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Extended Resilience Business Model Canvas: Integrating AI, Robotics, and Ecosystem Orchestration for Supply Chain Resilience

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Abstract - Global supply chains are increasingly vulnerable to geopolitical conflicts, energy shocks, extreme weather events, labor shortages, and logistics disruptions. Industry evidence shows a 38% rise in disruption alerts in 2024 [1], underscoring the fragility of traditional operating models. Consequently, organizations must move beyond reactive risk management by developing business models that anticipate disruptions, ensure operational continuity, and enable rapid recovery.

Supply-chain resilience is thus both an operational ability and a strategic component of business model design [2]. AI and Robotics are key tools for enhancing resilience. AI-powered predictive analytics can improve demand forecasts, detect early warning signs, assess supplier and logistics risks, and speed up decision-making. Robotic automation can increase process reliability, minimize downtime, and offer flexible capacity across warehousing, manufacturing, and distribution. Robot-as-a-Service (RaaS) allows companies to access robotic functions via subscription or usage-based models, reducing significant upfront costs. However, organizations need to address automation risks such as cybersecurity threats, technology failures, data dependency, and human–machine coordination [3].

This study introduces an Extended Resilience Business Model Canvas (ER-BMC) that combines AI prediction, autonomous robotics, resilience strategies, servitization, and ecosystem orchestration into the traditional Business Model Canvas. Drawing on industry reports, supply-chain case studies, and academic literature, it shows how these capabilities enable disruption detection, resource flexibility, continuity, and recovery. The framework is especially useful for firms in emerging markets and developing countries, where RaaS and ecosystem collaboration provide scalable access to advanced technologies. It offers a practical pathway from reactive operations toward predictive, adaptive, and ecosystem-centric business models.

Keywords: Business Model Innovation; Artificial Intelligence; Robotics; Organizational Resilience; Robot-as-a-Service; Supply Chain Disruption; Ecosystem Orchestration.

1. INTRODUCTION

Supply chains have become a strategic concern for senior management because disruptions are frequent and their causes vary. Resilinc, which monitors supply-chain events through its EventWatchAI database, reported that global supply chain disruptions increased 38% in 2024 compared with the previous year [1], [4]. Trade press coverage of the same data described this as a nearly 40% annual increase [2]. In 2024, firms experienced average financial losses equivalent to approximately 8% of their annual revenue due to operational disruptions. Moreover, the mean delivery time for raw materials extended to 81 days in October 2024, compared with 65 days prior to the pandemic.[5].

Most responses to such instability tend to be operational, like stocking extra inventory, adding suppliers, or using monitoring software. However, a business-model perspective questions how the firm can create, deliver, and capture value amid constant disruption [17], [18]. Two key technology areas enable redesigns in such environments. The first is artificial intelligence (AI), which aids in forecasting, risk assessment, and decision-making within supply chains [22]. The second is robotics, which helps ensure reliable processes and flexible capacity but also brings technology-related risks [3].

Existing literature treats business models, supply-chain resilience, AI, and robotics largely as separate streams. This paper brings them together through the Extended Resilience Business Model Canvas (ER-BMC). It addresses three research questions:

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- RQ1. What disruption patterns have impacted global supply chains over the past two years, and what are their business consequences?
- RQ2. What does current evidence indicate about using AI and robotics to address these disruptions, while also considering their risks?
- RQ3. How can the Business Model Canvas be extended so that resilience becomes a built-in property of the business model?

2. THEORETICAL BACKGROUND

2.1 Business models and the Business Model Canvas

Osterwalder and Pigneur outline the Business Model Canvas (BMC) using nine key building blocks: customer segments, value propositions, channels, customer relationships, revenue streams, key resources, key activities, key partnerships, and cost structure. [17]. Teece frames the business model as how a firm creates, delivers, and captures value, and links business-model design to strategy and innovation [18]. Zott, Amit and Massa review the literature and show that the business model has become a distinct unit of analysis for explaining firm performance and innovation [19].

2.2 Supply-chain resilience

Christopher and Peck argued that resilience must be built into supply-chain design, with visibility and collaboration as central elements [20]. Kamalahmadi and Parast reviewed the literature on the principles of enterprise and supply-chain resilience and consolidated the main concepts [21]. This body of work analyses resilience mainly at the operational and network levels. It does not treat resilience as a property of the business model.

2.3 AI in supply-chain risk management

Baryannis et al. reviewed AI applications in supply-chain risk management and mapped the state of the art and future research directions [22]. Dubey et al. examined data analytics capability and organizational flexibility as complements to supply-chain resilience [23]. Ivanov and Dolgui proposed a digital supply-chain twin for managing disruption risks and resilience in the era of Industry 4.0 [24]. At the macroeconomic level, Ginn and Saadaoui used a Bayesian vector autoregression model to find that supply-chain disruptions significantly influence global economic stability, particularly through aggregate inflation and the policy responses that accompany it [7].

2.4 Automation, robotics and technology-related risk

Ekren et al. conduct an integrative review of disruptions related to technology in highly automated warehouse systems. They categorize five primary disruptions—cyberattacks, technological sabotage, failures, power and network outages, and human–machine interaction issues—and identify 48 associated vulnerabilities. The authors propose a research agenda comprising 17 pathways targeting prevention, detection, mitigation, and recovery strategies. Additionally, the paper defines Robot-as-a-Service (RaaS) as a model that provides robotic capabilities through subscription or usage-based mechanisms rather than outright ownership.

2.5 Servitization and business ecosystems

Servitization denotes the transition from purely product-based offerings to the enhancement of value through the integration of services [27]. Ecosystem research conceptualizes value creation as the outcome of the interactions among interdependent actors, whose activities necessitate alignment [25], [26]. These two concepts form the foundational basis for the servitization approach and ecosystem orchestration within the ER-BMC framework.

2.6 Research gap

The studies above address business models, resilience, AI, automation risk and ecosystems separately. No single framework in the sources reviewed places AI-enabled prediction, autonomous robotics, resilience mechanisms, servitization, and ecosystem orchestration inside the business model itself. The ER-BMC is proposed to fill this gap.

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3. RESEARCH METHODOLOGY

3.1 Design

This descriptive-analytical study relies on secondary data synthesis, with no primary data collected. It integrates quantitative information from industry reports and surveys alongside peer-reviewed literature to develop a conceptual framework.

3.2 Sources and verification

Three source types were used: (a) industry data and survey reports (Resilinc, ABI Research, Gartner, Deloitte, McKinsey, and market-research publishers, as reported by the cited sources); (b) peer-reviewed journal articles; and (c) trade-press reports describing specific disruption events, such as the ILA U.S. port strike and the Canadian rail strike in 2024 [2], [4]. Figures were verified against the publisher or press page cited. When the original report was unavailable, the figure was attributed to the secondary source that reported it, as stated in the text or table notes. The study is not a formal PRISMA-style systematic review, and no counts of records screened are provided.

3.3 Analysis

Three analyses were applied: (i) trend analysis of year-over-year disruption indicators; (ii) comparison of reported adoption, intent and potential-gain figures across sources; and (iii) framework development, in which the findings were mapped onto the nine BMC blocks and four additional layers. Table 1 links each research question to its method and location in the paper.

Table 1. Research questions, methods and evidence

Research question	Method	Section	Main evidence
RQ1: Disruption patterns and impact	Trend analysis of secondary data	4	Resilinc 2024 data [1], [4]; business impact figures [5], [6]; macro effects [7]
RQ2: AI and robotics as responses	Comparison of survey and report figures; literature review	5	ABI Research [8], [9]; Gartner [10]; Deloitte via [11], [12]; McKinsey via [13]; Ekren et al. [3]
RQ3: Extending the BMC	Framework development	6	ER-BMC (Fig. 7; Tables 8–11)

Source: authors' design.

4. FINDINGS I: THE DISRUPTION LANDSCAPE

4.1 Scale and categories of disruption

Resilinc's 2024 data show a 38% increase in disruptions compared with 2023. Of the 22,522 EventWatchAI notifications issued, 59% were significant enough to trigger the creation of a WarRoom, a virtual platform in which customers and their suppliers collaborate to assess and resolve a disruption [1], [4]. Table 2 summarizes the main categories, and Fig. 1 shows the growth rates.

Table 2. Main disruption categories in 2024 (Resilinc EventWatchAI data)

Category	Reported figure	Source
All disruptions	+38% vs 2023; 22,522 notifications; 59% triggered a WarRoom	[1], [4]
Factory fires	Top disruption for the sixth consecutive year; 2,299 alerts; down 20% from the previous year	[2], [4]
Labor disruptions	+47% year over year, second-ranked disruption; includes the ILA U.S. port strike (over 47,000 workers) and the Canadian rail strike	[2], [4]

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Category	Reported figure	Source
Extreme weather	+119% overall; flood alerts +214%; forest fires +88%; hurricanes/typhoons +101%	[4]
Geopolitical risk	+123% after a brief dip in 2023	[4]
Regulatory change (tariffs, laws, environmental regulations, bans)	+128% year over year	[4]
Protests and riots	+285%, the largest growth among all tracked risk events	[4]
Most disrupted industries	Life sciences, healthcare, general manufacturing, high-tech and automotive	[4]

Note: alert counts reflect Resilinc's monitoring database and may not equal the total number of real-world events.

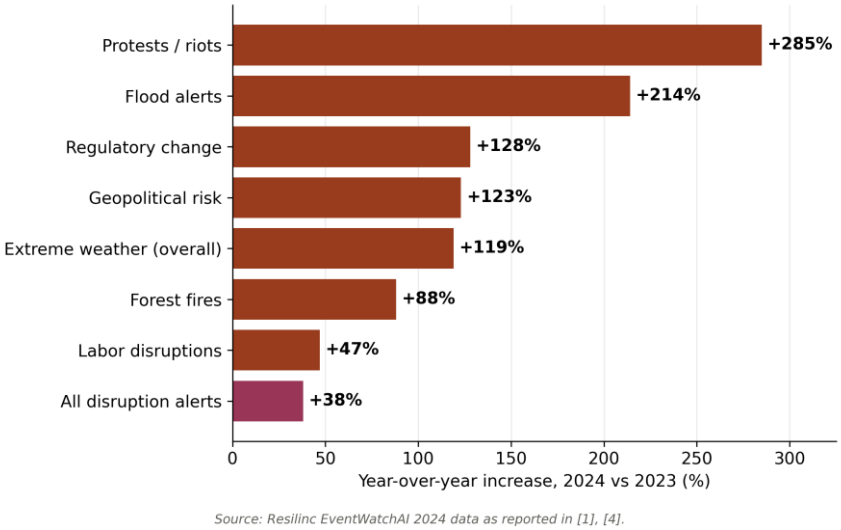


Fig. 1. Year-over-year growth in supply-chain disruption alerts by category, 2024 vs 2023.

4.2 Business and macroeconomic impact

Table 3 summarizes the reported indicators for costs and delivery times. In 2024, companies faced average financial losses of approximately 8% of their annual revenue. Additionally, raw-material delivery times increased to 81 days in October 2024, up from 65 days before the pandemic—an increase of about 25% (see Fig. 2) [5]. According to Z2Data, Gartner estimates that disruptions cost aerospace and defense manufacturers $184 million annually [6]. Changes in trade policies also impacted trade flows: U.S. imports from the EU grew by over 14% between January and July 2025 compared to the same period in 2024, and a 25% tariff on foreign cars and auto parts was announced in March and took effect in May 2025 [6]. On a macroeconomic level, supply-chain disruptions notably affect global economic stability through inflation and policy responses [7].

Table 3. Reported business and macroeconomic impact indicators

Indicator	Reported figure	Source
Average financial loss from 2024 disruptions	About 8% of annual revenue	[5]
Raw-material delivery time	81 days (Oct. 2024) vs 65 days pre-pandemic, about +25%	[5]
Annual cost of disruption, aerospace and defense manufacturers	$184 million (Gartner, as reported)	[6]
U.S. imports from the EU	Over +14%, Jan.–Jul. 2025 vs same period of 2024	[6]
U.S. tariff on foreign cars and auto parts	25% (announced March, implemented May 2025)	[6]

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Indicator	Reported figure	Source
Macroeconomic effect	Significant influence on aggregate inflation and policy responses	[7]

Note: the 8% and delivery-time figures are reported by a secondary source [5] without a named primary study.

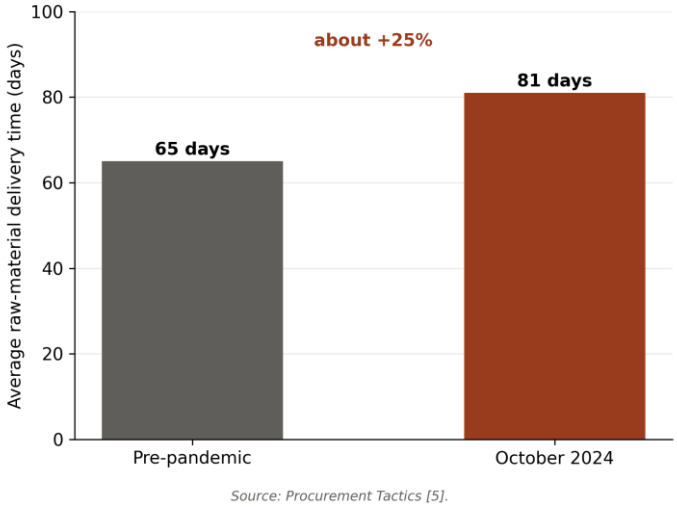


Fig. 2. Average raw-material delivery time before the pandemic and in October 2024.

4.3 Interpretation

Evidence indicates that disruptions originate from human, physical, geopolitical, and regulatory causes occurring simultaneously. The rapidly increasing categories listed in Table 2—such as protests, regulatory changes, geopolitical risks, and flooding—are different in nature from factory fires, which remain the longest-standing top category. There is no single operational solution capable of addressing all these issues, reinforcing the idea that resilience is an inherent aspect of the business model's design.

5. FINDINGS II: AI AND ROBOTICS AS RESPONSES

5.1 Adoption and intent

Table 4 and Fig. 3 summarize survey evidence. In ABI Research's 2025 survey, 64% of supply-chain leaders said AI and generative AI capabilities are important when evaluating new technology investments [8]. In a survey of 490 supply-chain professionals in the United States, Mexico, Germany, and Malaysia, 94% planned to use AI or generative AI for decision support over the next two years; 91% for customer service and demand forecasting; and 85% for inventory management. Planned use for risk management was lower, at 37% [9]. ABI Research also found that 76% of respondents agreed that AI agents can be used for supplier relationship management [8].

Table 4. Reported AI adoption, intent and strategy indicators

Indicator	Reported figure	Source
Rate AI/GenAI capability important in technology investment decisions	64% of supply-chain leaders	[8]
Plan to use AI/GenAI for decision support within two years	94% (n = 490; U.S., Mexico, Germany, Malaysia)	[9]
Plan AI/GenAI for customer service; for demand forecasting	91%; 91%	[9]
Plan AI/GenAI for inventory management	85%	[9]
Plan AI/GenAI for risk management	37%	[9]
Agree AI agents can be used for supplier relationship management	76%	[8]

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Indicator	Reported figure	Source
Supply-chain organizations that deployed generative AI	72% (Gartner, as reported)	[11]
Supply-chain leaders with a formal AI strategy	23% (Gartner survey of 120 leaders who had deployed AI, Dec. 2024–Jan. 2025)	[10]
Organizations that increased AI investment in the prior 12 months; planned further increase	85%; 91% (Deloitte, 2025, as reported)	[11]
Typical time to reasonable AI return on investment	2–4 years (Deloitte, as reported)	[11]
Organizations that saw ROI in under one year	6% (Deloitte, as reported)	[12]

Note: surveys differ in sample, geography and wording, so figures are not directly comparable. Deloitte and Gartner figures marked 'as reported' were taken from the secondary sources cited.

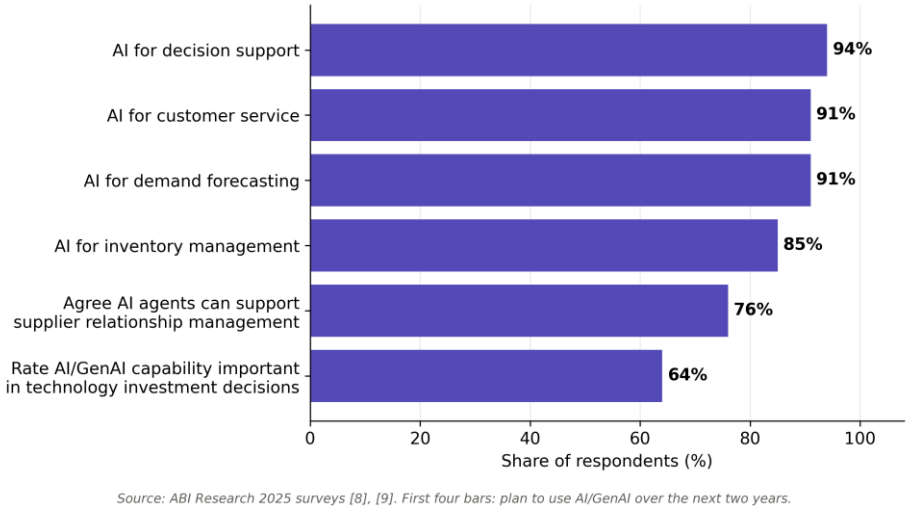


Fig. 3. Reported AI adoption intent in supply chains.

5.2 Reported potential gains

A 2024 McKinsey analysis, cited in [13], suggests that integrating AI into distribution operations could cut inventory by 20% to 30%, logistics expenses by 5% to 20%, and procurement costs by 5% to 15% (see Table 5, Fig. 4). These numbers indicate potential savings. Since attribution ranges differ among secondary sources, these figures are approximate.

Table 5. Reported potential reductions from AI in distribution operations

Area	Reported range	Source
Inventory	20%–30% reduction	[13]
Logistics costs	5%–20% reduction	[13]
Procurement spend	5%–15% reduction	[13]

Note: McKinsey analysis as reported by a secondary source.

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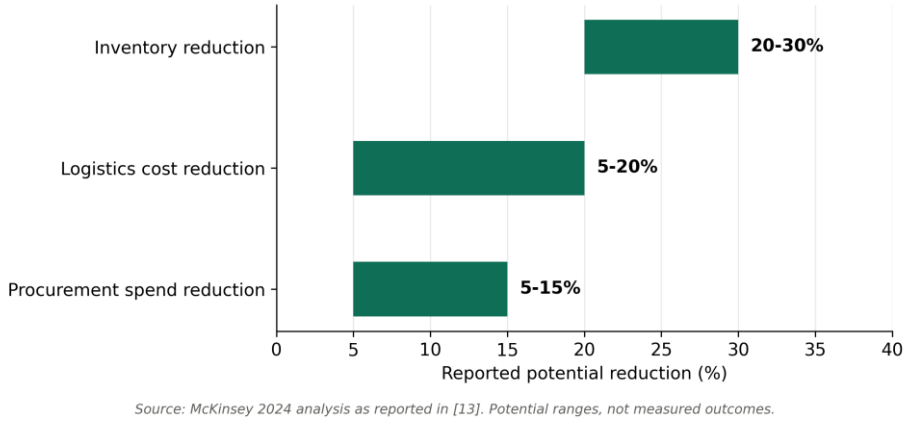


Fig. 4. Reported potential reductions from AI in distribution operations.

5.3 The gap between adoption and value

AI adoption differs from its value. In Gartner's survey, only 23% of supply-chain leaders reported having a formal AI strategy [10]. Deloitte's research indicated that 85% of organizations increased their AI investments, but only 6% experienced a return within one year, with most taking two to four years [11], [12] (Fig. 5). The survey also revealed that leaders mainly assess AI based on efficiency, decision speed, and cost—prioritizing these over revenue and innovation. This points to AI being viewed mainly as an efficiency enhancer rather than a catalyst for new business models [28].

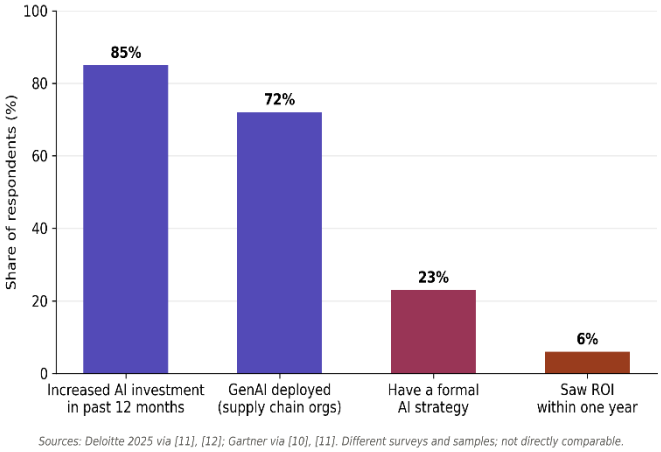


Fig. 5. The gap between AI adoption and realized value.

5.4 Market scale and the divergence of estimates

Precedence Research estimates the AI-in-supply-chain market at $9.94 billion in 2025, increasing to $13.81 billion in 2026 and approximately $236.42 billion by 2035, with a CAGR of 37.29% from 2026 to 2035 [14] (Fig. 6). Other sources report significantly lower figures (Table 6), so these market size estimates should be seen as general indicators of growth rather than exact predictions.

Table 6. Published estimates of the AI-in-supply-chain market

Publisher	Base value	Projection	CAGR	Source
Precedence Research	$9.94B (2025); $13.81B (2026)	$236.42B by 2035	37.29% (2026–2035)	[14]
MarketsandMarkets (report published Feb. 2025)	$14.49B (2025)	$50.01B by 2031	22.9%	[15]
MarketsandMarkets (release dated 2026)	$13.93B (2025)	$50.41B by 2032	20.2%	[16]

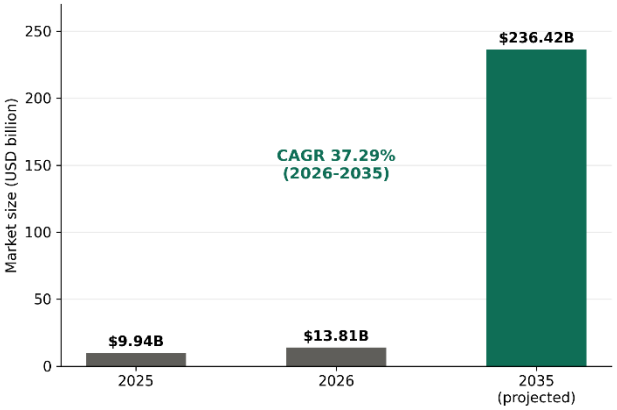
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Note: definitions and scope differ by publisher.

5.5 Robotics, RaaS and technology-related risk

Robotic automation can improve process reliability, decrease downtime, and offer adaptable capacity in warehousing, manufacturing, and distribution. RaaS reduces initial costs by offering subscription or usage-based access, although the reviewed sources did not supply specific RaaS outcome data. The literature also discusses the risks involved. Table 7 consolidates Ekren et al.'s findings on highly automated warehouse systems [3].



Source: Precedence Research [14]. Other publishers report much lower values (see Table 6).

Fig. 6. AI-in-supply-chain market size according to Precedence Research.

Table 7. Technology-related risks in highly automated warehouse systems

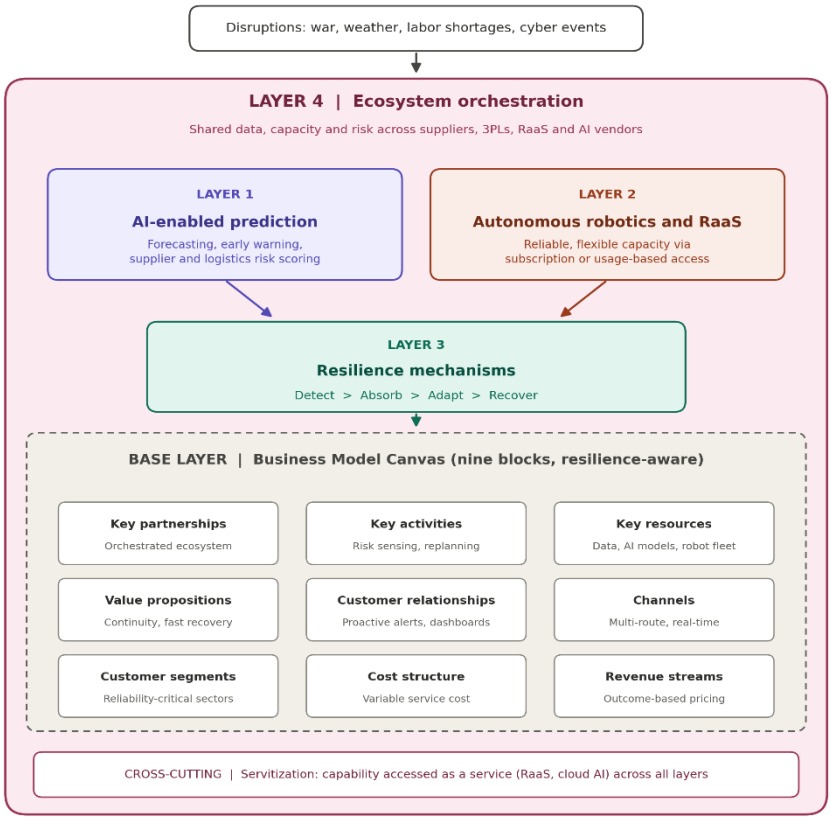
Item	Finding of Ekren et al. [3]
Major disruptions identified	Cyberattacks; technology sabotage; technology failures; power and network outages; human–machine interaction issues
Vulnerabilities identified	48 technology-related vulnerabilities across all disruptions
Coverage of risk management strategies	Unevenly covered in the literature.
Research agenda	17 pathways to enhance prevention, detection, mitigation and recovery

Source: abstract of [3].

6. THE EXTENDED RESILIENCE BUSINESS MODEL CANVAS (ER-BMC)

6.1 Design logic

The ER-BMC retains the nine blocks of the original canvas [17] and adds four layers, depicted in Fig. 7: Layer 1, AI-driven prediction; Layer 2, autonomous robotics and RaaS; Layer 3, resilience mechanisms—detect, absorb, adapt, recover; and Layer 4, ecosystem orchestration. Servitization extends across these layers, as capabilities are accessed as services rather than owned [27]. This framework is a conceptual proposal by the authors, based on the capabilities outlined in the abstract and supported by the evidence in Sections 4 and 5; it has not yet been empirically validated



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6.2 The four added layers

- **Layer 1:** AI-enhanced prediction involves demand forecasting, early-warning signals, supplier and logistics risk assessment, and quicker managerial decisions, supported by AI literature [22]–[24] and survey data in Table 4.
- • **Layer 2:** Autonomous robotics and RaaS offer process reliability, lower downtime, and adaptable capacity, accessible through subscription or usage-based models. Table 7 [3] outlines the risks linked to this layer.
- • **Layer 3:** Resilience mechanisms enable detection, absorption, adaptation, and recovery, ensuring that technology layers support a specific response rather than just reporting [20], [21].
- • **Layer 4**: Ecosystem orchestration involves coordinating suppliers, logistics providers, and technology vendors, leveraging ecosystem theory [25], [26]**.**

Table 8. Traditional BMC compared with the ER-BMC (proposed)

Dimension	Traditional BMC [17]	ER-BMC (proposed)
Structure	Nine blocks	Nine blocks plus four layers
Treatment of disruption	Not an explicit design element	Built in through Layer 3 (detect, absorb, adapt, recover)
Role of AI	Not specified	Prediction layer within the model (Layer 1)
Physical capacity	Key resources, typically owned	Flexible capacity through robotics and RaaS (Layer 2)
Partnerships	Key partnerships block	Orchestrated ecosystem (Layer 4)
Orientation	Not specified	Reactive to predictive, adaptive, and ecosystem-oriented

Source: authors' proposal.

Table 9. ER-BMC building blocks and proposed extensions

BMC block	Extension in the ER-BMC
Customer segments	Segments that value reliability and continuity of supply
Value propositions	Continuity and rapid recovery in addition to price and quality
Channels	Multi-route channels with real-time visibility
Customer relationships	Proactive alerts based on early-warning signals
Revenue streams	Service-based and usage-based models enabled by servitization
Key resources	Data, AI models and robotic capability (owned or via RaaS)
Key activities	Continuous risk sensing, scenario evaluation and adaptive planning
Key partnerships	Orchestrated ecosystem of suppliers, logistics providers and technology vendors
Cost structure	Shift from upfront capital to usage-based service cost.
Layers 1–4 (added)	AI-enabled prediction; autonomous robotics and RaaS; resilience mechanisms; ecosystem orchestration

Source: authors' proposal.

6.3 Propositions

The following propositions are offered for future empirical testing. They are not findings of this study.

Table 10. Propositions for empirical testing

No.	Proposition	Layers	Basis
P1	Firms that embed AI-enabled prediction in their business model detect disruptions earlier and recover faster than firms that use AI only as an operational tool.	1, 3	[10], [22]–[24]

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No.	Proposition	Layers	Basis
P2	Access to robotics through RaaS increases capacity flexibility and lowers the upfront investment barrier.	2	Abstract; [3]
P3	Ecosystem orchestration strengthens the resilience effect of AI and robotics.	4	[25], [26]
P4	The resilience benefit of automation depends on managing cybersecurity, technology failure, and human–machine interaction risks.	1, 2	[3]

Source: authors' proposal.

6.4 Implementation pathway

The abstract describes a pathway from reactive operations to predictive, adaptive, and ecosystem-oriented business models. Table 11 relates each stage to the layers it mainly emphasizes. Because Deloitte research, as reported, indicates a typical two-to-four-year horizon for reasonable AI returns [11], a phased approach is consistent with the evidence.

Table 11. Implementation pathway and layer emphasis

Stage	Focus	Layer emphasis
Reactive	Responding after disruption occurs	None
Predictive	Forecasting and early warning	Layer 1
Adaptive	Flexible capacity and defined response	Layers 2 and 3
Ecosystem-oriented	Coordination across partners	Layer 4

Source: authors' proposal, following the pathway stated in the abstract.

7. DISCUSSION

Resilience must be integrated into the core business model, as disruption sources are becoming more varied and widespread (see Table 2), with substantial financial and operational impacts (see Table 3). No single operational tool can address this diversity, so companies need to embed resilience into their value creation and delivery processes to maintain adaptability across different situations. Adoption trends reveal a gap between companies' intentions and their strategic execution. While reported intent to implement AI is high (see Table 4), only 23% have formal AI strategies [10], and Gartner's survey suggests success is mainly measured by efficiency and cost savings [28].

This gap highlights the importance of the Extended Resilience Business Model Canvas (ER-BMC), which focuses on designing resilient business models rather than merely adopting tools. A notable weakness appears in risk management: ABI Research shows 94% of organizations plan to use AI for decision support, but only 37% for risk management [9]. Because resilience relies on early detection, this shortfall is problematic, especially for Layer 1, underscoring the need for ER-BMC to focus on this aspect. Technology serves both as a facilitator and a potential risk source. Disruptions in automated warehouses [3] highlight the need for governance in Layers 1 and 2, supporting the inclusion of Layer 3 and Proposition P4. The framework also applies to emerging markets, where Robot-as-a-Service (RaaS) and ecosystem collaborations can enable scalable access to advanced technologies. However, the lack of India-specific data makes this argument theoretical, underscoring the need for future research to verify its relevance in resource-limited environments.

7.1 Managerial and theoretical implications

- Managers can use the ER-BMC as a checklist for where resilience is, or is not, designed into the model.
- Service-based access (RaaS, cloud AI) can be considered where upfront capital is limited, with attention to the risks in Table 7.
- Theoretically, the paper adds resilience as an explicit design objective to business-model research and locates resilience in value creation and capture, not only in operations.

8. CONCLUSION

This study underscores the need to embed resilience within business models as firms face increasingly diverse disruptions and significant financial losses. While AI and robotics provide mechanisms for detection, flexibility, and

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recovery, evidence reveals persistent gaps between adoption and strategy, extended return times, and technology-related risks. The Extended Resilience Business Model Canvas (ER-BMC) is proposed as a framework that integrates AI-enabled prediction, autonomous robotics and RaaS, resilience mechanisms, and ecosystem orchestration, offering a pathway from reactive to predictive, adaptive, and ecosystem-oriented models.

At the same time, the research is limited by reliance on secondary and vendor-based evidence, divergent market estimates, and non-comparable surveys. Quantified outcomes for RaaS are absent, and the ER-BMC along with propositions P1–P4 remain untested, with no India-specific data analyzed. Future research should empirically validate the framework through case studies and expert interviews, collect primary data from Indian firms on RaaS and AI adoption, trace statistics to original sources, and develop measurable resilience indicators. Addressing these gaps will strengthen the ER-BMC's applicability, particularly in emerging markets, and advance resilience as a core business-model capability in an era of persistent disruption.

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