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# Artificial intelligence-enabled antifragility in production and supply chain operations

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**ABSTRACT**
Manufacturing and supply chain operations increasingly face persistent volatility that makes traditional optimisation and resilience logics insufficient. This paper examines how artificial intelligence (AI) can enable antifragility, defined as the capability that improve through exposure to volatility. Drawing on Interpretive Structural Modelling supported by Delphi and Nominal Group Technique with insights from senior practitioners from advanced manufacturing firms,this study identifies thirteen AI-enabled functions for antifragiltiy. It further organises these functions into a hierarchical capability architecture. Foundational functions provide predictive sensing, causal diagnostics, and continuous learning loops. Mid-tier functions use these learning capabilities to orchestrate flexibility, inventory, logistics, and sourcing reconfiguration, while upper tiers turn turbulence into innovation, demand reframing, and strategic capacity shifts that culminate in adaptive scheduling and autonomous control. The study moves antifragility from metaphor to mechanism and positions AI as a structured capability system, offering a strategic roadmap for sequencing AI investments towards higher-order autonomy in production contexts.

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**KEYWORDS**
Antifragility; artificial intelligence; disorder; exploitation; strategic roadmap; supply chain resilience

## 1. Introduction

Manufacturing operations face structural volatility from geopolitical instability, climate events, pandemics, and shifting demand patterns (Aldrighetti et al. 2021; Ivanov 2022). These conditions challenge optimisation logics that assume stability and predictable disturbance patterns (Ivanov 2022). Resilience has therefore become a central concern and has shifted attention from pure efficiency towards continuity and recovery after shocks (Azadegan and Dooley 2021). However, resilience still focuses on restoring a pre-disruption or otherwise acceptable state. When volatility is persistent, this recovery logic may not be sufficient for long-term competitiveness (Ghobakhloo et al. 2025a; Priyadarshini et al. 2022).

Under such circumstances, antifragility has been proposed as a more advanced response to turbulence. Taleb (2012) describes antifragile systems as ones that improve through exposure to volatility, using disturbances as inputs for capability formation rather than only as stressors. Recent work in manufacturing and supply chains frames antifragility as a strategic orientation that treats disruption as a source of information and opportunity instead of a purely negative event (Bag et al. 2023; Munoz and Zhou 2023). Studies also link antifragility to long-term adaptation under uncertainty (Nikookar, Stevenson, and Varsei 2024; Priyadarshini et al. 2022). However, this emerging literature offers limited guidance on how antifragility can be translated into an operational logic for production and supply chain systems (Becker et al. 2024; Ghobakhloo et al. 2025a).

In parallel, Artificial Intelligence (AI) has diffused into industrial operations to enhance forecasting, scheduling, quality control, inventory decisions, and supply chain visibility (Culot, Podrecca, and Nassimbeni 2024; Toorajipour et al. 2021). AI applications can identify weak signals, uncover complex interdependencies, and support rapid decisions under uncertainty (Helo and Hao 2022). Their value is in the ability to update inferences as conditions change (Helo and Hao 2022; Mendonça and Junior 2023). This adaptive behaviour resonates with antifragility, which focuses on gaining capability through interaction with variability rather than suppressing it (Becker et al. 2024).

Despite this conceptual proximity, research has not yet clarified how antifragility can be operationally created through AI in production and supply chains. Studies on antifragility often remain conceptual and describe it as a desirable property without specifying the underlying mechanisms (Becker et al. 2024; Nikookar, Varsei, and Wieland 2021). Work on AI in operations mainly addresses prediction, efficiency, and resilience, and only rarely examines whether AI can generate systematic capability improvement through turbulence (Dubey et al. 2022; Singh, Modgil, and Shore 2024).

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As a result, antifragility and AI evolve as related but largely separate developments in operations management (Bag et al. 2023; Becker et al. 2024).

This disconnect creates a specific knowledge gap. Existing studies suggest that antifragility could be technologically realisable, but they do not specify which operational functions of AI enable antifragile behaviour or how these functions interact (Bag et al. 2023; Becker et al. 2024). Without such clarification, antifragility risks remaining a strategic metaphor rather than a design principle. There is also a practical risk that firms adopt AI mainly as a tool for faster recovery. In that case, AI-enabled systems may restore performance more quickly after shocks but still return to their prior state without becoming more capable because of those shocks (Dubey et al. 2022; Singh, Modgil, and Shore 2024).

The purpose of this paper is to address this gap by examining AI as a functional enabler of antifragility in production and supply chain operations. Rather than treating antifragility as a high-level label or assuming that AI naturally resolves turbulent conditions, the paper clarifies how antifragile performance is operationally created. It first articulates the practical requirements of antifragile operations, including rapid feedback and sensing, learning loops that update routines and decision rules, experimentation capacity supported by safe to fail mechanisms, and governance arrangements that enable adaptation while controlling downside risk. It then identifies specific AI enabled functions through which these requirements can be supported and scaled, and explains their operational logic. The central premise is that antifragility isthe outcome of multiple interacting mechanisms that convert disruption into learning, adaptation, and long-term improvement. These mechanisms must be explicitly identified and structured before antifragility can be designed into manufacturing systems. At the same time, we acknowledge that several antifragility requirements can be pursued through non-AI mechanisms, such as managerial practices, organisational design, and complementary digital technologies. The contribution of this study is to specify and structure the distinctive AI enabled functional mechanisms that support antifragility, while making clear the boundary conditions under which they can be effective.

Accordingly, the contribution of this paper is to clarify how antifragility is operationally enabled through AI by identifying the functions through which AI supports capability improvement under volatility and by establishing the structural relationships among those functions. This provides a system-level foundation for understanding antifragile behaviour in production and supply chain operations and creates a basis for subsequent modelling through interpretive structural methods. In doing so, the paper responds to calls for manufacturing systems that not only withstand disruption but also learn and strengthen through it, and it shows how AI can turn that aspiration into a technologically actionable capability (Ghobakhloo et al. 2025a; Nikookar, Stevenson, and Varsei 2024).

This study followed a multi-stage research design to specify and structure AI-enabled mechanisms of antifragility in production and supply chain operations. First, a systematic search and screening process within the literature was used to identify and extract an initial set of candidate AI-enabled functions relevant to antifragile behaviour. Second, a two-round Delphi process with industry experts refined the function set and established consensus on relevance and clarity. Third, a Nominal Group Technique (NGT) session elicited directional relationships among the validated functions based on expert reasoning about operational influence. Fourth, Interpretive Structural Modelling structured these relationships into a hierarchical model that explains how the functions interact and provides an implementation-oriented roadmap. Finally, MICMAC analysis examined driver and dependence characteristics, highlighting which functions act as foundational enablers versus downstream outcomes. The overall output is a validated set of AI-enabled antifragility functions and a structurally grounded roadmap that clarifies their interaction logic and sequencing.

## 2. Antifragility in production and supply chain operations

In operations and supply chain management, antifragility can be understood as the ability of a system to become more capable as it is exposed to disruption (Nikookar, Varsei, and Wieland 2021; Taleb 2012). Fragile systems deteriorate under disorder, robust systems aim to shield themselves, and resilient systems restore performance. Antifragile systems use disturbance as a source of information that reveals how resources, processes, and network structures should be reconfigured in order to act more effectively under future uncertainty (Ghobakhloo et al. 2025a).

This understanding positions antifragility alongside but distinct from viability and resilience. Viability-oriented designs emphasise continued functioning through internal adaptability and coordination. Resilience-oriented designs focus on regaining acceptable performance after disruption (Ivanov 2022; Ruel et al. 2021). Both treat the pre-disruption or acceptable state as the main reference point. Antifragility is more expansive as it exploits disturbances to uncover structural weaknesses, latent flexibilities, behavioural patterns, and new opportunity spaces that are not visible under stable conditions (Ghobakhloo et al. 2025a; Nikookar, Varsei, and Wieland 2021). Where resilience seeks to neutralise disruption, antifragility seeks to learn from it and translate that learning into positional or operational advantage.

This orientation is particularly relevant for production and supply chains that operate under persistent and non-linear fluctuation rather than rare shocks. Systems that only stabilise can become locked in cycles of disruption and recovery with limited cumulative learning (Aldrighetti et al. 2021). In contrast, systems that treat disturbance as a learning opportunity can gradually strengthen as volatility increases. Recent contributions therefore frame antifragility as a potential strategic capability for technology-intensive manufacturing firms, especially as they adopt data-rich, digitally mediated coordination structures that can support continuous learning under turbulence (Bag et al. 2023; Padovano and Ivanov 2025). This perspective suggests that antifragility may reshape expectations of operational excellence by shifting emphasis from continuity towards intelligent adaptation and by linking this shift to notions of viable and self-adjusting supply chains (Ivanov 2022; Ruel et al. 2021).

The opportunities revealed by turbulence appear at different system levels. At the process level, disturbances highlight inefficiencies and constraints that remain hidden in steady-state operations. At the resource and configuration level, shocks expose which forms of redundancy or flexibility generate useful information rather than only cost. At the network and market level, volatility reveals supplier reliability patterns, early shifts in demand fundamentals, and alternative configuration paths that are not visible when conditions are stable (Aldrighetti et al. 2021; Munoz and Zhou 2023). In each case, disturbance produces data about how the system behaves under stress. If the system is architected to capture, interpret, and retain this data, it can convert turbulence into capability. Recent work on supply chain viability and resilience argues that long-term survival increasingly depends on the ability to reinterpret shocks as signals for structural redesign rather than as anomalies to suppress (Padovano and Ivanov 2025; Ruel et al. 2021).

Despite this conceptual development, the operational mechanics of antifragility in manufacturing supply chain operations remain under-specified. Most contributions explain why antifragility is attractive but say little about how it is enacted in day-to-day operations or embedded in system design (Bag et al. 2023; Nikookar, Varsei, and Wieland 2021). In particular, they seldom identify the specific functions that allow production and supply chain systems to transform shocks into lasting improvement. Without this level of detail, antifragility remains an ambition rather than an actionable design principle.

In this paper, antifragility is therefore treated as an outcome of concrete functional mechanisms. These mechanisms include sensing capabilities that reveal how disruptions propagate, analytical capabilities that turn disruption data into insight, and reconfiguration capabilities that use this insight to adjust structures and policies. The next subsection examines AI as a technological foundation through which such mechanisms can materialise in operational practice.

### 2.1. Operational requirements of antifragile production and supply chains

Moving from antifragility as a concept to antifragility as an operational design principle requires specifying what must be in place for disruption to generate improvement rather than only recovery. In production and supply chains, disturbances become valuable when the operating system can capture what they reveal, interpret it with sufficient speed and depth, and embed that learning into routines, policies, and structural choices (Aldrighetti et al. 2021; Nikookar, Varsei, and Wieland 2021). This perspective implies a set of practical requirements. First, antifragility presupposes observability and fast feedback, meaning that stress signals are detected early and traced across key flows and constraints before responses collapse into symptom correction. Second, it requires diagnostic depth, since gaining from disorder depends on understanding how disruptions propagate and which structures amplify or dampen their effects, rather than only measuring performance loss. Third, it requires learning loops and organisational memory that translate disruption insights into updated decision rules, revised parameters, and refined operating routines, so the system becomes more capable across episodes rather than returning to prior settings (Aldrighetti et al. 2021). Fourth, it requires experimentation capacity supported by safe-to-fail mechanisms, because antifragility depends on testing alternative policies and configurations under uncertainty while bounding downside risk through controlled pilots, staged rollouts, and modular changes (Ivanov 2022; Nikookar, Varsei, and Wieland 2021). Fifth, it requires reconfiguration capacity across levels, from process adjustments to resource redeployment and network choices, with emphasis on changes that increase future option value rather than only restore short-term equilibrium (Ivanov 2022; Ruel et al. 2021). Finally, these requirements depend on governance and decision discipline, including decision rights, escalation rules, accountability, and risk thresholds that determine whether learning is implemented as structural change rather than repeatedly displaced by short-term stabilisation pressures (Padovano and Ivanov 2025; Ruel et al. 2021).

These requirements are mutually reinforcing. Faster feedback improves diagnosis, diagnosis strengthens learning loops, learning guides where experimentation is warranted, experimentation provides evidence for reconfiguration, and governance ensures that adaptation remains disciplined and cumulative. Importantly, such requirements can be pursued through managerial practices, organisational design, and different technology combinations. The focus of this paper is on AI because it offers a distinctive foundation for strengthening several of these requirements in environments characterised by high-dimensional signals, non-linear interactions, and persistent volatility. The next subsection therefore explains why AI is particularly relevant for enabling the functional mechanisms through which antifragility becomes operationally observable in production and supply chains.

### 2.2. Why AI enables antifragile operations

The mechanisms outlined above place strong demands on a system's capacity to observe, interpret, and remember how it behaves under stress. Modern production and supply environments generate more volatility, signals, and interaction effects than can be interpreted through human cognition and static rule-based systems alone. Conventional digitalisation captures large volumes of data, but it does not automatically turn that data into structural learning. Many optimisation tools are designed to dampen variability and restore equilibrium, which is valuable for resilience but only partly aligned with the logic of gaining from disorder (Ivanov 2022; Toorajipour et al. 2021). Work on supply chain viability further suggests that systems that focus only on rapid recovery without structural learning struggle to remain competitive under prolonged turbulence (Ivanov 2026; Padovano and Ivanov 2025).

AI is distinct because it can learn from exposure to irregular and high-dimensional data rather than only operate under expected conditions. Machine learning models can detect subtle anomalies, identify emerging patterns in demand or disruption propagation, and refine their internal representations as additional data become available (Gupta et al. 2024; Naz et al. 2022). In manufacturing and supply chain operations, repeated process deviations can improve process control and calibration, fluctuating flows can refine allocation logic, and accumulated disruption histories can inform structural redesign (Belhadi et al. 2021; Helo and Hao 2022). Empirical studies on AI-enabled supply chain capabilities show that such systems enhance visibility, predictive sensing, and adaptive response, which together reduce recovery times and improve reconfiguration decisions after shocks (Gupta et al. 2024; Naz et al. 2022).

Accordingly, AI does not only protect the operating system from volatility. When designed and governed with learning in mind, AI can improve the quality of decision making as volatility continues. Recent work suggests that AI, digital twins, and cybernetic feedback loops can act as core enablers of resilient and viable supply chains because they support learning from disruption rather than only buffering its effects (Fosso Wamba et al. 2024; Ivanov 2026). In this respect, AI is not an adjunct to antifragility. It is a technology class that can make antifragile operations feasible in practice by delivering the sensing, analytical, and reconfiguration functions described above. At the same time, the feasibility of disruption-driven learning depends on the characteristics of available data and on the learning regime adopted, which warrants explicit qualification to set realistic implementation expectations. Disruption episodes are often heterogeneous, partially non-repeating, and weakly labelled, and they may exhibit strong class imbalance, which limits the effectiveness of purely supervised retraining on disruption labels. For clarity, this study does not assume that antifragile learning requires continuous full retraining on large labelled disruption datasets. Rather, antifragility-oriented learning can draw on approaches better suited to sparse and evolving contexts, such as transfer learning from related operational domains, self-supervised learning on operational traces to build robust representations before disruptions occur, few-shot adaptation to incorporate emerging event types, and simulation-to-real learning supported by digital twins or synthetic scenario generation when empirical disruption data is limited. These considerations reinforce the value of specifying antifragility in terms of operational functions, since different functions may rely on different learning regimes and data conditions in practice.

## 3. Research design and method

This study adopted an integrated research design that combined a systematic search and screening process with expert-based interpretive structuring. The objective was to move from a theoretically grounded understanding of antifragility towards a structured capability roadmap that shows how AI can be leveraged to build antifragile behaviour in production and supply chain operations. Because antifragility cannot be observed directly but must be inferred from the functions that generate it, the study required a multi-stage design rather than reliance on a single identification technique. The overall methodological flow is illustrated in Figure 1.

The process began with a literature-based systematic search and screening process that identified an initial set of AI-enabled operational functions for antifragility in production and supply chain contexts and provided the conceptual foundation for the study. This was followed by a Delphi-based expert refinement stage, in which a panel of senior practitioners iteratively assessed and adjusted the initial set to achieve consensus on the relevance and meaning of each function. Once the functions had been validated, a NGT session was conducted to elicit the directional relationships among them and to construct an Interpretive Logic-Knowledge Base (ILB) that captured the experts' reasoning about how and why each function influences others.

Interpretive Structural Modelling (ISM) was subsequently applied to synthesise these judgements into a hierarchical capability structure, which was then interpreted as a strategic roadmap distinguishing foundational AI capabilities from higher order outcomes as firms progress towards antifragility. This integrated Delphi–NGT-ISM design was chosen because antifragility is relational, emergent and knowledge based, and therefore requires expert interpretation rather than direct measurement. A panel of eleven domain experts participated in the refinement and structuring stages, consistent with established guidance that seven to twelve experts provide a methodologically sound basis for Delphi-interpretive modelling with homogeneous experts (e.g. Okoli and Pawlowski 2004). The subsequent subsections describe each stage in more detail, including expert selection, the Delphi procedure, the NGT session and the ISM modelling steps.

### 3.1. Systematic identification of AI antifragility functions

The first stage of the research aimed to identify how AI contributes to antifragile behaviour in production and supply chain operations. Antifragility is still an emerging concept in operations research and is often discussed through adjacent notions such as adaptive learning, self-improving systems, and performance enhancement under variability. Therefore, a content-centric literature review was conducted using Scopus and Web of Science, which together provide broad coverage of industrial, operations, and AI-related publications.

As illustrated in Figure 2, the database search identified 220 documents. Three exclusion criteria were applied during screening. First, papers not written in English or without accessible full text were removed. Second, studies in which antifragility or AI were mentioned only superficially, without conceptual or operational relevance, were excluded. Third, papers were removed if they did not discuss how AI contributes to or enables mechanisms that strengthen capability under volatility in production or supply chain settings. Applying these criteria led

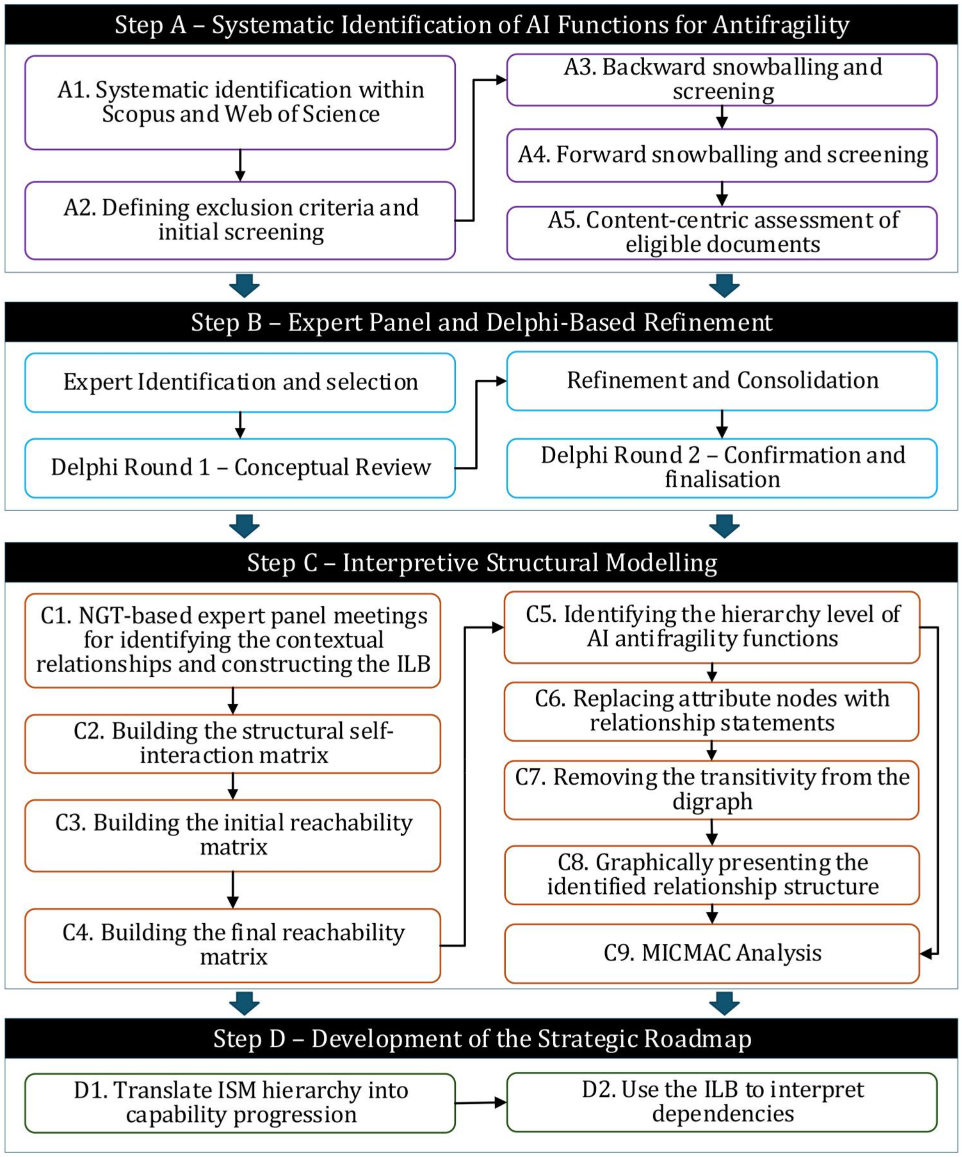



Figure 1. Overview of the research design (source: the authors).

to the exclusion of 183 papers, leaving 37 for detailed assessment.

To ensure broader coverage and capture relevant studies not retrieved in the initial search, both backward and forward snowballing were applied. Backward snowballing involved examining the reference lists of the 37 shortlisted papers and yielded 46 additional documents, of which 9 met the inclusion criteria. Forward snowballing identified newer studies citing the shortlisted papers and produced 43 additional documents, of which 12 were retained after screening. Together, these steps resulted in 58 documents selected for full-text analysis.

The final stage involved a comprehensive content assessment of these 58 studies to extract a preliminary set of AI functions contributing to antifragility. Each document was examined to determine whether it provided conceptual reasoning for antifragility or described mechanisms through which AI enhances learning, adaptation or capability improvement under disruption or volatility. Conceptual papers were analysed for theoretical clarity, while empirical and technical papers were assessed for operational insight into AI-enabled performance improvement. Recurring themes and terminologies were coded to capture specific AI-related mechanisms aligned with antifragile behaviour.

This analysis followed an iterative coding process. Descriptive codes were first assigned to AI-driven mechanisms such as predictive adjustment, adaptive control, automated learning, and self-optimisation. These codes were then clustered into higher-order categories that reflected their role in fostering antifragile capability. Coding was conducted manually by the research team and supported by cross-checking and discussion to ensure interpretive rigour and consistency. The outcome of this synthesis was a preliminary list of thirteen AI-enabled antifragility functions, which formed the basis for expert evaluation and refinement in the Delphi-based stage described in the next section.

### 3.2. Expert panel and Delphi-Based refinement

Following the systematic identification of AI enabled antifragility functions, a Delphi based expert refinement was

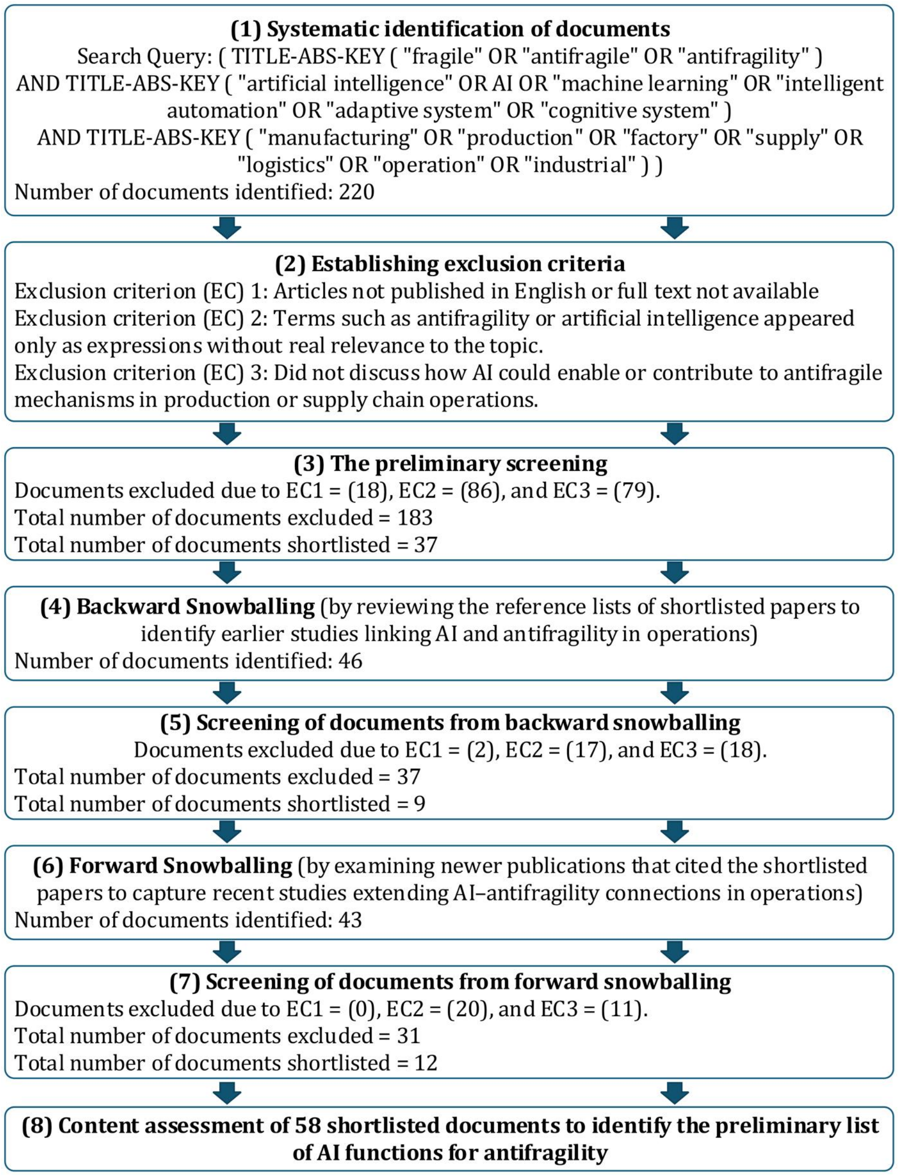



**Figure 2.** The systematic AI function search and screening process (source: the authors).

conducted to ensure conceptual clarity, completeness and practical validity. The Delphi method facilitates structured expert consensus through iterative feedback and controlled information sharing (Okoli and Pawlowski 2004). It is well suited to emerging, cross disciplinary constructs such as AI driven antifragility, where empirical evidence is limited and expert interpretation is required to balance theoretical precision with operational relevance (Ghobakhloo et al. 2025a). The objective was to consolidate the preliminary list of functions into a validated and industry relevant set of AI capabilities that contribute to antifragile performance in production and supply chain operations.

An expert panel of eleven professionals was established using purposive sampling to secure depth and diversity of expertise. All participants were senior representatives of large multinational manufacturing firms recognised for advanced digital transformation and strong technology exploitation capabilities. Their organisations operate in turbulence intensive and innovation driven sectors such as consumer electronics, electric vehicles, industrial automation and semiconductor related equipment, where supply uncertainty, short product life cycles and volatile demand are pervasive. The panel included operations directors, digitalisation strategists, AI programme leaders and senior data science specialists with responsibility for transformation portfolios, risk and continuity planning or technology enabled business model development. Each expert had at least ten years of experience in deploying or governing AI based systems in industrial operations and had been directly involved in responding to major disruptions. This composition combined technical fluency in AI with strategic insight into how operational capabilities are shaped under volatility.

The Delphi process consisted of two iterative rounds (Okoli and Pawlowski 2004). In Round 1, experts received the preliminary list of AI functions and concise definitions. They rated each function against four criteria: conceptual clarity, perceived importance for antifragility, operational applicability and technological feasibility within current manufacturing systems. Open ended feedback captured suggestions for rewording, merging or expanding function definitions. Responses were submitted anonymously to reduce groupthink. Feedback was analysed qualitatively to identify areas of agreement and disagreement and quantitatively using median and interquartile range values, with an IQR of 1.0 or below indicating satisfactory convergence.

Functions showing high consensus were retained, while those with divergent assessments were revised and, where appropriate, consolidated. Expert comments informed refinement of terminology and descriptions. The revised list and a summary of aggregated feedback were then circulated for Round 2, in which experts reassessed each function in light of group level responses.

Round 2 concluded when at least 80 percent agreement had been reached on the definition and operational significance of each function. Kendall's coefficient of concordance (W) was used to assess inter-expert agreement across the function set in each round. Kendall's W ranges from 0 to 1, where higher values indicate stronger agreement. In Delphi applications, values around 0.3 are often interpreted as weak agreement, around 0.5 as moderate agreement, and 0.7 or higher as strong agreement. In this study, W indicated moderate to strong agreement in Round 1 ($W = 0.62$) and strong agreement in Round 2 ($W = 0.78$), suggesting clear convergence of expert judgements across rounds. Results from both rounds were also compared to confirm the stability of opinions. Qualitative comments were reviewed once more to ensure that no critical functions were omitted and that the final set reflected both theoretical coherence and industrial feasibility.

The two round Delphi process thus produced a validated set of thirteen AI enabled antifragility functions. The refined set, presented in Table 1, represents the consolidated outcome of the literature synthesis and expert validation phases, and each function is introduced in the following section. While Table 1 defines the functional mechanisms, their operational realisation depends on governance arrangements that validate recommendations before execution and specify accountability, escalation, and override logic. These requirements become increasingly important as functions progress towards autonomy and as decisions affect service levels, safety, compliance, or other critical operations.

***Adaptive scheduling (ADS)*** uses learning-based optimisation to resequence production dynamically as conditions change instead of following a fixed or periodically updated plan (Liu, Piplani, and Toro 2022). Reinforcement learning and digital twins are often used to test alternative schedules offline and estimate their impact on flow time, utilisation and due-date performance (Chang et al. 2023). If ADS is effectively implemented, the AI component learns which routings and priorities work best under different combinations of delays, machine degradation and shifting customer requirements. Over repeated shocks it builds a mapping between disruption patterns and effective scheduling responses, so the system allocates work with less trial and error (Panzer and Bender 2022).

***Autonomous process control (APC)*** denotes intelligent control logic that adjusts production parameters in real time without human intervention, based on continuous interpretation of sensor data and process feedback (Cohen and Singer 2021). It typically combines adaptive control, model predictive control and reinforcement learning to update policies whenever the process exhibits drift, material inconsistency or environmental fluctuation (Bloor et al. 2025; Vega-Zambrano, Diangelakis, and Charitopoulos 2025). When APC is in place, deviations and transient disturbances can be logged and linked to contextual conditions, then used to refine process models and control rules. Each episode of instability improves understanding of safe operating envelopes and effective corrections, so the controller gradually widens the region in which it can keep quality and throughput stable under variable conditions.

***Capacity realignment (CAR)*** uses AI-enabled reasoning to rebalance production capacity across machines, shifts or sites in response to shocks rather than following a fixed capacity plan (Esteso et al. 2023). Reinforcement learning and scenario-based optimisation are employed to explore alternative load configurations and estimate their impact on utilisation, lead times and service levels before implementation (Tseng et al. 2025). If CAR is systematically applied, demand swings, machine failures and supply interruptions become data about which reallocation patterns work best in practice. Performance feedback from each realignment episode updates the estimated value of options such as overtime, cross-training, rerouting or inter-plant transfer, so capacity decisions become faster and more precise over time (Panda, Xiang, and Liu 2024).

***Causal diagnostics (CAD)*** applies AI to determine why disruptions occur by identifying structural drivers rather than only flagging anomalies (Li et al. 2025). It uses causal inference, Bayesian structural learning and graph reasoning to reconstruct event pathways and separate genuine causes from correlated noise (Kitson et al. 2023). When disturbance histories are consistently fed into CAD, each failure or near miss helps to update the causal graph and validate or refute hypothesised links. Over time, diagnostic models become more accurate, root cause investigations are shortened and improvement actions can be targeted more precisely.

***Continuous learning loops (CLL)*** embed adaptive learning directly into operational logic so that models are updated during execution instead of only in isolated improvement projects (De Lange et al., 2022). Online learning, incremental reinforcement learning and meta-learning architectures adjust model parameters as disruptions unfold (Hospedales et al. 2022). If organisations manage to establish CLL around key decision functions, performance deviations, errors and drift become learning signals that support incremental updating of the models and decision policies that drive scheduling, control, or routeing. Disturbances then refine model calibration rather than being treated as exceptions, and the intelligence layer remains aligned with the latest volatility patterns.

***Disruption-driven innovation (DDI)*** uses AI to mine disturbance data for redesign opportunities in products,

Table 1. AI-enabled antifragility functions and their key characteristics.

| Acronym | Function Name | Operational Definition | Antifragility Mechanism | Primary Application Domain* | Key Enabling AI Technologies |
|---|---|---|---|---|---|
| **ADS** | Adaptive Scheduling | Real-time rescheduling that dynamically reallocates production tasks based on disturbances in machines, labour, materials, or demand. It substitutes static plans with situational optimisation. | Gains from variability by redirecting workload towards available or better-performing capacity nodes during disruption. | P | Reinforcement Learning (RL)-based Scheduling, Digital Twin Optimisation |
| **APC** | Autonomous Process Control | Self-tuning process control that autonomously adjusts parameters based on sensor feedback and contextual deviation. Reduces dependence on manual recalibration. | Converts operational volatility into performance improvement by continually refining control accuracy under stress. | P | Edge AI, Deep RL, Adaptive Control |
| **CAR** | Capacity Realignment | Real-time scaling or reallocation of productive capacity across units, machines, or shifts to accommodate fluctuating loads. | Uses demand or supply shocks to strengthen capacity responsiveness and elasticity over time. | P & OS | Capacity ML, Scenario Simulation, Elastic Control Systems |
| **CAD** | Causal Diagnostics | AI identifies not just anomalies but underlying structural causes of disruptions using causal inference models. Enables learning from disorder rather than suppression of symptoms. | Converts failure into structural knowledge that increases future robustness and adaptation ability. | C | Causal ML, Bayesian Networks, Explainable AI (XAI) |
| **CLL** | Continuous Learning Loops | Continuous retraining and adaptation of AI models based on real feedback from disruptions, drift, or instability. | Each disturbance becomes a training signal that improves the model's future reaction quality. | C | Online Learning, Meta-Learning, RL |
| **DDI** | Disruption-Driven Innovation | Disturbances are mined for insights that lead to reshaped processes, product redesigns, or new sourcing logic. | The system evolves through disorder rather than merely restoring baseline stability. | C | Pattern Mining, Generative AI, Knowledge Graphs |
| **DMI** | Demand Intelligence | Real-time modelling of demand volatility and micro-shifts in consumption patterns to detect change faster than classical forecasts. | Treats demand turbulence as opportunity to optimise mix, pricing, or responsiveness. | OS | Transformer Forecasting, Market Signal AI |
| **FLO** | Flexibility Orchestration | AI allocates and coordinates available flexibility (process, routeing, supplier, material) depending on disruption type. | Variability triggers positive reconfiguration rather than a fallback to rigid buffering. | P & IS | Multi-Agent AI, Flexibility Analytics |
| **IVI** | Inventory Intelligence | Dynamically adjusts inventory positions and safety stock based on volatility in supply or demand signals. | Variability becomes input to adaptive inventory strategy, increasing viability under shocks. | IS & OS | Probabilistic Optimisation, ML-based Multiechelon Control |
| **LOG** | Logistics Optimisation | Re-optimizes routes, modes, and capacity allocations in real time as conditions shift in transport networks. | Turbulence in flows becomes a source for more efficient network adaptation. | IS & OS | Graph AI, Routeing Optimisation |
| **PRS** | Predictive Sensing | Detects early warning signals before disruption materialises, across production, supplier, or demand environments. | Anticipation converts shock into pre-emptive advantage rather than reactive stabilisation. | C | Sensor Fusion, Time-series AI, Early Warning ML |
| **SSI** | Supplier Substitution Intelligence | Identifies and validates alternative suppliers, materials, or configurations rapidly when primary sourcing becomes unstable. | Disruption becomes a trigger for diversification and stronger sourcing posture. | IS | Similarity AI, Sourcing Graphs |
| **SRI** | Supply Risk Intelligence | Continuous AI-based exposure scanning of supplier fragility, lead-time shock, geopolitical risk, and upstream vulnerabilities. | Uses instability as mobilisation signal to structurally reshape sourcing before cascading failure. | IS | Risk Scoring ML, Bayesian Risk Networks |

*Note: P = Production; IS = Inbound Supply; OS = Outbound Supply (Customer-side); C = Cross-cutting (applies to both production and supply).

processes and sourcing logic. Pattern mining, generative models and knowledge graphs are applied to failure logs, complaints, quality deviations and supply disruptions to identify recurring weaknesses and candidate solution spaces (Gidiagba, Tartibu, and Okwu 2025; Kosasih et al. 2024). When such pipelines are in place, clusters of disruption events can be systematically linked to product or process changes, such as simplified architectures, more modular routings or new service offerings. This allows firms to channel volatility into targeted innovation activity rather than only corrective maintenance.

***Demand intelligence (DMI)*** uses AI to model demand volatility and micro-shifts in consumption patterns more accurately and quickly than classical forecasts (Bergsma, de Ruijt, and Bhulai 2025; Taşcı, Omar, and Ayvaz 2023). Transformer-based forecasting, market signal analytics and multi-source data fusion detect early changes in order composition, channel mix and regional trends (Dehaybe, Catanzaro, and Chevalier 2024). If DMI insights feed into product mix, capacity and pricing decisions, each period of instability sharpens understanding of how demand responds to shocks. Over repeated episodes, models improve their ability to distinguish temporary noise from structural shifts, and the firm learns which adaptations yield robust performance.

***Flexibility orchestration (FLO)*** is the intelligent allocation of alternative pathways in production and supply chains based on the specific nature of a disturbance (Kassa et al. 2023; Zamani et al. 2022). AI-supported decision logic coordinates levers such as rerouting jobs, switching machines, changing batch sizes, drawing from parallel suppliers or substituting materials within capacity and quality constraints (Li et al. 2025). When disruption histories are used to evaluate these combinations, FLO can learn which patterns of flexibility deliver the best results for different disruption signatures. The organisation then uses its flexibility assets more selectively and effectively instead of relying on generic buffers.

***Inventory intelligence (IVI)*** applies AI to dynamically position and size inventory buffers based on live volatility rather than static safety stock rules (Bergsma, de Ruijt, and Bhulai 2025). Probabilistic forecasting, neural optimisation and multi-echelon learning determine where slack should be held or reduced as variability changes across the network (Dehaybe, Catanzaro, and Chevalier 2024; Svoboda and Minner 2026). If disruption outcomes are systematically fed back into these models, each spike, delay or quality issue reveals where inventory effectively absorbs risk and where it mainly adds cost. Over time, stock levels and locations can be recalibrated to maintain service under turbulence with leaner and better targeted buffers.

***Logistics optimisation (LOG)*** provides adaptive routeing and allocation that reconfigures transport flows in response to disturbances instead of keeping them fixed (Barua, Zou, and Zhou 2020). Graph analytics, real-time optimisation and predictive models account for lane reliability, capacity shocks, congestion risk and changing customer priorities (Flores-García et al. 2025). When historical and real-time disruption evidence is used to update and recalibrate these models, each delay, detour, or missed slot improves the estimated performance of routes and carriers under different conditions. The transport network can then be routed through disruption on the basis of accumulated evidence rather than static rules.

***Predictive sensing (PRS)*** is the capability through which AI-enabled systems detect early signals of potential disruption across production, sourcing and logistics before they are operationally visible (Taşcı, Omar, and Ayvaz 2023). It combines time series models, sensor fusion and feature extraction, and may include graph-based reasoning that links shop-floor, supplier and transport data (Kosasih et al. 2024; Wen et al. 2023). If alerts are systematically validated against realised outcomes, PRS can refine what counts as a meaningful precursor to instability. Over repeated events, it becomes better at distinguishing harmless fluctuations from genuinely risky developments, enabling earlier and more targeted interventions.

***Supplier substitution intelligence (SSI)*** uses AI-based similarity matching, knowledge graphs and feasibility screening to identify workable alternatives when primary supply is unstable (Kosasih et al. 2024). It evaluates technical compatibility, quality records, logistics implications and commercial terms to shortlist candidates that can realistically replace the original source (Gidiagba, Tartibu, and Okwu 2025). When each substitution episode is recorded and evaluated, empirical evidence accumulates on lead times, qualification effort and performance of alternatives. This gradually enlarges and refines the set of validated options that can be activated when new disruptions occur.

***Supply risk intelligence (SRI)*** provides continuous AI-based assessment of upstream fragility through exposure monitoring, probabilistic risk scoring and early warning analytics (Das and Perona 2025; Liu et al. 2021). It integrates signals such as lead time instability, quality drift, financial stress, geopolitical events and logistics volatility into forward-looking risk profiles, often via supply chain knowledge graphs (Kosasih et al. 2024). If disruptions and near misses are used to update and recalibrate these models, SRI can gradually sharpen the sensitivity and specificity of its indicators and improve the timing of alerts. Firms that act on these updated signals can anticipate upstream problems earlier and adjust orders, contracts or sourcing before risks fully materialise.

### 3.3. Interpretive Structural modelling

Following the validation of the thirteen AI-enabled antifragility functions, ISM was applied to establish the hierarchical structure among the functions. ISM was selected because it provides a systematic and transparent approach for identifying and arranging complex interrelationships among variables based on expert judgement. It enables qualitative expert reasoning to be transformed into a structured, quantitative model that clarifies how the identified functions interact and collectively contribute to antifragile capability development (Priyadarshini et al. 2022).

The ISM process began with the development of the Structural Self-Interaction Matrix (SSIM), which captured the

Table 2. SSIM of AI-enabled antifragility functions.

| | ADS | APC | CAR | CAD | CLL | DDI | DMI | FLO | IVI | LOG | PRS | SSI | SRI |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ADS | – | A | A | A | A | O | A | A | A | A | A | O | O |
| APC | | – | O | A | A | O | O | O | O | O | A | O | O |
| CAR | | | – | O | A | A | A | A | A | V | A | A | A |
| CAD | | | | – | V | V | O | V | O | O | A | O | O |
| CLL | | | | | – | O | V | V | V | V | X | V | V |
| DDI | | | | | | – | O | V | O | O | O | A | O |
| DMI | | | | | | | – | V | V | V | O | V | O |
| FLO | | | | | | | | – | V | V | O | V | O |
| IVI | | | | | | | | | – | V | O | O | O |
| LOG | | | | | | | | | | – | O | O | O |
| PRS | | | | | | | | | | | – | V | V |
| SSI | | | | | | | | | | | | – | O |
| SRI | | | | | | | | | | | | | – |

Table 3. IRM derived from SSIM.

| | ADS | APC | CAR | CAD | CLL | DDI | DMI | FLO | IVI | LOG | PRS | SSI | SRI |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ADS | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| APC | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| CAR | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| CAD | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| CLL | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| DDI | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| DMI | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 0 |
| FLO | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 1 | 0 |
| IVI | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 |
| LOG | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| PRS | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 |
| SSI | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| SRI | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |

contextual relationships among the validated functions. To ensure analytical rigour, the SSIM was constructed through two NGT meetings with the same expert panel that participated in the Delphi phase. In NGT meeting 1, experts evaluated all possible pairs of the thirteen functions to determine the direction of influence between each pair using the standard ISM notation: V (function *i* influences *j*), A (function *j* influences *i*), X (both influence each other), and O (no relationship). In NGT meeting 2, the experts collectively interpreted the functionality and contextual meaning of each direct relationship to ensure shared understanding of why and how one function influences another. This interpretive step allowed the panel to preserve the causal logic underlying each directional link. The final consensus-based SSIM, shown in Table 2, represents the relational direction for each pairwise connection among the AI-enabled antifragility functions.

The SSIM was then transformed into a binary Initial Reachability Matrix (IRM) by converting the symbolic relationships into numerical values, as shown in Table 3. The IRM captured all direct influences between the functions. Transitivity was subsequently applied to produce the Final Reachability Matrix (FRM) presented in Table 4, ensuring logical completeness and internal consistency. FRM summarises the final set of direct and transitive reachability relations among functions after applying the ISM rules, and it provides the basis for level partitioning and the hierarchical model. According to the principle of transitivity, if function *i* influences *j* and *j* influences *k*, then *i* is assumed to influence *k*. This step allowed both direct and inferred dependencies to be captured systematically. In Table 4, driving power indicates how strongly a function shapes the rest of the system, measured by the number of other functions it influences directly or indirectly. Dependence power indicates how strongly a function is shaped by the system, measured by the number of other functions that influence it.

Table 4. FRM after applying transitivity.

| | ADS | APC | CAR | CAD | CLL | DDI | DMI | FLO | IVI | LOG | PRS | SSI | SRI | *DrP* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ADS | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | *1* |
| APC | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | *2* |
| CAR | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | *3* |
| CAD | 1 | 1 | **1** | 1 | 1 | 1 | **1** | 1 | **1** | **1** | **1** | **1** | **1** | *13* |
| CLL | 1 | 1 | 1 | **1** | 1 | **1** | 1 | 1 | 1 | 1 | 1 | 1 | 1 | *13* |
| DDI | **1** | 0 | 1 | 0 | 0 | 1 | 0 | 1 | **1** | **1** | 0 | **1** | 0 | *7* |
| DMI | 1 | 0 | 1 | 0 | 0 | **1** | 1 | 1 | 1 | 1 | 0 | 1 | 0 | *8* |
| FLO | 1 | 0 | 1 | 0 | 0 | **1** | 0 | 1 | 1 | 1 | 0 | 1 | 0 | *7* |
| IVI | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | *4* |
| LOG | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | *2* |
| PRS | 1 | 1 | 1 | 1 | 1 | **1** | **1** | **1** | **1** | **1** | 1 | 1 | 1 | *13* |
| SSI | **1** | 0 | 1 | 0 | 0 | 1 | 0 | **1** | 0 | **1** | 0 | 1 | 0 | *6* |
| SRI | **1** | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | **1** | 0 | 0 | 1 | *4* |
| *DeP* | *13* | *4* | *10* | *3* | *3* | *7* | *4* | *7* | *7* | *11* | *3* | *7* | *4* | |

Note: *DeP*, Dependence power; *DrP*, Driving power. Bold **1**s indicate relationships added through the application of transitivity.

The next phase involved level partitioning to extract the hierarchical order of the functions. For each function, reachability, antecedent, and intersection sets were derived from the FRM. A function was assigned to a level when its reachability and intersection sets were identical, indicating that it did not lead to any other function beyond itself within that iteration. Once extracted, these functions were removed from subsequent iterations, and the process was repeated until all functions were assigned a hierarchical level. The complete level partitioning procedure and the sequential extraction of hierarchies are detailed in Table 5. The final ISM model, illustrated in Figure 3, was constructed by arranging the functions according to the hierarchies identified in reverse order, placing the most driving (foundational) functions at the bottom and the most dependent (outcome) functions at the top. Vector arrows were used to depict the contextual relationships among the functions, following the directional logic established through the SSIM and transitivity analysis. This visual representation provides a structured overview of the relational architecture of AI-enabled antifragility.

A classic binary MICMAC analysis was conducted to assess the driving and dependence powers of the thirteen AI-enabled antifragility functions. Using the row and column sums of the FRM, each function was positioned on the driver–dependence grid shown in Figure 4, which separates functions into Autonomous, Dependent, Linkage and Independent clusters.

The results show a clear structural pattern. CAD, CLL and PRS fall within the independent quadrant and exhibit the strongest driving power with very low dependence, confirming their role as fundamental enablers of antifragility. DDI and FLO appear in the linkage quadrant and show both high driving and high dependence power, indicating that they are highly interactive and sensitive to changes elsewhere in the system. ADS, LOG, CAR and IVI are located in the dependent quadrant and display high dependence with limited driving influence, consistent with their position as outcome-oriented capabilities. Finally, APC, SRI and SSI lie in the autonomous

Table 5. Hierarchical extraction.

| Function | Antecedent Set | Reachability Set | Intersection Set | Extraction Level |
|---|---|---|---|---|
| ***Iteration 1*** | | | | |
| ADS | ADS, APC, CAR, CAD, CLL, DDI, DMI, FLO, IVI, LOG, PRS, SSI, SRI | ADS | ADS | 1 |
| APC | APC, CAD, CLL, PRS | ADS, APC | APC | |
| CAR | CAR, CAD, CLL, DDI, DMI, FLO, IVI, PRS, SSI, SRI | ADS, CAR, LOG | CAR | |
| CAD | CAD, CLL, PRS | ADS, APC, CAR, CAD, CLL, DDI, DMI, FLO, IVI, LOG, PRS, SSI, SRI | CAD, CLL, PRS | |
| CLL | CAD, CLL, PRS | ADS, APC, CAR, CAD, CLL, DDI, DMI, FLO, IVI, LOG, PRS, SSI, SRI | CAD, CLL, PRS | |
| DDI | CAD, CLL, DDI, DMI, FLO, PRS, SSI | ADS, CAR, DDI, FLO, IVI, LOG, SSI | DDI, FLO, SSI | |
| DMI | CAD, CLL, DMI, PRS | ADS, CAR, DDI, DMI, FLO, IVI, LOG, SSI | DMI | |
| FLO | CAD, CLL, DDI, FLO, PRS, SSI | ADS, CAR, DDI, FLO, IVI, LOG, SSI | DDI, FLO, SSI | |
| IVI | CAD, CLL, DDI, DMI, FLO, IVI, PRS | ADS, CAR, IVI, LOG | IVI | |
| LOG | CAR, CAD, CLL, IVI, LOG, PRS, SRI | ADS, LOG | LOG | |
| PRS | CAD, CLL, PRS | ADS, APC, CAR, CAD, CLL, DDI, DMI, FLO, IVI, LOG, PRS, SSI, SRI | CAD, CLL, PRS | |
| SSI | CAD, CLL, DDI, FLO, PRS, SSI | ADS, CAR, DDI, FLO, LOG, SSI | DDI, FLO, SSI | |
| SRI | CAD, CLL, PRS, SRI | ADS, CAR, LOG, SRI | SRI | |
| ***Iteration 2*** | | | | |
| APC | APC, CAD, CLL, PRS | APC | APC | 2 |
| CAR | CAR, CAD, CLL, DDI, DMI, FLO, IVI, PRS, SSI, SRI | CAR, LOG | CAR | |
| CAD | CAD, CLL, PRS | APC, CAR, CAD, CLL, DDI, DMI, FLO, IVI, LOG, PRS, SSI, SRI | CAD, CLL, PRS | |
| CLL | CAD, CLL, PRS | APC, CAR, CAD, CLL, DDI, DMI, FLO, IVI, LOG, PRS, SSI, SRI | CAD, CLL, PRS | |
| DDI | CAD, CLL, DDI, DMI, FLO, PRS, SSI | CAR, DDI, FLO, IVI, LOG, SSI | DDI, FLO, SSI | |
| DMI | CAD, CLL, DMI, PRS | CAR, DDI, DMI, FLO, IVI, LOG, SSI | DMI | |
| FLO | CAD, CLL, DDI, FLO, PRS, SSI | CAR, DDI, FLO, IVI, LOG, SSI | DDI, FLO, SSI | |
| IVI | CAD, CLL, DDI, DMI, FLO, IVI, PRS | CAR, IVI, LOG | IVI | |
| LOG | CAR, CAD, CLL, IVI, LOG, PRS, SRI | LOG | LOG | 2 |
| PRS | CAD, CLL, PRS | APC, CAR, CAD, CLL, DDI, DMI, FLO, IVI, LOG, PRS, SSI, SRI | CAD, CLL, PRS | |
| SSI | CAD, CLL, DDI, FLO, PRS, SSI | CAR, DDI, FLO, LOG, SSI | DDI, FLO, SSI | |
| SRI | CAD, CLL, PRS, SRI | CAR, LOG, SRI | SRI | |
| ***Iteration 3*** | | | | |
| CAR | CAR, CAD, CLL, DDI, DMI, FLO, IVI, PRS, SSI, SRI | CAR | CAR | 3 |
| CAD | CAD, CLL, PRS | CAR, CAD, CLL, DDI, DMI, FLO, IVI, PRS, SSI, SRI | CAD, CLL, PRS | |
| CLL | CAD, CLL, PRS | CAR, CAD, CLL, DDI, DMI, FLO, IVI, PRS, SSI, SRI | CAD, CLL, PRS | |
| DDI | CAD, CLL, DDI, DMI, FLO, PRS, SSI | DDI, FLO, IVI, SSI | DDI, FLO, SSI | |
| DMI | CAD, CLL, DMI, PRS | DDI, DMI, FLO, IVI, SSI | DMI | |
| FLO | CAD, CLL, DDI, FLO, PRS, SSI | DDI, FLO, IVI, SSI | DDI, FLO, SSI | |
| IVI | CAD, CLL, DDI, DMI, FLO, IVI, PRS | IVI | IVI | |
| PRS | CAD, CLL, PRS | CAD, CLL, DDI, DMI, FLO, IVI, PRS, SSI, SRI | CAD, CLL, PRS | |
| SSI | CAD, CLL, DDI, FLO, PRS, SSI | DDI, FLO, SSI | DDI, FLO, SSI | |
| SRI | CAD, CLL, PRS, SRI | SRI | SRI | |
| ***Iteration 4*** | | | | |
| CAD | CAD, CLL, PRS | CAD, CLL, DDI, DMI, FLO, IVI, PRS, SSI, SRI | CAD, CLL, PRS | |
| CLL | CAD, CLL, PRS | CAD, CLL, DDI, DMI, FLO, IVI, PRS, SSI, SRI | CAD, CLL, PRS | |
| DDI | CAD, CLL, DDI, DMI, FLO, PRS, SSI | DDI, FLO, IVI, SSI | DDI, FLO, SSI | |
| DMI | CAD, CLL, DMI, PRS | DDI, DMI, FLO, IVI, SSI | DMI | |
| FLO | CAD, CLL, DDI, FLO, PRS, SSI | DDI, FLO, IVI, SSI | DDI, FLO, SSI | |
| IVI | CAD, CLL, DDI, DMI, FLO, IVI, PRS | IVI | IVI | 4 |
| PRS | CAD, CLL, PRS | CAD, CLL, DDI, DMI, FLO, PRS, SSI, SRI | CAD, CLL, PRS | |
| SSI | CAD, CLL, DDI, FLO, PRS, SSI | DDI, FLO, SSI | DDI, FLO, SSI | 4 |
| SRI | CAD, CLL, PRS, SRI | SRI | SRI | 4 |
| ***Iteration 5*** | | | | |
| CAD | CAD, CLL, PRS | CAD, CLL, DDI, DMI, FLO, PRS | CAD, CLL, PRS | |
| CLL | CAD, CLL, PRS | CAD, CLL, DDI, DMI, FLO, PRS | CAD, CLL, PRS | |
| DDI | CAD, CLL, DDI, DMI, FLO, PRS | DDI, FLO | DDI, FLO | 5 |
| FLO | CAD, CLL, DDI, FLO, PRS | DDI, FLO | DDI, FLO | 5 |
| DMI | CAD, CLL, DMI, PRS | DDI, DMI, FLO, PRS | DMI | |
| PRS | CAD, CLL, PRS | CAD, CLL, DDI, DMI, FLO, PRS | CAD, CLL, PRS | |
| ***Iteration 6*** | | | | |
| CAD | CAD, CLL, PRS | CAD, CLL, DMI, PRS | CAD, CLL, PRS | |
| CLL | CAD, CLL, PRS | CAD, CLL, DMI, PRS | CAD, CLL, PRS | |
| DMI | CAD, CLL, DMI, PRS | DMI | DMI | 6 |
| PRS | CAD, CLL, PRS | CAD, CLL, PRS | CAD, CLL, PRS | |
| ***Iteration 7*** | | | | |
| CAD | CAD, CLL, PRS | CAD, CLL, PRS | CAD, CLL, PRS | 7 |
| CLL | CAD, CLL, PRS | CAD, CLL, PRS | CAD, CLL, PRS | 7 |
| PRS | CAD, CLL, PRS | CAD, CLL, PRS | CAD, CLL, PRS | 7 |

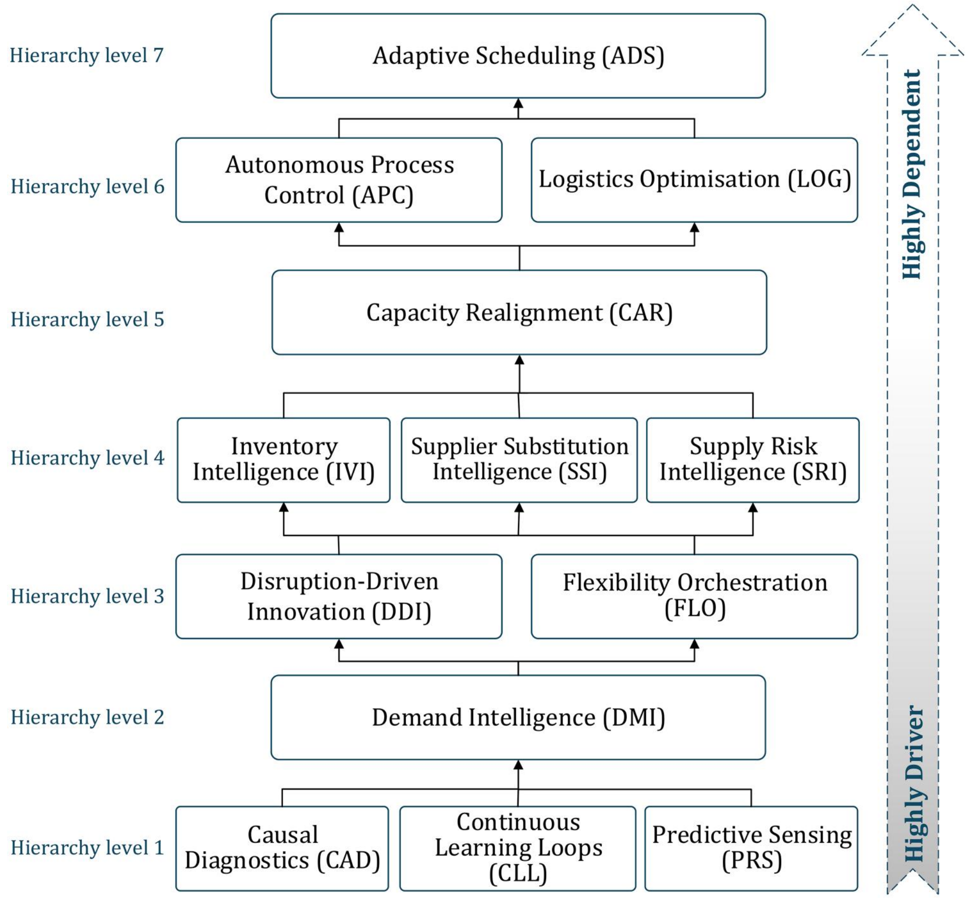



Figure 3. ISM-based hierarchy of AI-enabled antifragility functions (source: the authors).

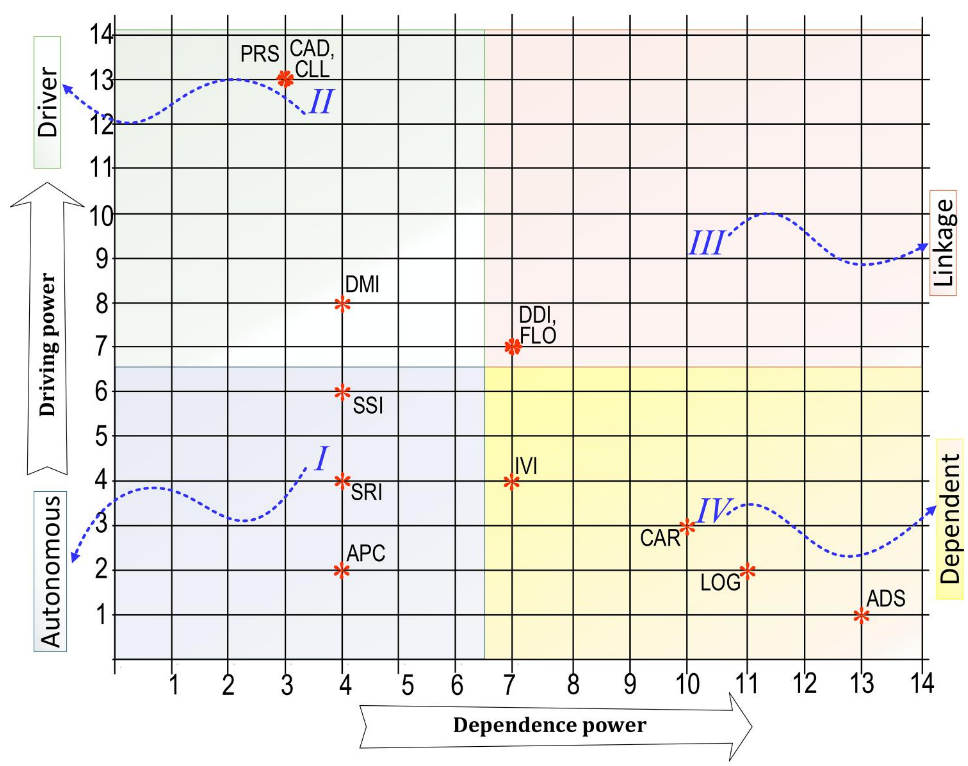



Figure 4. MICMAC analysis (source: the authors).

quadrant and show low interaction with the rest of the model.

MICMAC reinforces the ISM findings by highlighting CAD, CLL and PRS as key drivers, identifying DDI and FLO as dynamic linkage elements, and confirming ADS and related functions as dependent outcomes within the antifragility structure.

## 4. Strategic roadmap for AI-enabled antifragility

The strategic roadmap in Figure 5 integrates the hierarchical model derived from the ISM with the interpretive reasoning captured in the ILB (Figure 6). Together, these elements show how antifragile capability can be established through the coordinated development of thirteen AI-enabled functions. The ISM hierarchy specifies the structural dependencies that govern capability progression, while the ILB explains the mechanisms that give each dependency its operational meaning. In combination, they allow the roadmap to be read as a developmental architecture that describes how the system learns, reorganises, and strengthens through exposure to variability.

The roadmap begins with foundational learning and diagnostic functions at the lowest tier. These encompass the system's ability to detect precursors to instability, identify causal patterns in disturbance and embed continuous feedback into model refinement. Their position reflects their role as the informational substrate on which all subsequent antifragile behaviour rests. As indicated by their extensive outgoing links in the ILB, these functions provide the signals, explanations and structural knowledge that enable the rest of the system to respond productively to volatility.

The intermediate tiers contain functions responsible for reconfiguring material flows, sourcing pathways and operational flexibility. Their placement reflects the principle that structural adaptation presupposes reliable sensing and diagnostic intelligence. ILB relations show that these mid-tier capabilities draw on earlier learning functions to manage exposure, orchestrate alternative options and redistribute operational load in ways that convert variability into system-level benefit. They form the bridge between understanding disturbance and acting on it.

Above these reconfiguration functions lie the capabilities that exploit turbulence for innovation, demand refinement and capacity restructuring. Their ILB patterns indicate that they depend both on diagnostic and predictive intelligence and on an underlying malleability in how resources and market signals can be recombined. At this level the system begins to translate disruption into opportunity, treating shocks as inputs for redesign rather than simply as conditions to adapt around.

At the uppermost tier are the functions that operationalise antifragility through autonomous decision cycles and real-time synchronisation of production activity. These capabilities represent the culmination of the developmental pathway, since they rely on mature sensing, learning, risk interpretation and reconfiguration mechanisms. Only when the system can interpret its environment continuously, reshape its supply and resource structure and stabilise its intelligence base can autonomy and adaptive planning improve performance through volatility rather than merely sustain it.

The roadmap should be interpreted as a structure of enabling conditions rather than a rigid temporal sequence.

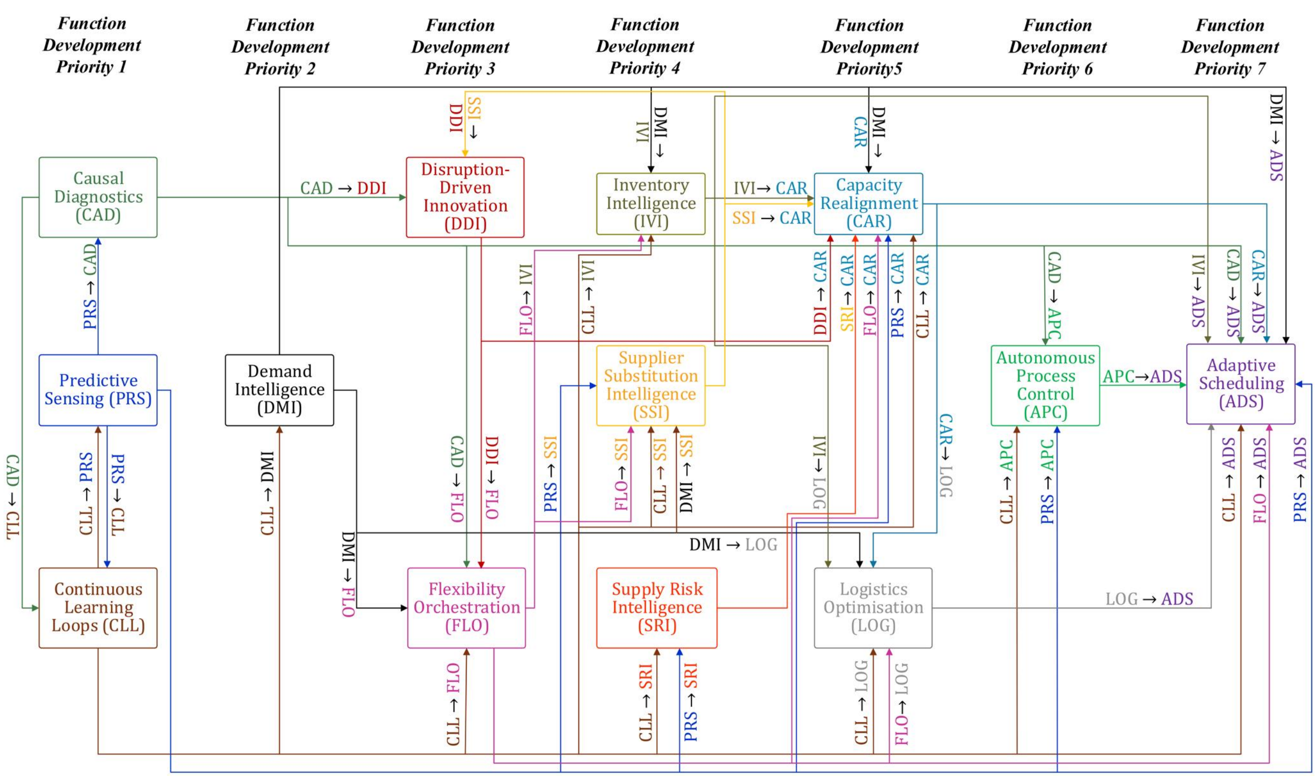



Figure 5. Strategic roadmap for AI-enabled antifragility (source: the authors).

| Contextual relationship | Enabling role |
|---|---|
| | *Autonomous Process Control (APC)* |
| APC → ADS | Reduces cycle-time variability by continuously tuning process parameters, giving planning systems stable and reliable execution data; prevents small deviations from escalating, which limits the amount of corrective resequencing required; provides accurate real-time performance signals so adjustments are guided by actual capability rather than noise; ensures that any rescheduling decisions stay feasible under changing conditions by maintaining consistent process behaviour during disruptions. |
| | *Capacity Realignment (CAR)* |
| CAR → ADS | Provides real-time visibility of available and adaptable capacity so prioritisation and sequencing decisions reflect actual executable options; reduces the risk of infeasible planning by aligning workloads with the resources that remain responsive under volatility; turns capacity shocks into signals for smarter workload redirection. |
| CAR → LOG | Enables better coordination of transport and flow decisions by exposing shifts in production capacity early; supports route and mode adjustments based on where output will materialise during disruption; prevents network imbalances by synchronising logistical choices with the most resilient capacity nodes. |
| | *Causal Diagnostics (CAD)* |
| CAD → ADS | Identifies the real source of delays so adjustments focus on true constraints; clarifies disruption propagation to guide more stable resequencing; removes false signals that would trigger unnecessary changes. |
| CAD → APC | Pinpoints which parameters actually drive deviations, enabling more accurate autonomous tuning; prevents overreaction to noise; improves the stability of corrective control actions. |
| CAD → CLL | Converts disruptions into labelled learning events; removes misleading correlations and highlights meaningful features; strengthens retraining cycles through higher-quality feedback. |
| CAD → DDI | Reveals structural weaknesses that inspire redesign options; links recurring failure patterns to innovation opportunities; prioritises changes that reduce future fragility. |
| CAD → FLO | Maps each disruption to its underlying cause so flexibility levers are activated precisely; avoids excessive reconfiguration by targeting the actual driver of variability; supports smarter rule formation for dynamic adjustments. |
| | *Continuous Learning Loops (CLL)* |
| CLL → ADS | Improves the accuracy and responsiveness of planning decisions by feeding models with updated performance patterns; shortens the time it takes for scheduling logic to adapt to new operating conditions; reduces reliance on outdated assumptions when disturbances shift behaviour. |
| CLL → APC | Enhances autonomous control through continuous calibration based on fresh process data; corrects drift before it causes instability; strengthens corrective behaviour as the system learns from repeated deviations. |
| CLL → CAR | Refines the understanding of capacity elasticity by learning from past load fluctuations; improves prediction of when and where capacity should be shifted; supports more confident adjustments during sudden demand or supply changes. |
| CLL → DMI | Learns from evolving consumption signals to improve demand responsiveness; adapts to emerging patterns that classical models miss; converts demand volatility into more accurate forward-looking adjustments. |
| CLL → FLO | Enhances the selection of flexibility options by learning which reconfiguration choices performed best under previous disruptions; reduces trial-and-error in deploying flexibility levers; strengthens orchestration logic as the environment evolves. |
| CLL → IVI | Improves stock adjustment rules by incorporating new volatility patterns; reduces over- or under-buffering by aligning safety stock logic with observed instability; sharpens responsiveness to emerging supply–demand mismatches. |
| CLL → LOG | Refines routing and flow decisions by learning from actual transport performance under different disruption types; enhances network adaptability; reduces persistent inefficiencies by correcting for real-world outcomes. |
| CLL → PRS | Enhances early-warning accuracy by incorporating new signal patterns; reduces false alarms and missed detections; boosts sensitivity to weak indicators of future disruptions. |
| CLL → SSI | Improves alternative sourcing decisions by learning which substitutes performed well under pressure; reduces repeated evaluation cycles; strengthens diversification logic based on past outcomes. |
| CLL → SRI | Enhances exposure assessments through continuous integration of geopolitical, supplier performance, and reliability data; improves forecasting of cascade risks; strengthens proactive sourcing decisions. |
| | *Disruption-Driven Innovation (DDI)* |
| DDI → CAR | Converts disruption insights into improved capacity configurations; identifies where capacity bottlenecks consistently appear and drives redesign of allocation rules; encourages structural shifts in how capacity is organised to better exploit volatility. |
| DDI → FLO | Generates new flexibility options by revealing which reconfiguration paths work best under real stress; encourages development of alternative routing or resource substitution strategies; strengthens the system's ability to transform disruption lessons into more adaptive flexibility mechanisms. |
| | *Demand Intelligence (DMI)* |
| DMI → ADS | Provides early visibility of demand shifts so workload adjustments reflect the most current market signals; reduces the risk of over- or under-committing resources; aligns execution plans with emerging customer patterns during volatility. |
| DMI → CAR | Highlights upcoming load changes that require proactive capacity repositioning; enables scaling decisions before bottlenecks form; strengthens elasticity by linking capacity moves to real market turbulence. |
| DMI → FLO | Guides flexibility choices by revealing how demand variability impacts product mix and routing; supports targeted reconfiguration rather than broad adjustments; improves responsiveness to short-term customer shifts. |
| DMI → IVI | Adjusts stock positions based on live demand movements; reduces buffer misalignment by linking inventory decisions to market-driven volatility; supports adaptive replenishment strategies during rapid change. |
| DMI → LOG | Signals where transport and flow adjustments are needed as customer demand shifts geographically or by product type; supports proactive rerouting before imbalances appear; helps logistics anticipate load rather than react to it. |
| DMI → SSI | Identifies when demand changes create exposure in sourcing or material availability; triggers early evaluation of substitutes as customer needs evolve; strengthens sourcing adaptability by linking it to downstream volatility. |
| | *Flexibility Orchestration (FLO)* |
| FLO → ADS | Provides clear information on which routing, process or resource options are actually available at a given moment; prevents planning from assigning work to rigid or temporarily constrained routes; turns disturbances into triggers for using more suitable alternative paths. |
| FLO → CAR | Coordinates how different flexibility levers absorb shocks so capacity shifts are targeted rather than ad hoc; ensures that reallocation decisions draw on the most adaptable machines, lines or sites; helps convert local flexibility into system-wide capacity responsiveness. |
| FLO → IVI | Aligns stock policies with the real degree of operational and sourcing flexibility; reduces unnecessary safety buffers where reconfiguration options are strong; highlights where limited flexibility must be compensated by more strategic inventory positioning. |
| FLO → LOG | Connects routing and mode choices to the current configuration of production and sourcing options; supports rapid rerouting when the operative path changes; avoids transport plans that no longer fit the reconfigured network. |
| FLO → SSI | Signals when internal or existing network flexibility is insufficient so supplier or material substitution becomes the preferred lever; guides selection of alternatives that best complement the current reconfiguration; helps embed substitution into the broader flexibility strategy. |
| | *Inventory Intelligence (IVI)* |
| IVI → ADS | Provides real-time visibility of stock availability so scheduling decisions avoid assigning tasks dependent on constrained or delayed materials; reduces planning instability caused by hidden shortages; aligns production sequencing with the actual state of inventory under volatility. |
| IVI → CAR | Signals when inventory imbalances require shifts in productive capacity or load distribution; prevents overloading units facing material shortages and redirects work toward resource nodes with healthy stock positions; helps convert inventory volatility into more coordinated capacity decisions. |
| IVI → LOG | Highlights where transport priorities must shift due to emerging stock risks or replenishment delays; guides routing and mode choices that stabilise material flow during uncertainty; strengthens flow continuity by linking logistics decisions to real-time stock conditions. |
| | *Logistics Optimisation (LOG)* |
| LOG → ADS | Provides real-time visibility on transport delays, flow constraints and inbound variability, allowing schedules to be adjusted according to the true state of material and delivery availability; reduces planning instability caused by uncertain arrival times; helps align production timing with actual logistics performance under volatile conditions. |
| | Predictive Sensing (PRS) |
| PRS → ADS | Provides early signals of machine, material or demand disturbances so future workloads can be adjusted before the disruption fully materialises; reduces last-minute plan changes by turning weak signals into advance rescheduling triggers; helps prioritise critical orders when impending shocks are detected. |
| PRS → APC | Detects deviations in process behaviour at an incipient stage, allowing control logic to intervene earlier and with smaller corrective moves; limits drift and oscillation by signalling when conditions are about to exit stable ranges; supports more anticipatory rather than purely reactive parameter adjustments. |
| PRS → CAR | Anticipates load surges, capacity losses or upstream interruptions so reallocation decisions can be taken before queues build up; highlights where standby resources will be needed; enables smoother ramp-up/down of capacity in response to forecasted disturbances. |
| PRS → CAD | Supplies time-stamped anomaly patterns and precursors that make causal analysis more precise; narrows the search space for potential root causes; improves the quality of diagnostic models by linking causes to early observable signals. |
| PRS → CLL | Enriches learning datasets with labelled pre-disruption signals and associated outcomes; accelerates improvement of models that recognise early-warning patterns; supports the shift from learning only after failure to learning from near misses and weak indicators. |
| PRS → SSI | Identifies signs of upcoming supplier or lane instability, prompting earlier evaluation of alternative sources; allows substitution to be prepared and validated before a disruption becomes critical; reduces dependence on emergency switching. |
| PRS → SRI | Feeds exposure models with forward-looking indicators such as geopolitical events, financial stress or performance drift at suppliers; enhances the ability to forecast risk escalation; supports more proactive reconfiguration of sourcing portfolios. |
| | *Supplier Substitution Intelligence (SSI)* |
| SSI → CAR | Identifies viable supplier or material alternatives when primary sources become unstable; enables capacity to shift toward units with steady material availability; prevents production delays by aligning workload with secure input streams. |
| SSI → DDI | Reveals substitution-related performance gaps and opportunities that inspire redesign or new sourcing strategies; turns supplier failures into insights for improving product, process or network design; supports innovation driven by real sourcing disruptions. |
| | *Supply Risk Intelligence (SRI)* |
| SRI → CAR | Continuously scans suppliers, regions and lanes for emerging exposure so production can be shifted away from fragile nodes before failures occur; highlights which plants, lines or partners are structurally more robust, guiding where additional load should be placed; turns risk signals into triggers for redistributing capacity in a way that reduces concentration risk and strengthens the overall ability to absorb upstream shocks. |

Figure 6. The ILB matrix.

Development of functions can proceed in parallel, but the ISM hierarchy clarifies which capabilities must be conceptually or operationally established before others can be effective. By combining the structural view from ISM with the functional explanations in the ILB, the roadmap offers a coherent account of how AI can be sequenced and combined to support antifragile production and supply chain operations.

## 5. Discussion

The hierarchical configuration of AI functions identified in this study suggests that antifragile behaviour in production and supply chain operations is best understood as an architecture of interdependent capabilities rather than as a static property of the system. The pattern that emerges from the ISM and ILBis a layered configuration in which some AI functions create informational preconditions for others, and some acquire antifragile meaning most clearly when embedded in this broader structure. This view goes beyond much of the existing antifragility discourse, which often treats the concept as a conceptual ideal or a metaphor for desirable robustness (Nikookar, Varsei, and Wieland 2021), by showing how AI can provide concrete mechanisms through which a system may move from surviving volatility to learning and strengthening through it.

A first key insight is that the expert-derived hierarchy gives learning and diagnostic functions a foundational role that many operational resilience models have not fully articulated. Existing work on resilience, flexibility, and agility typically recognises the importance of sensing and information processing but often treats them as peripheral enablers of recovery (Tukamuhabwa et al. 2015). In contrast, the base layer in this study positions AI-driven functions that infer causality from disruption, detect weak signals, and continuously update models as structurally central within the elicited architecture. The experts were clear that without such functions the rest of the system may react more quickly but is less likely to evolve in a cumulative manner. This finding aligns with recent arguments that resilience and antifragility are fundamentally learning constructs that emerge from the way organisations interpret and update their mental models after rare and surprising events (Ghobakhloo et al. 2025a), yet it adds a technical dimension by specifying how AI may modify the learning process by scaling the volume of signals that can be absorbed, by uncovering non-obvious structure in disturbances and by embedding that learning into models that adapt operational logic over time.

A second insight concerns the way flexibility and reconfiguration are repositioned in light of AI. The literature on supply chain agility, postponement, and flexible manufacturing has long argued that structural options for routeing, sourcing, and buffer management are essential for coping with turbulence (Yang and Yang 2010).The present results challenge the assumption that flexibility is inherently beneficial. The mid-tier functions in the model indicate that flexibility is more likely to become antifragile when guided by AI-based interpretations of exposure, alternatives, and trade-offs. The experts described how, in advanced industrial settings, it is no longer sufficient to have options. What matters is the ability of AI systems to evaluate continuously which options are most likely to improve the system's posture under current and anticipated conditions. This reframes flexibility from a static design choice to an AI-mediated decision process and suggests that earlier work which treated flexibility as a structural attribute may underestimate the cognitive layer required for antifragile use of those options.

A third important theme is how the upper tiers of the hierarchy reframe the relationship between disruption and strategic change. There is growing interest in the idea that volatility can be a source of innovation and market insight, but much of that literature remains descriptive or crisis-specific (Dahlke et al. 2021; Orlando et al. 2022). The functions in the upper-middle layers of the model suggest that AI can play an important role in operationalising this idea. Demand-related turbulence, repeated process failures or supplier disturbances may become more systematically informative when AI systems are in place that can detect patterns, link them to underlying mechanisms, and surface redesign opportunities across products, processes or capacity footprints (Bag et al. 2023). The experts' experience from front-running firms suggests that organisations that benefit from disorder are those that allow disruption to be treated as structured input into redesign rather than as a sequence of anomalies to be corrected. This shifts the antifragility discussion from an attitude or culture of embracing shocks to a capability to algorithmically extract redesign opportunities from disruption exposure.

Perhaps the most striking result relates to how autonomy and optimisation are repositioned. Much of the AI and Industry 4.0 literature implicitly assumes that the introduction of autonomous control or advanced optimisation is itself a path to resilience (Ghobakhloo et al. 2025b). The structure elicited from the experts challenges this assumption. Autonomous control and adaptive scheduling appear as antifragile mechanisms at the top of the hierarchy, after a wide set of sensing, learning, risk, and flexibility functions are in place. In addition, autonomy at this level presupposes governance mechanisms for validation, accountability, and human override, without which rapid automated decisions can propagate errors and create new forms of fragility. In other words, autonomy built on a weak or fragmented intelligence base risks amplifying fragility by reacting quickly but in poorly informed ways. This interpretation problematises simplistic narratives around self-optimising factories and suggests that, from an antifragility perspective, the sequencing of AI investments matters at least as much as the sophistication of any single application, which echoes recent arguments on such mechanisms (Bag et al. 2023).

The role of practice-based expert knowledge in shaping these results is also important for how the findings should be interpreted. The structure and logic captured in the model do not represent a theoretically verified account of how antifragility works under all conditions. They reflect patterns that have been observed, tested, and refined in firms that are already using AI to operate under high levels of uncertainty and competitive pressure. At the same time, the fact that these experts converge on a layered, dependency-rich architecture raises questions for future research. It suggests that antifragility, when pursued through AI, may be path-dependent and may lock organisations into particular trajectories of capability development. It also hints at possible tensions and trade-offs that the current model does not yet fully expose, such as the risk that very strong learning and sensing capabilities create dependence on data infrastructures and digital platforms that introduce new forms of fragility.

Taken together, the findings invite a reframing of antifragility in operations as a property that can emerge when specific AI functions are sequenced and orchestrated in a way that makes volatility a systematic source of information, reconfiguration, and performance improvement. Rather than treating AI as a generic enabler of smart operations, the model indicates that antifragile behaviour is associated with particular constellations, such as learning functions that change how disturbance is represented, flexibility functions that change how options are evaluated, and strategic functions that change how disruption is translated into structural change (Ghobakhloo et al. 2025a; Nikookar, Varsei, and Wieland 2021). This perspective suggests that AI is well suited to support antifragility by enabling continuous reinterpretation of the operational environment and embedding that interpretation into decision mechanisms at multiple levels of the system. How far this architecture generalises beyond the advanced manufacturing contexts studied here, and how it interacts with organisational, human, and institutional factors, remains an open and important question for subsequent research.

### 5.1. Feasibility conditions

A critical point of consideration is that the roadmap presupposes some capacity to learn from disruption exposure, which may raise practical questions about data availability, event heterogeneity, and the learning regimes required for implementation. In operational settings, the evidence created by turbulence is often uneven. Many signals are noisy and indirect, critical events may be rare, and ground truth labels are typically incomplete or contested. This makes it risky to interpret antifragility as a straightforward modelling problem solved by routinely retraining predictive models on past shock cases. A more defensible interpretation is that capability accumulation is achieved through layered learning mechanisms that match the hierarchy. At the lower levels, value is created by improving representation, inference, and early detection using abundant routine operational traces, which strengthens the system's ability to recognise weak signals and diagnose propagation mechanisms when stress occurs. At higher levels, the main learning challenge shifts from model updating to policy improvement, meaning the disciplined revision of decision rules, thresholds, escalation logic, and response playbooks based on feedback from interventions. Where real exposure is limited or too costly, safe-to-learn environments become central, particularly scenario generation and digital twin-based stress testing that allow calibration and comparison of alternative policies without committing the live system to irreversible changes. These considerations also elevate boundary conditions from an implementation detail to a core part of the roadmap, including data governance and interoperability, monitoring for drift and bias, traceability of decisions, and decision rights that support controlled experimentation. Under such conditions, the roadmap remains actionable because it links each function layer to a feasible learning mechanism, rather than assuming that all improvement comes from accumulating labelled disruption datasets.

In this sense, antifragility implies a learning regime oriented towards policy and structural improvement from stress exposure, whereas robustness and resilience more often emphasise stability and recovery within a largely unchanged operating model, at least in the immediate response horizon.

### 5.2. Governance and accountability

The feasibility conditions discussed above also point to a further requirement for implementing the roadmap in practice. Even when learning mechanisms are realistic and data constraints are acknowledged, AI-enabled antifragility still depends on how decisions are governed across multiple systems, organisations, and operational layers. Without explicit validation, accountability, and oversight arrangements, the same functions that accelerate sensing and response can also scale errors, propagate misalignment, and create new forms of operational fragility.

Because production and supply chains span heterogeneous data sources and decision domains, the roadmap becomes credible as managerial guidance only when it is paired with governance mechanisms that validate recommendations prior to execution and clarify ownership of outcomes. A practical implementation pathway therefore requires staged validation routines, such as offline evaluation using historical traces and stress scenarios, sandbox or digital twin testing where available, shadow-mode deployment in which AI recommendations are evaluated against human decisions without execution, and controlled rollouts with explicit acceptance criteria. These routines reduce the risk that locally well-performing models create system-level side effects when deployed across tightly coupled operations.

Governance becomes even more consequential as firms move towards autonomy. When AI influences service levels, safety, compliance, or other critical operations, organisations must define decision rights and escalation rules that specify when actions require approval, when automated execution is permitted, and how overrides are triggered. Accountability cannot be delegated to a model, particularly when complex models are difficult to interpret. This requires auditable decision pipelines, including logging of inputs, recommendations, actions, and outcomes, documentation of model scope and assumptions, monitoring for drift and bias, and post-event review procedures that can reconstruct why decisions were taken. Under these conditions, autonomy is best understood as a governed capability that is earned through validation and control rather than as a direct outcome of adopting more advanced algorithms.

From a roadmap perspective, these governance requirements are not external constraints. They shape when higher-layer functions can be responsibly activated and scaled, particularly those that automate decisions or coordinate actions across sites and partners. As a result, investment sequencing should be interpreted as including governance capability building, such as validation routines, audit trails, and decision rights, alongside technical capability development. Building on the feasibility and governance considerations discussed above, the next subsection translates the hierarchy into practical guidance on how managers can use the roadmap for implementation planning and decision-making.

### *5.3. From roadmap to implementation*

The proposed hierarchy can be used as an implementation guide by treating it as a set of readiness relationships rather than as a menu of isolated AI applications. In practical terms, the roadmap helps managers decide what to build first, what depends on what, and which initiatives are likely to underperform if pursued before enabling capabilities are in place. Three elements are particularly important for using the roadmap effectively: minimal prerequisites, sequencing logic, and decision-context translation.

A minimal set of prerequisites is implied by the roadmap. First, data and integration readiness are required so that operational traces, disruptions, and outcomes can be captured across production, logistics, and sourcing interfaces with sufficient quality and traceability. Second, process routines and ownership are needed so that model outputs translate into decisions and so that decision outcomes are recorded through disciplined feedback loops that support calibration and learning. Third, governance readiness is required, including validation routines, decision rights, escalation and override rules, and auditability, particularly where decisions affect service levels, safety, compliance, or other critical operations. Without these prerequisites, AI functions may produce local improvements but fail to align decisions across systems or sustain learning at scale.

Within these prerequisites, the roadmap supports a simple sequencing logic that managers can apply as a planning heuristic. Foundational functions such as predictive sensing, causal diagnostics, and continuous learning loops establish the informational and learning infrastructure that makes later reconfiguration decisions credible. Mid-tier functions then use this infrastructure to coordinate flexibility, inventory, logistics, and sourcing reconfiguration in a disciplined manner, enabling targeted rather than generic buffering and enabling adaptation based on interpreted exposure and trade-offs. Upper-tier functions that translate disruption into innovation, demand reframing, capacity realignment, and higher-order autonomy should be pursued after the earlier layers are stabilised, because they presuppose reliable sensing, consistent diagnostics, and governed reconfiguration capacity. In this sense, the roadmap can be applied as a readiness map, where lower-layer capabilities act as gates for moving towards more consequential and potentially risk-amplifying forms of automation.

A concise illustration, derived from recurring scenarios discussed by the experts during the NGT sessions, shows how managers can use the roadmap in common decision contexts. The experts repeatedly referred to situations in which manufacturer may face concurrent transport delays, intermittent supplier quality drift, and demand swings that jointly destabilise production schedules and service performance. In the experts' account, the first priority is to strengthen predictive sensing and supply risk intelligence so weak signals can be detected across suppliers, lanes, and internal constraints before they propagate into schedule instability. The next step is causal diagnostics, which the experts described as essential for distinguishing whether instability is primarily driven by specific suppliers, logistics corridors, internal bottlenecks, or inventory policy choices, rather than treating all disturbances as equivalent noise. With this visibility, flexibility orchestration becomes more selective, enabling targeted use of alternatives such as rerouting, machine switching, or material substitution within capacity and quality constraints. In parallel, inventory intelligence is used to recalibrate buffer placement and sizing as volatility changes, and supplier substitution intelligence supports structured qualification of alternatives for recurring sources of instability. The experts further noted that adaptive scheduling becomes meaningfully more effective only after these sensing, diagnostic, and reconfiguration functions are in place, because resequencing decisions can then draw on higher-quality signals and a clearer set of feasible response options. In this way, the vignette illustrates how the roadmap translates into an implementation sequence that connects directly to scheduling under turbulence, inventory policy adaptation, and sourcing reconfiguration, as reflected in the expert reasoning captured through the NGT process.

Taken together, these points clarify how the roadmap can be used as an implementation tool, while remaining consistent with the boundary conditions and governance requirements highlighted in the preceding subsections.

## 6. Implications and future research

This study is believed to have important implications for future research and practice, which should be understood in light of its limitations and can be further expanded by subsequent studies in several important ways.

### *6.1. Theoretical implications*

This study offers several contributions to the theoretical understanding of antifragility in operations and supply chain research. First, it moves antifragility from an abstract system property to a structured, AI-enabled capability architecture. By identifying thirteen functions and specifying their interdependencies through ISM and the ILB, the study shows that antifragility is a multi-layer configuration of sensing, learning, reconfiguration and autonomous response mechanisms rather than a homogeneous construct. This provides a more granular basis for theorising antifragility than work that treats it as a generic attribute or metaphor for 'benefitting from disorder' without specifying operational mechanisms.

Second, the findings refine how antifragility relates to resilience, agility and flexibility. The hierarchy suggests that resilience and agility can be viewed as intermediate states within a broader capability ladder. AI-driven learning functions resemble resilience in their focus on detecting and absorbing disturbances, while reconfiguration functions align with classical agility. Antifragility emerges only when these layers are coupled to functions that convert disturbance into innovation, demand reframing and structural capacity shifts. This supports a capability continuum and indicates that antifragility is not simply 'more resilience' but a qualitatively different regime.

Third, the results help integrate AI more systematically into operations and supply chain theory. Existing work often treats AI as a generic enabler or as isolated applications. By distinguishing AI functions and placing them in a dependency structure, this study frames AI as a capability system with distinct roles at different levels of the firm's response to turbulence. This opens a path for future research to develop and test constructs such as AI-enabled causal diagnostics or AI-enabled flexibility orchestration instead of treating AI adoption as a single variable.

Fourth, the expert-derived architecture invites theoretical work on path dependence and sequencing in digital operations. The hierarchy and roadmap indicate that antifragility emerges only when certain AI functions are present in combination and with sufficient maturity. This implies that the order and logic of AI capability development matter for long-term system behaviour. Future studies can examine how different sequencing patterns affect the evolution of operational capabilities, how firms become locked into particular trajectories and how misaligned AI portfolios may reinforce fragility.

Finally, the strong grounding in industrial experience strengthens the external validity of antifragility theory in manufacturing. The model is an abstraction of patterns observed and validated in firms that already deploy AI under turbulent conditions rather than a purely hypothetical configuration. This supports a more practice-based theorisation of antifragility and provides a firmer empirical basis for subsequent analytical and empirical research.

### *6.2. Managerial implications*

For practitioners, the findings translate into a set of actionable insights on how to exploit AI for antifragility rather than for isolated efficiency gains. The roadmap makes clear that antifragility unlikely be achieved by investing directly in high-profile applications such as autonomous scheduling or advanced optimisation while neglecting the underlying intelligence base. Managers should view antifragility as a staged capability journey in which early investment is directed towards AI functions that strengthen sensing, causal understanding, and continuous learning across operations and the supply chain.

In practical terms, this means prioritising functions that improve the organisation's ability to interpret variability before those that automate responses to it. Capabilities related to diagnostics, predictive sensing, and learning loops form the analytical backbone that allows the firm to understand how and why volatility arises. Without such capabilities, more advanced AI systems risk reacting quickly but unwisely, potentially amplifying instability. Managers should therefore treat investments in data quality, event logging, causal analytics, and online learning as strategic, not merely technical, steps towards antifragility.

The roadmap also highlights the importance of AI-enabled reconfiguration mechanisms. Inventory, sourcing, logistics, and flexibility decisions have traditionally been treated as design choices that can be revisited periodically. The findings suggest that in turbulent environments these choices should be supported by AI functions that continuously reassess exposure, alternatives, and trade-offs. Firms aiming for antifragility should therefore deploy AI to maintain live views of supply risk, substitution options, inventory posture, and network flexibility, and to embed those views into routine decision processes. This requires cross-functional governance so that AI modelsinfluence how the wider system is rebalanced during disruptions.

At more advanced stages, managers can begin to use AI to convert volatility into structured input for innovation and strategic renewal. Functions that mine disruptions for redesign opportunities, reframe demand patterns or inform capacity shifting depend on the prior existence of robust sensing and flexibility capabilities. The implication is that firms should resist the temptation to treat innovation from disruption as an ad hoc or purely human-driven process. Instead, they can progressively build AI-supported mechanisms that capture patterns in failures, near misses, and market shifts and feed them into structured redesign discussions at product, process, and network levels.

Finally, the results caution against viewing AI autonomy as a shortcut to robustness. The expert-informed model indicates that autonomous control and adaptive scheduling are more likely to support antifragility when positioned at the end of a broader capability development pathway. Managers should therefore treat these technologies as the culmination of a longer process of building learning, diagnostic, and reconfiguration capabilities, not as the first step. Organisations that adopt autonomous optimisation without this foundation risk creating systems that are fast, opaque, and brittle. In contrast, firms that follow a sequenced development path are more likely to be better positioned to deploy AI in ways that make their operations genuinely stronger under sustained turbulence.

### *6.3. Limitations and future research*

This study has several limitations that shape how its findings should be interpreted and indicate directions for future work. The model is conceptual and structurally focused. ISM and ILB capture perceived enabling relationships among AI functions rather than statistically estimated causal effects or quantified performance impacts, and antifragility is theorised rather than directly measured. The hierarchy and roadmap should therefore be read as an expert-informed, theory-building account of how AI-enabled capabilities may relate to antifragile behaviour, not as evidence of realised performance gains. Future research should translate the identified functions into measurable constructs, develop operational indicators of antifragility such as post-shock improvement trajectories or learning rates, and examine the proposed relationships through empirical testing.

The architecture reflects the experience of senior experts from advanced multinational manufacturing firms that already deploy AI extensively in operations and supply chains. This supports relevance for front-running industrial contexts but may also limit transferability. The structure may be less applicable to firms with lower digital maturity, different sectoral conditions, or other institutional environments. Comparative and replication studies across industries, firm sizes, and regions could examine which functions and dependencies are context-specific and which represent more general patterns of AI-enabled antifragility. The ISM hierarchy and ILB are interpretive by design. They represent a coherent synthesis of literature and expert judgement at a particular point in time and do not exclude alternative architectures. Longitudinal case studies, mixed-method designs, and simulation-based work could be used to explore how AI capability structures evolve and how sequencing choices are associated with changes in fragility or antifragility over time.

Finally, the analysis focuses on AI and does not compare AI-enabled mechanisms with other digital or organisational pathways. While the findings suggest that AI is well aligned with several informational and learning requirements relevant to antifragility, the study does not establish whether other technologies or organisational responses could produce similar effects or act as substitutes or complements. Future research could extend the framework to include non-AI digital tools, human decision processes, and governance structures, and examine how different combinations of technological and organisational capabilities support antifragile behaviour in production and supply chain systems.

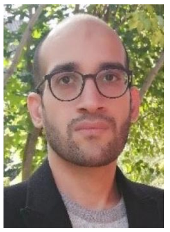
## Declaration

While preparing this work, the authors used an AI-based editing tool (ChatGPT 5.1) to proofread some parts of the manuscript. After using this tool/service, the authors reviewed and edited the content as needed and take responsibility for the publication's content.

## Disclosure statement

The authors report there are no competing interests to declare

## Notes on contributors



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## Data availability statement

The data that support the findings of this study are available from the corresponding author, Dr. Morteza Ghobakhloo, upon reasonable request.

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