those caused by external factors, like war, terrorist attacks or natural disasters. It is also expected that external incidents will have a higher impact as their occurrence is normally accompanied by grave consequences. In terms of risk manageability, even though it depends heavily on the SC components and their paths, internal risks are normally perceived to be more manageable than external ones (Brindley, 2017).

Table 2 gives an illustrative list of the considered risk types mapped to the P-I-M matrix. In other words, risk types with the same level of probability, impact and manageability will be grouped together. We rank the identified groups according to the total frequency of their sub-groups being mentioned in reviewed articles and name them alphabetically. Details regarding risk types in Groups A, B, C, D, E and F are discussed below. It should also be noted that the "risk in general" group (Group G) includes cases where risks are not clearly defined, or various types are examined at once. Hence, the P-I-M matrix would not be applied to this group.

Among the presented groups, *Group A* was mentioned the most (in 116 papers). Overall, these risk types are resulted from unprecedented external factors that could disrupt one or many parts of the SC network. Thus, they are classified as having low probability to happen, high impact and low manageability. Within this group, *facility disruptions* caused by environmental or social factors are the most frequently addressed, followed by *supply* and *demand disruptions*. Supply disruptions include issues like supplier capacity loss or product quality problems, while demand disruptions relate to stockouts or unexpected surges in consumer demand. *Cost*, *collection* and *production disruptions*, mostly leading to the unavailability of remanufacturing and collecting processes, are less frequently mentioned.

Group B is discussed 42 times and reflects risks with medium levels across all dimensions of the P-I-M matrix. These risks are more internal, occurring frequently during operations and

Table 2. Grouping of risk types

Risk group	Probability	Impact	Manageability	Type of risk	Number of papers
A	Low	High	Low	Facility disruption Supply disruption Demand disruption Collection disruption Cost disruption Production disruption	*116*
B	Medium	Medium	Medium	Supply risk Financial risk Logistics risk Collection risk	*42*
C	High	Low	High	Operational risk	*24*
D	Medium	High	Medium	Waste management risk Malicious attacks	*16*
E	Medium	Medium	Low	Demand risk	*6*
F	Medium	High	Low	Natural resource scarcity	*3*
G	Risk in general				*37*

Source(s): Author's own work

being more manageable. Examples include *financial risks* (cost variance and returns), *supply risks* (e.g., supply shortages or defective materials), *logistic risks* (transport variability and shipping damages) and *collection risks* (uncertainty in the number of products collected for RL).

The remaining groups have lower frequencies. *Group C* includes operational risks (24 mentions), characterised by inherent uncertainties in SC models, with high probability, low impact and high manageability. *Group D* (16 mentions) and *Group F* (3 mentions) cover specific causes such as waste, cybercrime and resource scarcity. These risks are medium in probability and high in impact, though manageability is higher for Group D due to the fact that it is more feasible for a business to improve its waste collection process and cybersecurity system than to control the shortage of natural resources. *Group E* (six mentions) highlights demand risks, particularly uncertain demand for used products, which have a medium probability and impact but low manageability due to their external dependence on customer behaviour.

The analysis of risks in RL and CLSC networks reveals structural characteristics that closely reflect the behaviour of complex systems. A first distinguishing feature is the strong *interdependence* between network components, particularly in processes unique to circular flows such as collection, resource recovery and waste handling. For instance, small variations in the timing, quantity or quality of products returned to collection points can restrict remanufacturing throughput, reduce recycling capacity or generate downstream shortages. This pattern aligns with the "ripple effects" often observed in complex multi-echelon networks, where localised shocks transmit through tightly coupled material, information and financial linkages (Dolgui and Ivanov, 2021).

A second characteristic is the *topological sensitivity* arising from structurally central nodes. Hybrid production–recovery facilities, distribution–collection hubs and multi-purpose processing centres sit at critical junctures of forward and reverse flows. Disruptions at these locations – often triggered by external hazards – produce disproportionately large system impacts since losses cascade simultaneously across multiple process loops. This reflects the behaviour of complex network topologies in which centrality, reciprocity and pooling amplify systemic vulnerability (Choi *et al.*, 2001; Pathak *et al.*, 2007).

Thirdly, the evaluation of risks across probability, impact and manageability dimensions points to pronounced *nonlinearity* in system responses. External or structurally oriented

disturbances typically exhibit low occurrence but very high consequence and limited controllability, whereas operational or process-level uncertainties occur more frequently but are absorbed more effectively. This asymmetrical structure means that seemingly modest deviations can cross design or capacity thresholds and trigger cascading effects far larger than the initiating event. The resulting disruptions are therefore not proportional to the size of the initiating perturbation, demonstrating a hallmark of nonlinear system behaviour.

Taken together, these patterns show that risks in RL and CLSC networks reflect interdependence, topology sensitivity and nonlinear amplification. This positions RL and CLSC resilience challenges firmly within a CST lens and establishes the need for mitigation strategies that explicitly contend with – and are designed around – the dynamics of such complex and tightly coupled systems.

4.2 Mitigation strategies for different risk types in RL and CLSC

4.2.1 Mitigation strategies. This second construct adapts the integrated view of SCRES proposed by Ali *et al*. (2017), which is widely regarded as one of the most comprehensive concept mappings for understanding the components of SCRES. In detail, mitigation practices identified in the literature were classified into three broad categories of strategies, aligned with the stages of the risk management process: proactive strategies (before a risk occurs), concurrent strategies (while a risk is occurring) and reactive strategies (after a risk has occurred). These strategies are further broken down into 11 essential elements for SCRES as shown in Figure 4. Detailed references of these mitigation strategies are included in Table S2 of the Supplementary Materials of this article.

As shown in Figure 4, elements supporting *proactive strategies* are talked about the most (251 times) since researchers strived to anticipate and prepare for the potential impact of SC risks before they happen. Specifically, designing or redesigning an RL or CLSC to make it more robust (Liu *et al*., 2021) and integrating different risk measures to gain better situational awareness (Lotfi *et al*., 2021b) are the two most popular practices. Few other attempts to implement proactive strategies include increasing SC visibility through information sharing (Mehrjerdi and Shafiee, 2021) or Internet of Things (IoT) sensors implementation (Hrouga *et al*., 2022), establishing risk or resilient management systems (Fang and Xiao, 2013), and building security by having contracts with reliable suppliers (Ghomi-Avili *et al*., 2021) or integrating blockchain technology into the SC (Hrouga *et al*., 2022).

Meanwhile, concurrent and reactive strategies are mentioned at more modest frequencies, which are 95 and 21 times, respectively. The idea of *concurrent strategies* is to cope with

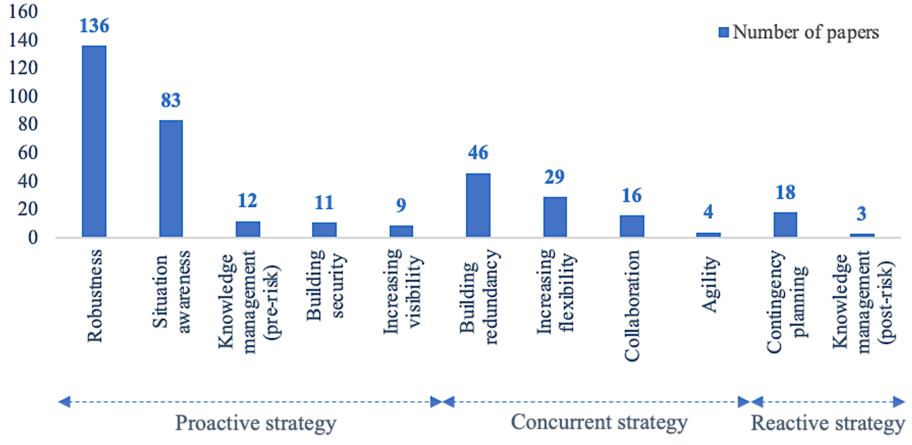

Figure 4. Classification of mitigation elements. **Source(s):** Authors' own work

disturbances during the risk phase. This is reflected in themes, such as building redundancy through extra inventory (Ghomi-Avili *et al.*, 2017), multi-level safety stock (Fazli-Khalaf *et al.*, 2019) and backup suppliers (Sugimura and Murakami, 2021); increasing flexibility through two-hub facility locations (Ghadge *et al.*, 2016), multiple sourcing (Zare Mehrjerdi and Shafiee, 2020) and alternative route decision (Babaeinesami *et al.*, 2021); initiating collaboration through profit-sharing or revenue-sharing contracts (Hosseini-Motlagh *et al.*, 2020); and improving agility by studying the recovery speed during risk (Dev *et al.*, 2021). *Reactive strategies*, on the other hand, refer to what is required in the post-risk phase to help the SC recover. Hence, practices like lateral transhipment (Ghomi-Avili *et al.*, 2019), dynamic allocation (Mishra and Singh, 2020) and risk impact analysis (Duan *et al.*, 2021) are counted here.

The popularity of proactive strategies in RL and CLSC contrasts sharply with the trend observed in traditional SCs, where the focus has predominantly been on reactive strategies (Wieland and Wallenburg, 2013; Ali *et al.*, 2017). This contrast can be attributed to the relatively recent emergence of RL and CLSC as a research area, which began gaining significant attention in the early 2000s (Gallegos *et al.*, 2024). This later development allowed RL and CLSC research to build upon the experiences and lessons learned from the more established forward SCs. With insights into the challenges faced in forward flows and the inherently greater complexity of RL and CLSC systems, researchers and practitioners have been more inclined to adopt proactive approaches to risk management. Furthermore, RL and CLSC systems are closely tied to sustainability goals and the circular economy, where preventing adverse situations is critical for maintaining smooth and efficient operations. The growing interest in smart SCs, driven by recent technological advancements, has also provided the tools necessary to support the implementation of proactive capabilities in RL and CLSC.

4.2.2 Relationship between mitigation strategies and risk groups in RL and CLSC. To reveal more insights from this taxonomy, we further investigate how each type of strategy has been studied in accordance with each specific risk group, as demonstrated in Table 3.

Overall, the two most popular mitigation elements, i.e., robustness and situation awareness, are applied in almost all risk circumstances, showing great interest in network design problems and risk sensing methods in the RL and CLSC context. Other elements are often suggested under disruption situations as they come with low probability but have high impact and low manageability. Hence, disruption risks as listed in Group A are attracting more attention, and accordingly, more mitigation strategies are being considered for them. Another notable point is that even though collaboration, agility and contingency planning are usually viewed as some of the most widely known elements to enhance resilience (Ali *et al.*, 2017; Shekarian and Mellat Parast, 2021), they appear to have rather limited application in the context of RL and CLSC.

Table 3. Distribution of mitigation elements by risk groups

Mitigation strategies	Mitigation element	Risk group A	B	C	D	E	F	G	Number of papers
Proactive	Robustness	69	24	11	9	4	–	19	*136*
	Situation awareness	29	30	3	5	2	1	13	*83*
	Knowledge management (pre-risk)	3	–	–	2	–	–	7	*12*
	Building security	7	–	–	2	–	–	2	*11*
	Increasing visibility	5	1	–	1	–	1	1	*9*
Concurrent	Building redundancy	35	2	1	1	1	–	6	*46*
	Increasing flexibility	20	1	1	2	–	–	5	*29*
	Collaboration	15	1	–	–	–	–	–	*16*
	Agility	3	–	–	–	–	–	1	*4*
Reactive	Contingency planning	11	1	1	1	–	1	3	*18*
	Knowledge management (post-risk)	1	1	–	–	–	–	1	*3*

Source(s): Authors' own work

To complement the risk-strategy mapping, Table 4 provides a sectoral view of dominant risk types and commonly deployed mitigation elements across the reviewed studies. Three cross-sector insights stand out. Firstly, exposure profiles differ: facility disruptions dominate capital-intensive and tightly coupled systems (e.g., automotive, healthcare), whereas waste management and collection risks are more salient in hazardous/solid-waste and consumer-goods sectors, where reverse flows and regulatory thresholds matter. Secondly, mitigation portfolios are selective rather than uniform: although robustness and situational awareness recur across sectors, automotive/electronics often emphasise redundancy and flexibility to buffer component shortages; healthcare combines flexibility with contamination-aware design; and waste sectors rely heavily on visibility and security to manage hazardous transport and compliance. Finally, hybrid nodes play a defining role: sectors dependent on hybrid production–recovery or distribution–collection facilities tend to prioritise design-stage robustness because disruptions at these hubs propagate through both forward and reverse loops. It is also worth noting that 76 papers in the sample do not specify any industry or sector, and therefore could not be assigned to a sectoral category.

The observed pattern of mitigation strategies further reinforces the complex-systems interpretation of RL and CLSC resilience. The dominance of proactive measures – particularly robustness and situational awareness – reflects a strong emphasis on *anticipatory adaptation* within CST (Choi *et al*., 2001; Pathak *et al.*, 2007). In RL and CLSC, where reverse flows introduce high variability and uncertainty, such design-time interventions help stabilise system behaviour by reducing sensitivity to upstream fluctuations.

Concurrent strategies – redundancy, flexibility, collaboration and agility – provide a second layer of resilience by enabling real-time absorption of disturbances rather than relying solely on *ex ante* preparation. These strategies mirror decentralised coordination and *self-organisation* principles in complex systems, where resilience emerges through distributed adjustments instead of centralised control (Peters *et al*., 2023). By adding structural slack and alternative response pathways, they help dampen shock propagation and address the non-linear volatility characteristic of RL and CLSC risks.

Meanwhile, reactive strategies, such as post-event learning and knowledge management, demonstrate the system's capacity to update routines, revise protocols and redesign processes following disruptions. This aligns with CST's *adaptive learning* property, where resilience develops through iterative feedback and accumulated experience (Adobor, 2020).

When mapped against the risk groupings, proactive strategies appear across nearly all groups, underscoring their foundational role in shaping network architecture under both internal and external uncertainties. By contrast, concurrent and reactive strategies tend to cluster around low-probability, high-impact, low-manageability disruptions. This concentration indicates sensitivity to network topology, where disruptions at structurally important nodes or loops elicit disproportionate adaptive responses because they are more likely to trigger cascading effects across coupled forward–reverse flows.

Collectively, these patterns show that resilience in RL and CLSC emerges from the interplay between local responses and global network configuration rather than from any individual capability. This reinforces the view that RL and CLSC resilience is not a static set of risk-response routines but an adaptive system capability shaped by continuous interaction between structure (robust design) and behaviour (adaptive coordination and learning), consistent with the emergent properties of complex adaptive systems (Bozarth *et al*., 2009). Nevertheless, the relative scarcity of concurrent and reactive strategies compared with proactive ones suggests that RL and CLSC research still emphasises design-time interventions over run-time adaptability, despite CST highlighting the importance of dynamic, sense-and-respond mechanisms (Wieland and Wallenburg, 2013; Ivanov, 2020).

4.3 Approaches to develop mitigation strategies in RL and CLSC

4.3.1 Mitigation development approaches. This third construct focuses on the commonly used approaches for developing mitigation strategies, as proposed by researchers, to effectively

Table 4. Sectoral breakdown of RL and CLSC risks and common mitigation elements

Sector	Dominant risk types	Common mitigation elements	Exemplar papers
Automotive and mobility (*25 papers*)	- Facility disruption - Operational risk - Demand disruption - Supply disruption - Financial risk	- Robustness - Situation awareness - Building redundancy - Increasing flexibility - Building security - Increasing visibility	Gaur *et al*. (2020), Govindan and Gholizadeh (2021), Vali-Siar *et al.* (2022), Hosseini-Motlagh *et al.* (2023)
Electronics, electrical and semiconductor (*18 papers*)	- Supply disruption - Logistics risk - Demand risk	- Robustness - Situation awareness - Building redundancy - Increasing flexibility	Mutha *et al*. (2016), Abbey *et al.* (2017), Dou *et al.* (2024), Saeed *et al.* (2024)
Metals, glass and materials processing (*18 papers*)	- Facility disruption - Supply disruptions - Financial risk	- Robustness - Building redundancy - Contingency planning - Situation awareness - Building security	Jabbarzadeh *et al*. (2018), Cheramin *et al.* (2021), Zerbino *et al.* (2023), Nayeri *et al.* (2024)
Healthcare and pharmaceuticals (*13 papers*)	- Facility disruption - Waste management risk - Supply risk - Demand risk	- Robustness - Situation awareness - Increasing flexibility	Hosseini-Motlagh *et al*. (2020), Hussaini *et al*. (2023), Alizadeh *et al.* (2024), Amoozad Mahdiraji *et al.* (2024)
Food and agriculture (*10 papers*)	- Facility disruption - Supply disruptions	- Robustness - Situation awareness - Building redundancy - Building security	Kim *et al*. (2014), Yavari and Zaker (2019), Maya Rodríguez *et al.* (2023)
Hazardous and solid waste management (*9 papers*)	- Waste management risk - Logistics risk - Collection risk - Demand risk	- Situation awareness - Robustness - Building redundancy - Increasing visibility - Building security - Knowledge management (pre-risk)	Zhao and Ke (2017), De Oliveira *et al*. (2021), Hrouga *et al*. (2022)

(*continued*)

Table 4. Continued

Sector	Dominant risk types	Common mitigation elements	Exemplar papers
Home appliances and consumer goods (*9 papers*)	- Facility disruption - Demand disruption - Collection disruption - Financial risk	- Robustness - Situation awareness - Increasing flexibility - Building redundancy	Asl-Najafi *et al.* (2015), Özçelik *et al.* (2021), Yılmaz *et al.* (2021)
Plastics, polymers and packaging (*8 papers*)	- Financial risk - Waste management risk - Supply risk - Operational risk	- Robustness - Situation awareness - Knowledge management (pre-risk)	Yousefi-Babadi *et al.* (2017), Ebrahimi and Bagheri (2022), Sumrit and Keeratibhubordee (2024)
Logistics and e-commerce (*5 papers*)	- Facility disruption - Collection disruptions - Supply risk - Logistics risk	- Robustness - Situation awareness - Increasing flexibility - Building redundancy	Prakash *et al.* (2020), Lorenzo-Espejo *et al.* (2024), Sun *et al.* (2024)
Industrial and mechanical equipment (*3 papers*)	- Operational risk - Facility disruption - Supply disruptions	- Robustness - Situation awareness - Collaboration - Building security	Godichaud *et al.* (2012), Ghomi-Avili *et al.* (2018, 2021)

Source(s): Authors' own work

address the identified risks. While the second construct explains the mitigation strategies in theory, this construct emphasises the modelling approaches needed to implement these strategies in practice. The modelling approaches are categorised into two main groups: qualitative and quantitative. Among 194 papers, only 9 of them are qualitatively oriented (see Figure 5a). Meanwhile, the majority of the reviewed literature (185 papers) employed quantitative methods. The detailed approaches are illustrated in Figure 5. Detailed references of these modelling approaches are provided in Table S3 of the Supplementary Materials.

Within the large pool of quantitatively oriented papers (see Figure 5b), the reviewed literature identifies *optimisation* models as the most prominent modelling approach, accounting for 72% of these studies. They incorporate decision variables (such as facility locations, routing and capacity levels) along with objective functions (like cost minimisation, risk reduction and collection expansion) while handling uncertainties through techniques like scenario planning and robust optimisation to enable the identification of the most suitable design for the network in question.

Game theory, representing 12% of the studies, is often utilised to evaluate impacts and achieve coordination under disruptions, particularly in cases involving multiple recycling/collection channels or diverse (re)manufacturing modes. These models also help to propose revised production plans and coordination mechanisms, such as profit-sharing and risk-sharing contracts. Meanwhile, *Simulation* models (4%) focus on analysing the effects of disruptions and testing network performance under adverse conditions, such as material flow interruptions or disaster events. A smaller proportion of studies (4%) employ *hybrid* methods, which combine simulation with other methodologies. The final category, termed "*Others*",

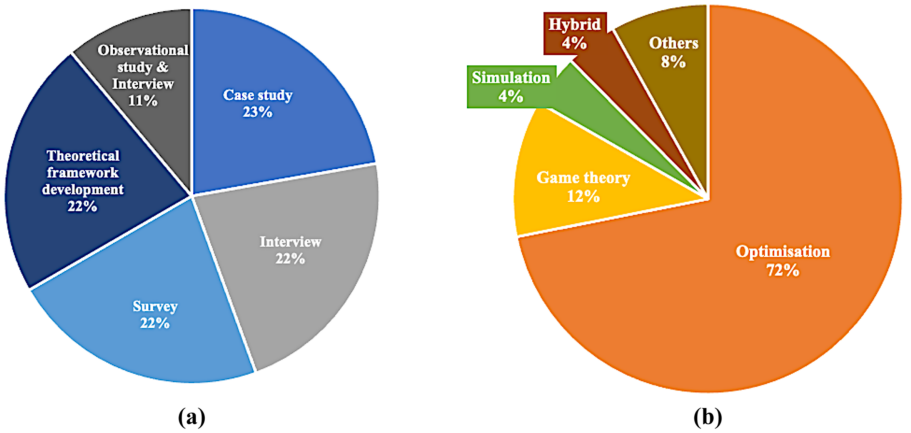

Figure 5. Classification of papers following (a) qualitative approaches and (b) quantitative approaches. **Source(s):** Authors' own work

includes unique approaches (8%) such as Multi-Criteria Decision-Making models, Bayesian networks and equation modelling.

While all the mentioned quantitative approaches are *model-based* and grounded in a physical understanding of SC systems, there is one study in the literature that applies a data-driven approach. This study utilised unsupervised machine learning (ML) to cluster RL risks into strategic, tactical and operational categories (Panjehfouladgaran and Lim, 2020), highlighting the early-stage development of data-driven methods in this domain. Unlike model-based approaches, data-driven methods rely on statistical analysis and ML techniques to identify patterns and predict trends without depending heavily on an underlying physical model. This makes them particularly useful in dynamic and complex environments like RL and CLSC systems under risk (Ivanov and Dolgui, 2021).

4.3.2 Relationship between mitigation development approaches and mitigation strategies in RL and CLSC. It is also important to highlight the relationship between the mentioned mitigation elements and mitigation development techniques, as depicted in Table 5.

Optimisation models, which constitute a significant portion of the modelling approaches, are widely implemented to help RL and CLSC networks develop proactive strategies by enhancing robustness and improving situational awareness. Specifically, these models strengthen network robustness through the integration of diverse objective functions and decision variables during the design process. Objective functions explicitly model trade-offs within these networks. By optimising these functions, the network can achieve an optimal balance aligned with the organisation's strategic priorities while remaining prepared for disruptions. On the other hand, the consideration and timely adjustment of decision variables, particularly those related to facility locations, material and product quantities, their flows within the networks, and routing decisions, enable the network to adapt dynamically to changes in risk scenarios. These variables also reflect real-world constraints, thereby improving the network's ability to respond effectively to challenges. Moreover, different types of risk measures are often merged in this design process, which helps the decision makers become more aware of the risks they might face.

The contribution of optimisation models in some concurrent and reactive elements, like building redundancy, increasing flexibility and contingency planning, is also worth noticing. This is made possible as strategies like multiple facility locations, capacity flexibility, extra or back-up options, lateral transhipment, dynamic allocation, etc., are incorporated in the SC network during the design stage.

Table 5. Distribution of mitigation elements by mitigation development approaches

Mitigation strategy	Mitigation element	Mitigation development approaches						Number of papers
			Quantitative					
		Qualitative	Optimisation	Game theory	Simulation	Hybrid	Others	
Proactive	Robustness	–	129	4	–	2	1	*136*
	Situation awareness	6	46	14	4	4	9	*83*
	Knowledge management (pre-risk)	3	2	–	2	1	4	*12*
	Building security	1	7	1	–	1	1	*11*
	Increasing visibility	1	5	1	1	–	1	*9*
Concurrent	Building redundancy	1	36	3	4	–	2	*46*
	Increasing flexibility	–	24	1	3	–	1	*29*
	Collaboration	–	7	7	2	–	–	*16*
	Agility	–	1	–	2	–	1	*4*
Reactive	Contingency planning	–	15	–	–	1	2	*18*
	Knowledge management (post-risk)	–	–	–	1	1	1	*3*

Source(s): Authors' own work

Considering the patterns observed in modelling approaches, the dominance of optimisation models indicates that most studies still represent RL and CLSC systems as static and design-oriented, focusing on optimal configurations under predefined risk scenarios. While this supports the development of proactive strategies, it also reflects an underlying assumption that the system is structurally controllable rather than dynamically adaptive. From a complex-systems perspective, such optimisation frameworks fulfil an *anticipatory design* function but are limited in capturing emergent, real-time responses once perturbations occur.

By contrast, the presence of game-theoretic and simulation-based models introduces interactive, feedback-driven and nonlinear mechanisms that are more consistent with CST. Game-theoretic formulations allow decentralised agents (e.g., suppliers, manufacturers, recyclers) to iteratively adjust their strategies, demonstrating how local decision rules can lead to self-organisation and emergent coordination (Treiblmaier, 2018). Similarly, discrete-event and system-dynamics simulations model nonlinear disruption propagation, mirroring the ripple effect and feedback coupling documented in complex supply networks (Dolgui *et al*., 2018). The small but growing adoption of hybrid and data-driven methods further signals a shift toward *adaptive learning* models capable of updating system parameters or structural assumptions over time – aligning more closely with CST's emphasis on learning and evolution (Wieland *et al*., 2016).

Table 5 shows that optimisation models overwhelmingly support proactive elements – robust topology, redundancy, controllability – thereby strengthening structural resilience. Yet in CST terms, this represents only one dimension of adaptive capacity. The relative absence of modelling approaches to support concurrent and reactive strategies – such as those incorporating feedback control, agent-based adaptation or reinforcement learning – highlights a gap in capturing dynamic resilience, where strategies evolve alongside environmental conditions.

Overall, the current modelling landscape provides strong foundations for structural robustness but underrepresents the adaptive and emergent behaviours that underpin real-world resilience. A future methodological agenda that combines optimisation's prescriptive capability with simulation's exploratory power and data-driven methods' adaptive intelligence would allow RL and CLSC models to capture the full anticipate–absorb–adapt–evolve cycle of resilience (Pettit *et al*., 2010). Embedding CST principles into modelling approaches would thus shift the field from designing merely robust systems to cultivating resilient, learning systems capable of evolving through disruption.

4.4 Conceptual framework: linking the constructs of resilience in RL and CLSC

Through a systematic review of the literature, a conceptual framework was developed to consolidate insights into resilience in RL and CLSC. This framework, illustrated in Figure 6, integrates three key constructs – risk types, mitigation strategies and mitigation development approaches – identified and refined during the review process. It provides a structured foundation for understanding how RL and CLSC networks can prepare for, adapt to and recover from risks.

In line with complex systems principles, the framework captures the multidimensional interactions among risk types, mitigation strategies and development approaches, enabling a holistic analysis of resilience in RL and CLSC. Firstly, through risk identification and evaluation, the framework highlights the diversity and complexity of risks inherent in RL and CLSC, reflecting the unpredictable and emergent behaviours of complex systems. Secondly, the focus on mitigation strategies emphasises the proactive, concurrent and reactive measures that enhance resilience, aligning with the core principles of resilience as a system-wide capability. By ensuring alignment between specific risks and targeted strategies, the framework underscores the importance of preparedness and adaptability – key attributes of resilient systems. Finally, the inclusion of mitigation development approaches reflects the need for practical tools and methods to operationalise resilience. This integration bridges the gap between theory and practice, enabling RL and CLSC systems to not only survive but thrive in complex environments.

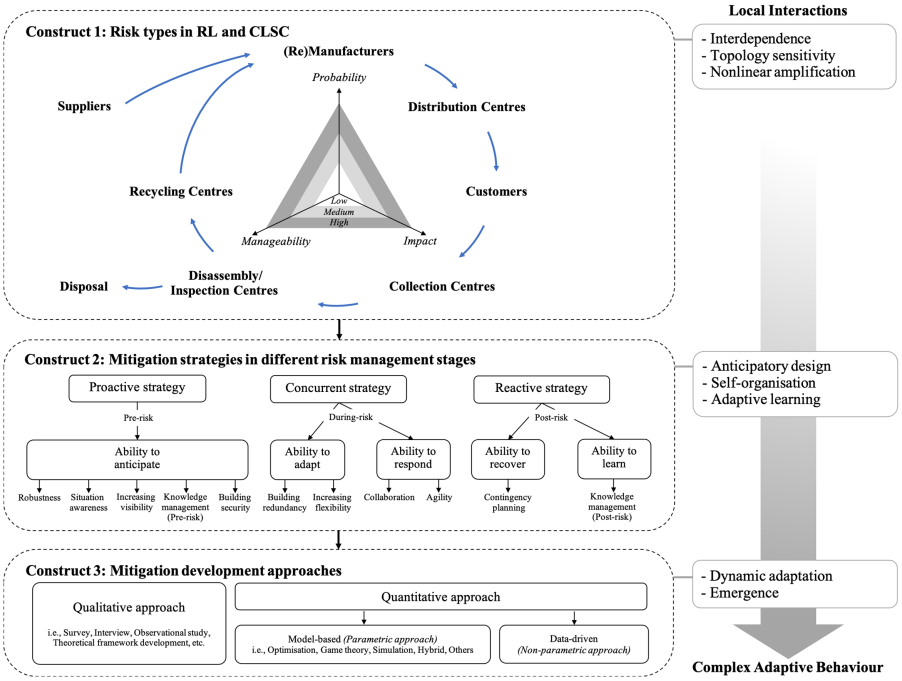

Figure 6. Conceptual framework. **Source(s):** Authors' own work

Altogether, the three constructs reveal that resilience in RL and CLSC emerges not from isolated capabilities but from the dynamic interactions between heterogeneous risks, multi-layered mitigation mechanisms and evolving modelling approaches. This interconnectedness reflects the defining properties of complex adaptive systems and explains why RL and CLSC networks exhibit distinctive resilience behaviour compared with traditional forward SCs.

The first construct shows that risks in RL and CLSC are structurally embedded within the network's topology – arising from interdependence between forward and reverse loops, the centrality of hybrid facilities and the nonlinear amplification of disturbances. The second construct demonstrates that mitigation is likewise distributed across different temporal layers: design-oriented anticipation, real-time adjustment and post-event learning. These layers act on different parts of the system and operate through different mechanisms, yet they co-produce resilience when aligned. The third construct highlights how methodological choices shape the system's adaptive potential, with optimisation models reinforcing structural robustness and emerging game-theoretic, simulation-based and data-driven approaches introducing feedback, learning and behavioural adaptation.

What the framework makes visible is the co-evolution of these constructs. Risk structures influence where and how mitigation is deployed; mitigation strategies, in turn, shape modelling needs; and modelling approaches feed back into the continuous redesign and recalibration of the system. This reciprocal shaping process mirrors CST's emphasis on emergence, where system-level resilience arises from distributed interactions. The framework, therefore, positions RL and CLSC resilience as a property that evolves through ongoing interaction between structure, behaviour and learning. This integrative interpretation provides a conceptual foundation for future research to move beyond static evaluations of risk or strategy toward a more holistic understanding of how resilience develops, degrades and regenerates within RL and CLSC networks.

5. Future research

The present review has consolidated knowledge around risk types, mitigation strategies and mitigation development approaches, revealing a dominance of proactive strategies and model-based methods. This imbalance underscores the need for studies that embrace the dynamic and interconnected nature of RL and CLSC systems – as characterised by CST – to develop more adaptive and comprehensive resilience mechanisms. Building on the above findings and the integrated conceptual framework, future research in RL and CLSC resilience should pursue novel, theoretically grounded avenues that address identified gaps while remaining methodologically feasible.

5.1 Development of risk identification and classification systems

While each SC faces unique risks, developing accurate identification techniques and universally accepted classifications is crucial to standardise risk assessment and mitigation strategies. For RL and CLSC, with their complex structures and diverse risk terminologies, comprehensive identification and classification systems are even more essential. Existing works about risk identification and classification, however, primarily focus on forward SCs, with data-driven models gaining popularity since 2015 (Deiva Ganesh and Kalpana, 2022).

The reviewed articles show limited efforts in identifying and categorising RL and CLSC risks, relying primarily on literature reviews, surveys and interviews. These methods are often outdated, prone to human bias and difficult to generalise due to small sample sizes. In contrast, advancements in information technology and big-data tools now enable real-time analysis of large datasets, offering evidence-based insights with greater efficiency. Future research, therefore, should leverage data-driven methods to systematically address risk identification and classification challenges in RL and CLSC, learning from advancements in forward SCs while adapting to the unique characteristics of reverse flows.

5.2 Investigation of risk interdependencies using complex systems and network analysis

The review demonstrates that RL and CLSC operate as interconnected networks, where disruptions in one area (such as regulatory changes or quality issues in returned materials) can propagate through multiple channels, causing ripple effects across the entire network. Without considering these interrelationships, mitigation plans might not be comprehensive enough, hence become more prone to failure.

Future studies can employ network science tools like agent-based modelling, system dynamics and network topology analysis to map and quantify these risk interdependencies. By explicitly modelling the cascading effects of disruptions, researchers can identify critical vulnerabilities and resilience nodes within RL or CLSC networks. For example, analysing centrality measures could reveal which nodes–such as major recycling hubs or key regulatory touchpoints – play pivotal roles in maintaining network stability. Empirical research could involve cross-case analyses or large-scale simulations to test the robustness of various mitigation strategies when facing interdependent risks. This approach advances theoretical understanding by conceptualising resilience as an emergent property arising from system-wide interactions rather than individual, isolated components, thereby making significant contributions to both SCRES theory and practice.

5.3 Focus on concurrent mitigation strategies

The literature review highlights a gap in the use of mitigation strategies in RL and CLSC, with most efforts focused on proactive measures based on experiences with known risks or past events. However, these strategies often fail when new risks emerge, as seen during the COVID-19 pandemic, which disrupted global SCs in unprecedented ways. This underscores the need for concurrent strategies that enable RL and CLSC networks to adapt in real time during risk events.

Therefore, more attention should also be paid to concurrent strategies. These strategies can help RL and CLSC networks adapt and respond to risk events more efficiently while they are happening. Adverse effects from global phenomena, like the COVID-19 pandemic, have created the urgency for more adaptable risk management systems that can gather real-time data to provide up-to-date information and help firms make accurate decisions under unfamiliar circumstances. With timely reflection about what is happening, firms can adjust their pre-designed plans and make accurate decisions in unfamiliar circumstances. For problems like the disrupted collection channels of remanufacturers in China, as stated in the introduction, frequent updates about alternative places to set up new factories, or available sources of materials to collect from, could support these remanufacturers in the decision-making process and help them restore their operations more quickly. Similarly, a system tracking the recycling process in real-time could help ship recyclers respond to the existing crisis by assisting them in allocating their labour force or organising their workflow more efficiently. Transitioning from purely proactive to concurrent approaches offers a promising direction for enhancing resilience in RL and CLSC and should be prioritised in future research and practice.

5.4 Integration of real-time, concurrent and reactive resilience strategies

The systematic review clearly indicates that while proactive measures have dominated scholarly discourse, strategies addressing real-time adjustments during disruptions (concurrent) and measures enacted after disruptions (reactive) remain significantly underexplored. Given the inherent complexity and dynamic interactions characterising RL and CLSC, future research should explore how digital technologies – such as the IoT, blockchain, cloud computing and real-time data analytics – can facilitate the transition from static proactive strategies towards dynamic concurrent and reactive approaches. For instance, real-time monitoring enabled by IoT sensors can offer early detection of disruptions in collection points, remanufacturing facilities or recycling centres, thereby allowing SC managers to initiate rapid interventions, such as inventory redistribution, dynamic route adjustments or production rescheduling.

Future empirical studies might leverage case studies and pilot implementations to test the effectiveness of digitally enabled concurrent and reactive strategies. Theoretically, this line of enquiry will necessitate re-examining resilience constructs to include aspects of adaptability, agility and real-time decision-making capabilities, thereby enriching the existing frameworks on SCRES.

5.5 Explore new data sources for resilience enhancement

Along with the application of model-based approaches, most studies rely on data from surveys, company records and simulation outputs, which often lack scale, timeliness or comprehensiveness. Advances in technology have introduced new data sources with immense potential for RL and CLSC resilience.

Machine-generated data can be found across all activities of an RL or CLSC, ranging from the customer side with their call log or web log data to the sensors used in product tracking, quality monitoring or contamination control. This real-time data provides actionable insights, such as identifying bottlenecks, improving customer journey strategies and predicting maintenance needs, enabling more efficient and proactive SC operations. Similarly, human-generated data, like social media posts and customer feedback, can uncover trends, enhance customer engagement and predict demand for pre-owned or refurbished products. For instance, as interest in pre-owned or refurbished products grows, second-hand market businesses should adopt a customer-centric approach. Social media can be used to promote products, enhance communication and gather valuable customer feedback to address risks and identify problems promptly. This feedback can also help predict demand for used products, enabling RL and CLSC networks to optimise operations and avoid supply-demand

mismatches. These new data sources, combined with text mining techniques, can transform risk management in RL and CLSC by providing actionable insights for resilience enhancement.

5.6 Application and development of data-driven methods

The application of data-driven methods – including artificial intelligence (AI), ML and digital twin technology – represents another critical frontier for RL and CLSC resilience research. The systematic review identified a notable dominance of quantitative, model-based techniques (e.g., optimisation and scenario analyses), whereas data-driven approaches remain largely untapped. This presents a significant opportunity to harness the growing availability of big data within SCs.

Future research should thus explore how predictive analytics and ML algorithms can be specifically tailored to the distinct peculiarities of reverse flows and circular systems. Early initiatives have demonstrated the potential of such approaches; for example, clustering algorithms have categorised RL risks into strategic, tactical and operational tiers, illustrating how pattern recognition can effectively inform risk prioritisation. Extending this work, researchers could develop AI models to forecast return volumes and product quality, predict disruption probabilities (e.g., forecasting policy changes or detecting early signals of disruptions in remanufacturing facilities) and prescribe optimal mitigation actions in real time.

Digital twins particularly offer an innovative means to integrate data-driven insights with practical decision-making. A digital twin of a CLSC can concurrently simulate disruptions (such as major product recalls or supplier failures in reverse loops) using real-time data feeds, allowing managers to virtually evaluate different response strategies before actual implementation, thereby enhancing reactive capabilities without risking live operations. Academically, developing digital twin frameworks specifically for RL and CLSC would demonstrate methodological innovation and significantly expand SCRES theory into the realm of cyber-physical systems and real-time analytics.

It is critical that scholars design these data-driven studies explicitly for circular SC complexities – such as stochastic product returns and multi-stage product life cycles – rather than borrowing models wholesale from forward SC applications. This approach offers dual benefits: empirically, providing data-driven tools to support resilience, and theoretically, enriching the understanding of how information flows and learning systems underpin SCRES. Future studies should encourage interdisciplinary collaborations among operations management, data science and engineering experts to develop and rigorously test these advanced resilience solutions in RL and CLSC contexts.

5.7 Cross-sectoral comparative studies for generalisable and contextual insights

Lastly, there is a compelling need for cross-sectoral comparative studies to discern which resilience mechanisms are generalisable across RL and CLSC networks and which are context-specific. The literature reviewed generally treats RL and CLSC resilience in aggregate, yet industries differ significantly regarding the nature of their RL activities, regulatory requirements and stakeholder involvement. For example, sectors such as healthcare and hazardous waste management prioritise strict safety and regulatory compliance to mitigate contamination risks, whereas electronics or automotive industries focus more on maximising material recovery and addressing rapid technological obsolescence. These fundamental differences imply that a strategy highly effective in one sector – such as stringent tracking systems mandated in pharmaceutical returns – may have limited applicability in another sector, where market-driven demand uncertainty is the more critical issue.

Future research should therefore systematically compare resilience practices across diverse sectors, examining, for instance, how mitigation strategies and resilience investments differ among consumer electronics, automotive parts, textiles and medical equipment supply loops. Such comparative studies could utilise case research, surveys or secondary data analysis to

uncover sector-specific patterns and identify universally applicable principles. They would answer critical questions, such as whether all sectors benefit equally from proactive strategies like inventory buffering or if some sectors depend more on reactive flexibility due to inherent demand volatility. Additionally, the comparative perspective would offer practical guidance, enabling firms to benchmark resilience capabilities not only against direct competitors but also against best-in-class practices across industries. Ultimately, this nuanced understanding ensures academic recommendations remain relevant and actionable under varying real-world conditions. Figure 7 summaries the future research in five levels.

6. Implications

6.1 Managerial and policy implications

The findings have been translated into a set of stakeholder-specific actions and measurable KPIs, as detailed in Table 6, providing a concrete operational pathway for practitioners. By aligning the P-I-M risk groups with specific organisational roles and quantifiable indicators, the study moves beyond generic resilience recommendations and offers decision-makers a more targeted and actionable framework.

For low-probability, high-impact, low-manageability disruptions (Group A), managers in original equipment manufacturers (OEMs), remanufacturing facilities, collection agencies and regulatory bodies can deploy strategies such as multi-route recovery pathways, visibility agreements and expedited emergency approvals. These actions directly address the systemic vulnerabilities associated with hybrid nodes and tightly coupled reverse flows identified in Section 4.1. Metrics such as time-to-recovery, network redundancy indices and visibility scores allow organisations to benchmark and monitor resilience capability over time.

For medium-level operational risks (Groups B and C), managerial interventions – including dynamic contracting for return inputs, automated inspection and grading technologies, flexible staffing and standardised disassembly procedures – provide mechanisms for stabilising operations subject to recurrent variability. The linked KPIs (e.g., inspection accuracy, material stability, line utilisation) make resilience investments traceable and support evidence-based resource allocation.

For cyber, waste-handling, demand and resource scarcity risks (Groups D, E and F), specialist interventions such as cyber-resilience upgrades, anomaly detection systems, demand-sensing analytics and resource recovery targets create structured pathways for addressing vulnerabilities that are distinctive to circular SCs. KPIs such as cyber incident frequency, anomaly detection latency or critical-resource dependency offer actionable signals for both operational and strategic monitoring.

Beyond firm-level actions, several policy implications also emerge. Firstly, regulatory agility – including faster approval processes and improved inter-agency coordination – is particularly necessary for Group A risks, where organisational manageability is structurally constrained. Secondly, resource circularity policies supporting secondary-material substitution and shared recycling infrastructure address long-term systemic scarcity (Group F). Thirdly, data governance and interoperability standards are essential to realise the benefits of visibility agreements, IoT sensing and digital traceability tools that underpin many of the resilience actions identified.

Collectively, these managerial and policy implications provide a structured mechanism for operationalising resilience, ensuring clear accountability for interventions (“who”), transparent mechanisms for action (“what”) and robust monitoring of outcomes (“how measured”).

6.2 Theoretical implications

This review advances theorising on resilience in RL and CLSC in four key ways. Firstly, the synthesis demonstrates that RL and CLSC risks exhibit three hallmark CST

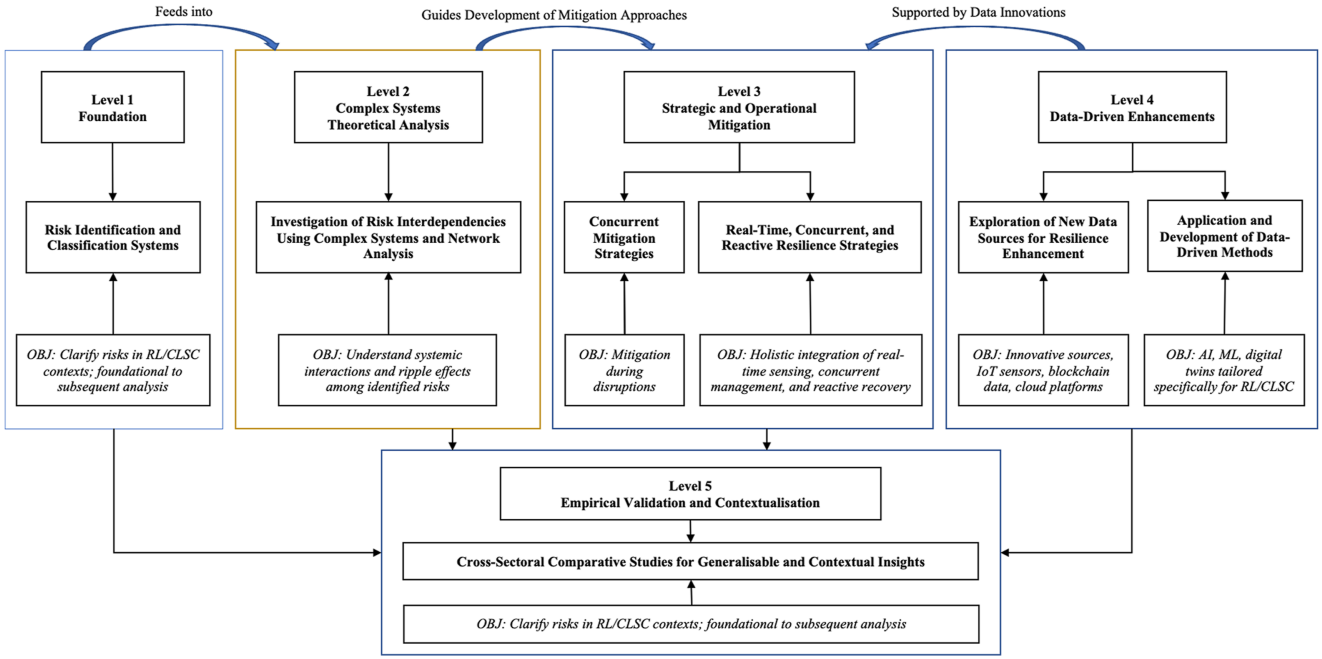

Figure 7. A conceptual framework for advancing research on resilience in RL/CLSC. **Source(s):** Authors' own work

Table 6. Translating RL and CLSC risks into stakeholder actions and KPIs

P-I-M risk group	Risk type	Stakeholder(s)	Recommended action	Key KPI(s)
A (*Low P–High I–Low M*)	- Facility disruption - Supply disruption - Demand disruption - Collection disruption - Cost disruption - Production disruption	OEMs/Re-manufacturers	- Develop multi-route and multi-facility recovery pathways and alternative processing capacity for hybrid facilities (production–recovery) - Have backup processors pre-contracted	- Time-to-recovery - % recovery throughput restored within 48 h - Network redundancy index
		Suppliers/ Collectors/3PLs	- Adopt visibility agreements for used-product flows and returned-material availability - Establish backup collection hubs - Introduce risk-tiered protocols for hazardous or sensitive returns	- Visibility score - Supply signal accuracy - Collection continuity rate - % hazardous loads processed without delay
		Regulators/public agencies	- Streamline emergency approvals - Improve disaster-response coordination across reverse flow actors	- Lead time for emergency approvals - Regulatory response time
B (*Medium P–Medium I–Medium M*)	- Supply risk - Financial risk - Logistics risk - Collection risk	OEMs	- Use dynamic contracting for variable-quality return inputs	- Material availability stability index
		Recyclers/ Remanufacturers	- Implement granular return-quality grading systems and automated inspection	- % returns correctly classified - Reprocessing defect rate
		Suppliers/ Logistics Partners	- Contract for improved visibility of used-product flows - Enhance forecast sharing and adopt continuous visibility tools for return volumes	- Forecast accuracy - Visibility score - Variance of inbound return flows
C (*High P–Low I–High M*)	- Operational risk	OEMs/Process Engineers	- Adopt flexible staffing or workstation configuration to accommodate routine variability	- Line utilisation rate - Worker cross-skill index
		Disassembly and Inspection Centres	- Standardise disassembly protocols - Implement digital checklists aligned with the organisation's Standard Operating Procedures to reduce epistemic uncertainty	- Processing time variance - % rework - Inspection accuracy

(*continued*)

Table 6. Continued

P-I-M risk group	Risk type	Stakeholder(s)	Recommended action	Key KPI(s)
D (*Medium P–High I–Medium M*)	- Waste management risk - Malicious attacks	OEMs, Public Sector	- Strengthen cyber-resilience for IoT-enabled collection and handling systems - Upgrade hazardous-waste handling systems	- Number of cyber incidents - Hazardous waste compliance rate - Successful audit rate
		Recyclers	- Introduce real-time monitoring for waste streams and anomaly alerts	- Detection accuracy - Response latency
E (*Medium P–Medium I–Low M*)	- Demand risk	Manufacturers/ Retailers	- Deploy demand-sensing algorithms for green-product shifts - Integrate near-real-time return analytics	- Forecast error - Demand volatility index
		Marketing/ Customer Interface	- Use behavioural nudges to stabilise return flows	- Return predictability score - Participation rate
F (*Medium P–High I–Low M*)	- Natural resource scarcity	OEMs/ Governments	- Develop closed-loop resource recovery targets for critical materials - Co-develop recycling infrastructure	- % secondary material substitution - Recycling yield - Critical-resource dependency index
		Recyclers	- Adopt high-efficiency extraction and recovery technologies	- Recovery efficiency - Cost per recovered unit
G (*P-I-M not applied*)	- Risk in general	All stakeholders	- Establish cross-functional resilience governance structures	- Resilience maturity score - Frequency of cross-functional meetings - % risks with assigned owners

Source(s): Authors' own work

properties – interdependence, topology sensitivity centred on hybrid nodes and non-linear amplification – that collectively explain why circular systems respond differently from linear, forward SCs. This shifts the discussion from descriptive inventories toward mechanism-based explanations of resilience behaviour. Secondly, the dominance of proactive elements (e.g., robustness, situational awareness) is shown not as a reporting artefact but as a structural consequence of RL and CLSC network characteristics, where high variability and tightly coupled dependencies necessitate anticipatory design. Concurrent and reactive elements, on the other hand, cluster around low-probability, high-impact, low-manageability contexts, consistent with decentralised adjustment and

learning mechanisms in complex adaptive systems. This links "what is used" to "why it works" under circular-system conditions. Thirdly, the field's current reliance on optimisation models predominantly theorises structural robustness but under-represents the feedback, emergence and learning processes that underpin dynamic resilience. The review therefore motivates the broader use of simulation, game-theoretic, hybrid and data-driven approaches to capture adaptation and co-evolution, aligning modelling choices more closely with CST mechanisms. Finally, the integrative framework clarifies how risk structures shape mitigation portfolios, how mitigation choices imply specific modelling paradigms and how modelling insights feed back into network redesign. This positions resilience as a co-evolving property of structure, behaviour and learning – rather than a static capability – and provides a unifying lens for future theory development in circular supply networks.

7. Conclusion

This literature review examined 194 articles to provide a comprehensive understanding of how SCRES has been conceptualised and operationalised within the RL and CLSC context. A conceptual framework was developed by synthesising three core constructs – risk types, mitigation strategies and mitigation development approaches – and used to address the research questions stated at the outset. Based on these analyses, several research gaps and future directions have been identified to advance scholarship in this area.

A key contribution of this study lies in demonstrating that RL and CLSC risks exhibit three hallmark properties of complex systems – interdependence, topology sensitivity and nonlinear amplification – which collectively differentiate the resilience behaviour of circular networks from that of traditional SCs. The review also enhances theoretical understanding by showing how mitigation elements correspond to CST mechanisms. Moreover, the analysis of modelling approaches reveals a strong emphasis on optimisation – which primarily supports structural robustness – while underrepresenting simulation, game-theoretic, hybrid and data-driven tools capable of capturing emergence, feedback and adaptive behaviours. The proposed framework brings these insights together by illustrating how risk structures, mitigation portfolios and modelling paradigms co-evolve to shape system-level resilience.

The practical relevance of the review has also been demonstrated through the translation of P-I-M risk groups into stakeholder-specific actions and measurable KPIs, providing managers and policymakers with a targeted, operational toolkit for enhancing resilience across different risk contexts. In addition, the seven identified research directions offer a foundation for further theoretical development, methodological innovation and real-world impact in the study of resilience in RL and CLSC.

One notable limitation of this study concerns the potential for subjective bias inherent in the categorisation and coding processes used to construct the framework. Although multiple validation steps were undertaken, the interpretative nature of content analysis may influence how risks, strategies and modelling approaches were classified. Future studies may mitigate this through triangulation with expert panels, inter-coder reliability assessments or automated text-analytic techniques.

Supplementary material

The supplementary material for this article can be found online.

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