AI-Driven Antifragile Knowledge Management System: Transforming ERP Simulated Disruptions into Learning Opportunities

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Abstract: *Purpose*: Enterprise Resource Planning (ERP) systems, such as SAP (Systems, Applications, and Products in Data Processing), are critical to modern enterprises, enabling the integration of core business functions and the management of essential data. Ensuring their availability, reliability, and adaptability is paramount, as disruptions can result in significant operational and financial consequences. Traditional Knowledge Management (KM) approaches emphasize the preservation of ERP-related knowledge but often lack responsiveness to emergent risks. This study introduces a novel framework grounded in the concept of antifragility—where systems grow stronger under stress—by simulating disruptions to enable continuous knowledge evolution and system adaptation. *Methodology:* A mixed-methods research design combines simulation-based inquiry with Design Science Research (DSR) to investigate antifragile KM within ERP environments. Artificial Intelligence (AI) tools are integrated into the KM system to analyse ERP failures, generate runbooks, and proactively manage recovery knowledge. Controlled simulations of kernel upgrades and failure scenarios—modelled on ITIL 4 incident typologies—serve as structured stressors to expose vulnerabilities. Lightweight LLMs, Retrieval-Augmented Generation (RAG) pipelines, and semantic search tools are employed to codify procedural knowledge and enhance the responsiveness of ERP operations. *Findings:* The results demonstrate that embedding antifragile principles into ERP KM improves organizational learning, responsiveness, and recovery capabilities. Transitioning from static knowledge repositories to dynamic, AI-enabled systems allows for autonomous decision-making, decentralized knowledge flow, and adaptive documentation. Each disruption becomes a learning event, reinforcing the resilience and self-improvement of the ERP knowledge ecosystem. *Implications:* Empirical insights suggest that AI-driven antifragile KM transforms ERP disruptions into opportunities for growth, rather than threats to stability. The proposed framework supports the development of systems that not only recover from failure but also become progressively more robust and adaptive through structured experimentation and continuous learning.

Keywords: Antifragility, Knowledge management, ERP, SAP, Artificial intelligence

1. Introduction

In today's rapidly evolving business landscape, organizations are under constant pressure to ensure the continuous availability, reliability, and adaptability of their Enterprise Resource Planning (ERP) systems. ERP systems streamline internal processes, promote data consistency, and enable informed decision-making across departments (Yılmaz Börekçi et al., 2020). However, their complexity and tight integrations across functions make them particularly vulnerable to disruptions and incidents. The advent of Artificial Intelligence (AI) technologies and advances in Knowledge Management (KM) frameworks offer new opportunities to enhance the resilience and intelligence of ERP systems (Jarrahi et al., 2023). More recently, the concept of antifragility, introduced by Nassim Nicholas Taleb, has emerged as a powerful paradigm that goes beyond resilience (Taleb, 2012). Unlike resilient systems that resist shocks and maintain function, antifragile systems improve and learn from disruptions (Taleb and Douady, 2013). This article positions antifragility as a central conceptual lens and explores how the strategic integration of ERP, AI, and KM systems can create the organizational conditions necessary for antifragile behaviours and capabilities to emerge in dynamic and uncertain environments.

2. Literature review

2.1 ERP Systems and Organizational Dependency

ERP systems integrate various business processes into a single unified system, offering a centralized data platform that spans finance, HR, procurement, manufacturing, inventory, and more (Moon, 2007). The main objectives include improving process efficiency, enhancing data accuracy, and reducing operational costs (Jacobs and Whybark, 2000). However, ERP systems are often criticized for their vulnerability during downtime periods (Prihandono et al., 2024). When such systems become inaccessible due to server issues, version conflicts, or system upgrades, the entire organization may face operational paralysis. Prolonged ERP downtimes can lead to data inconsistencies, decision-making delays, financial loss, and reputational damage.

2.2 ERP Systems as Complex and Wicked Systems

Modern ERP platforms, especially those based on SAP (Systems, Applications, and Products in Data Processing), have become increasingly complex and tightly coupled (Bansal and Negi, 2008). These systems resemble what Rittel and Webber (1973) termed "wicked problems": complex, dynamic issues that defy simple solutions (Crowley and Head, 2017). Misconfigurations in kernel upgrades, mismatches between portal systems and operating environments, and a lack of domain knowledge among system engineers exacerbate the risks. As such, organizations require more than routine resilience measures.

2.3 The Concept of Antifragility

Taleb's (2012) concept of antifragility refers to systems that benefit from disorder. Rather than merely resisting shocks, antifragile systems adapt and grow stronger when exposed to volatility. In organizational contexts, antifragility can be cultivated through proactive exposure to stressors, learning from incidents, and decentralizing knowledge flows (Adobor and Kudonoo, 2025). The progression from fragility to antifragility can be further clarified through visual representations that capture how systems respond to stress over time or under varying degrees of change. As shown in Figures 1, antifragile systems not only withstand shocks but improve and innovate as a direct result of them. While fragile systems tend to break under pressure and robust systems merely resist change, resilient systems recover, but it is the antifragile systems that learn, evolve, and thrive amid volatility.

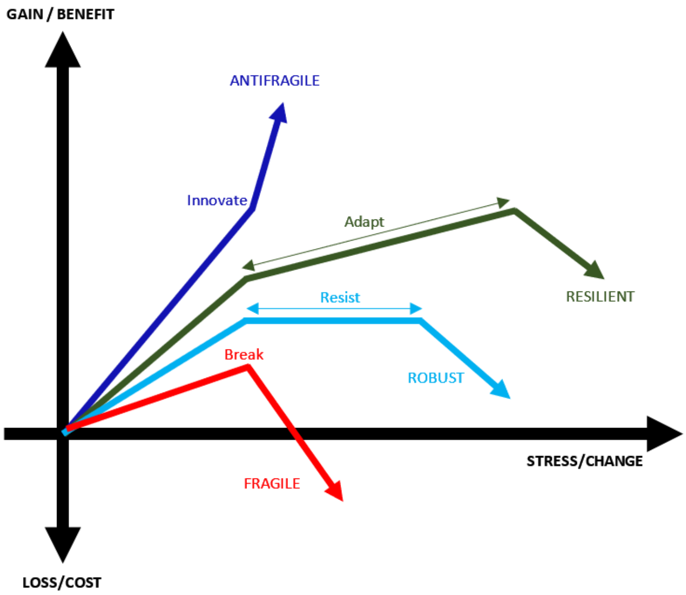

Figure 1: Behaviour of antifragile, resilient, robust and fragile systems. Source: (Tiwari and Bhatt, 2023)

2.3.1 Fragility, robustness, resilience, and antifragility in KM

To understand antifragile KM, it is necessary to contrast it with other modes of organizational behaviour:

- *Fragile KM systems* break under pressure. These systems rely heavily on specific individuals, are overly reliant on rigid procedures, or are not frequently updated. When disruption occurs, knowledge is lost, and processes come to halt (Hillson, 2023).
- *Robust KM systems* endure shocks without adapting. They may include redundancies or fail-safes, but they do not learn from disruption (Dufour and Steane, 2007).
- *Resilient KM systems* recover from setbacks. They absorb the damage and eventually return to their original state. This is often the goal of disaster recovery and continuity planning (Zieba, 2024).
- *Antifragile KM systems*, by contrast, improve through volatility. They learn from failures, adapt processes, update knowledge repositories, and modify organizational behaviours in response to challenges (Taherdoost and Madanchian, 2023).

Table 1 summarizes how different types of KM systems respond to disruption, highlighting the unique characteristics of antifragile KM.

Table 1: KM systems respond to disruption. Source: Authors

System specification	Fragile	Robust	Resilient	Antifragile
Behaviour at disruption	Breaks under stress; loses functionality	Withstands shocks without change	Absorbs impact and restores original state	Gains from stress; adapts and improves performance
Response Mechanism	Collapse or failure; high dependency on stability	Passive resistance; static buffers or redundancies	Active recovery; pre-planned response mechanisms	Dynamic adaptation; real-time learning and self-improvement
Knowledge flow	Disrupted or lost	Preserved but static	Temporarily stalled, then resumed	Enhanced through learning loops and feedback
Organizational learning	None; knowledge loss or erosion	Minimal; learning is not integrated	Moderate; learning after the fact	Continuous; learning is integral to the system's evolution
Adaptability	Rigid; unable to respond to change	Inflexible; designed to resist change	Flexible within predefined limits	Highly adaptive; thrives on variability and experimentation
Examples of KM practices	Unshared expertise; undocumented procedures	Backup systems; static knowledge repositories	Post-incident reviews; business continuity planning	Simulation-based testing; AI-driven scenario generation
Outcome over Time	Degrades	Stagnates	Returns to baseline	Evolves and strengthens

As shown, antifragile KM not only survives disruption but actively benefits from it, turning volatility into a catalyst for learning and continuous improvement.

2.3.2 Core principles of antifragile KM

Antifragile KM is not a product but a mindset, shaped by several interconnected principles:

- Learning from failure: Mistakes, near misses, and failures are rich sources of insight. Antifragile KM systems are built to document, analyse, and learn from these events systematically (Coelho and McClure, 2005).
- Distributed knowledge ownership: Knowledge should not reside in silos or be dependent on single individuals (Miller and Smith, 2012).
- Dynamic documentation: Instead of static knowledge bases, antifragile systems rely on living documents—constantly updated based on emerging insights and new data (Mehta et al., 2023).
- Scenario-based testing: Stress tests and "what-if" scenarios are central to antifragile learning (Cem Kaner, 2013). These simulations force organizations to confront blind spots and discover hidden weaknesses.
- AI and augmentation: AI enhances antifragile KM by identifying patterns, predicting risks, and generating new insights from historical and real-time data.
- Runbooks and institutional memory: Capturing experiential knowledge in clear, structured formats (e.g., runbooks) ensures that learning survives turnover and becomes institutional (Ferrara, 2024).
- Culture of curiosity and adaptation: Ultimately, antifragility is cultural. Organizations must embrace discomfort, value dissent, and reward iterative improvement (Adobor and Kudonoo, 2025).

2.4 KM System and Antifragility

KM plays a vital role in capturing, organizing, and reusing organizational knowledge. Traditional KM systems focus heavily on protecting existing knowledge and ensuring knowledge retention (Adobor and Kudonoo, 2025). However, in volatile environments, static KM approaches are insufficient. By aligning KM with the antifragility concept, organizations can create dynamic learning environments that evolve continuously in response to new experiences and data.

2.5 Integrating AI into KM and ERP Systems

Traditional ERP systems often lack the flexibility to meet rapidly evolving business needs, as they depend on static rules and fixed decision-making structures. With increasing demands for agility and customization, transforming conventional ERP architectures has become essential. AI-powered ERP systems address this need by automating tasks, offering intelligent recommendations, enhancing forecasting, and improving operational efficiency (Goundar et al., 2021). AI also significantly boosts the effectiveness of KM systems by streamlining processes and improving key performance indicators (Taherdoost and Madanchian, 2023). Integrating AI into KM enhances the capture, sharing, and application of knowledge, resulting in greater efficiency, higher-quality content, and increased user engagement.

2.6 Towards a Triadic Model: ERP + AI + KM with Antifragility

While recent studies have explored the integration of AI and KM into ERP systems, most focus narrowly on automation, efficiency, or decision support—often in isolation. Few address how these technologies can be combined to build systems that not only recover from disruption but improve because of it—what Taleb (2012) calls *antifragility*. ERP research typically centres on resilience within fixed recovery frameworks, lacking empirical insight into how systems can evolve under real stress.

This study addresses that gap by experimentally testing an AI-enabled ERP-KM framework based on principles of antifragility. Controlled stressors—simulated disruptions—serve as structured “disaster drills” to expose vulnerabilities, trigger adaptation, and reinforce learning. To ensure realism, disruption scenarios are based on common enterprise IT incidents, classified using the ITIL 4 framework (Agutter, 2020), which categorizes incidents by impact, urgency, and source. This alignment ensures that the antifragile model is not only conceptually sound but operationally relevant. A key exercise involved simulating kernel upgrades under complex configurations. In enterprise systems like SAP, kernel upgrades update the OS core to apply patches or improve performance. However, due to interdependencies across databases, OS, and applications, such upgrades can destabilize systems if not carefully managed (Kaplan and Oehler, 2011).

Focusing on kernel upgrade failures—classified under ITIL 4 as software-related incidents—allowed the study to simulate a high-risk, high-priority scenario. These include OS incompatibilities, application bugs, and misconfigurations. When a crash leads to a major service disruption, it qualifies as a critical event according to ITIL 4, justifying its use for antifragility testing. This classification grounds the experiment in real-world ERP risks and service management standards, enhancing the model's practical relevance.

2.7 Metrics for Evaluating Antifragile Behaviour

Two fundamental characteristics for measuring antifragility in organizational systems are self-organization and adaptation.

- *Self-Organization* (SO) refers to the spontaneous emergence of new structures, behaviors, or patterns within a system through the interaction of internal agents, without centralized control (Adobor and Kudonoo, 2025). This behavior is nonlinear and often unpredictable, yet it enables systems to reorganize and evolve in response to environmental changes.
- *Adaptation* (AD), on the other hand, involves the system's ability to learn from disruptions, experiment, and reconfigure itself to remain functional under new conditions (Adobor and Kudonoo, 2025). It reflects the organization’s capacity to evolve through feedback, innovation, and participatory decision-making, particularly in volatile or uncertain environments.

Both characteristics are essential indicators of a system's potential not just to recover from stress but to improve because of it. Taleb (2012) suggests that antifragility can be identified by examining how an organization asymmetrically responds to disorder or crisis. If the impact of stressors leads to disproportionately greater benefits than harms—producing more gains than losses—the system can be considered antifragile. Conversely, if the negative consequences of disruption outweigh the positive outcomes, the organization exhibits fragility.

2.8 Metrics for Evaluating Operational Functionality

To assess the system’s ability to recover from disruptions, two widely recognized continuity metrics are employed: Recovery Time Objective (RTO) and Recovery Point Objective (RPO) based on ISO 22301:2019. These measures provide a baseline for evaluating operational resilience in terms of downtime tolerance and acceptable data loss. These two metrics are defined as follows:

- *RTO*: The maximum acceptable time to restore a product, service, or activity after a disruption (Wong and Shi, 2014).
- *RPO*: The point in time to which data must be restored to resume operations (Wong and Shi, 2014).

2.9 Research Question and Research Objectives

To align theory with practice, this study is guided by a central research question integrating ERP systems, AI-driven KM, and antifragility. Based on this, specific research objectives were established to structure the design, simulation, and evaluation processes.

Research Question:

How can AI-driven approaches be used to develop antifragile KM systems that enhance ERP environments by not only coping with uncertainty but also benefiting from operational disruptions?

Research Objectives:

- To develop a conceptual framework that integrates ERP, KM, AI, and antifragility for improving organizational learning and system resilience.
- To simulate critical ERP failure scenarios (e.g., kernel upgrades) and assess the system's response using standardized IT continuity metrics (RTO and RPO).
- To evaluate the role of AI in automating knowledge codification and generating novel failure scenarios that enhance the system's adaptive capacity.
- To measure antifragility in ERP-based KM systems (SO and AD).
- To validate the antifragile KM model through iterative simulations and analyse how ERP systems evolve from fragile or resilient toward antifragile behaviour.

3. Method

This study follows a mixed-methods research design, combining Design Science Research (DSR) and simulation-based inquiry to develop, apply, and validate an antifragile KM framework integrated into an ERP environment. The methodological aim is to bridge theoretical innovation with practical application by iteratively designing and testing a model that enhances organizational learning and system resilience through AI-enhanced KM mechanisms. A kernel upgrade scenario was selected due to its known risk of disrupting ERP operations. Kernel updates were deliberately introduced in a test environment under real-world complexity.

3.1 Conceptual Model Construction

The research began with the development of a conceptual model that integrates four core domains: ERP, KM, AI, and antifragility. This phase reflects the DSR paradigm, which emphasizes the creation and refinement of artifacts (such as models or methods) intended to solve complex, real-world problems. Figure 2 illustrates the conceptual framework developed for this study.

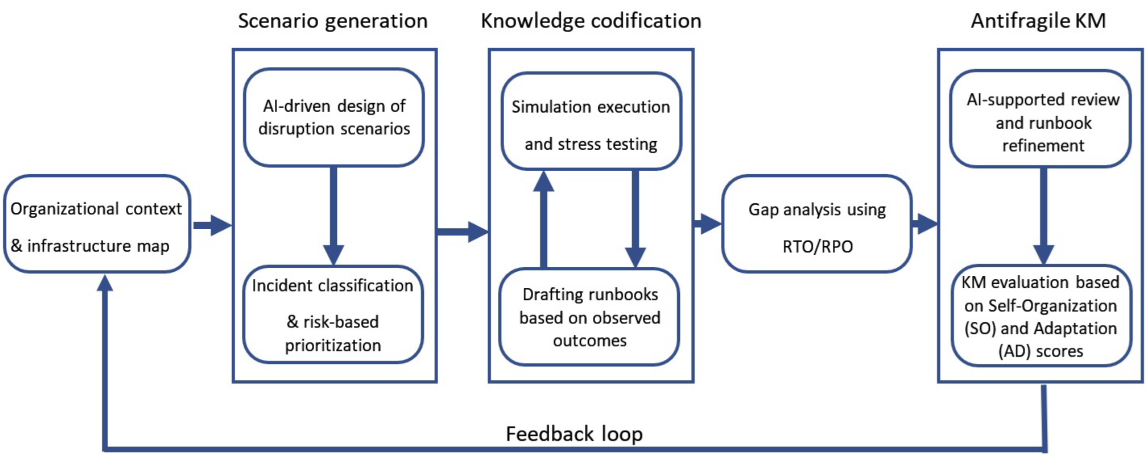

Figure 2: Conceptual model

This model demonstrates how AI-supported knowledge mechanisms, scenario planning, and simulation testing are combined to create an adaptive, learning-focused ERP ecosystem. Key features include:

- Use of AI to suggest new risk scenarios,
- ERP stress testing in a laboratory environment,
- AI-supported knowledge codification (e.g., runbooks),
- Outputs include reduced system downtime, improved knowledge retention, and structured incident prediction.

3.2 Simulation-Based Experimental Validation

The second phase of the research applied a simulation-based inquiry to test and validate the conceptual model in a controlled environment. Simulations were conducted within an SAP ERP system to replicate real-world operational disruptions, with a particular focus on kernel upgrade scenarios, chosen due to their high risk of failure and complexity of system dependency.

3.3 AI-Augmented Scenario Planning and Knowledge Codification

AI played a central role in enhancing documentation by generating structured, accurate runbooks and analysing prior incidents to propose new, ERP-specific stress scenarios. This shifted the approach from reactive incident handling to proactive resilience building. To operationalize this, an AI-based assistant was developed to automate recovery documentation from ERP logs and expert simulations. At its core, the system utilized a local large language model (Mistral, via the Ollama framework) to extract structured, YAML-formatted steps from unstructured log data.

To enhance contextual relevance, a Retrieval-Augmented Generation (RAG) pipeline was implemented utilizing FAISS for rapid similarity search and Sentence Transformers (MiniLM-L6-v2) for document embedding. Argos Translate enabled bilingual documentation for multilingual usability.

The assistant featured a Streamlit interface for uploading logs, generating or editing runbooks, and exporting them in YAML and DOCX formats. It also offered semantic search to retrieve relevant content using natural language queries or metadata tags.

The simulation process produced the following key outputs:

- A comprehensive runbook for technical staff
- A library of probable incident patterns
- A noticeable reduction in average recovery time
- Evidence of improved ERP system understanding among the technical team

These AI-generated runbooks were continuously refined through simulations, aligning with the antifragility model by transforming disruptions into drivers of learning and system evolution.

3.4 Measurement Framework

To assess how the ERP-based KM system responds to disruption and improves over time, this study employs a quantitative antifragility framework across four dimensions: two operational (RTO and RPO) and two behavioral (SO and AD). RTO and RPO measure recovery speed and data retention, while SO-Score and AD-Score capture structural and cognitive evolution post-disruption. Deliberate kernel modifications—such as version mismatches and compatibility issues with the portal kernel—were used to simulate real-world complexity and expose vulnerabilities stemming from tight couplings among kernel, OS, and database versions. Multiple failure modes were introduced to test recovery limits and build a repeatable runbook. Repeating these exercises enabled improvements in response time and reliability, with each iteration enriching a structured knowledge base used during real incidents. Antifragile behavior was quantitatively evaluated using expert assessments and simulation data across the four key dimensions: SO, AD, and Recovery (RTO/RPO).

3.4.1 Measurement of SO

To quantitatively evaluate SO as a dimension of antifragile behaviour, the underlying qualitative characteristics—such as centralization, autonomy, knowledge flow, emergence, and responsiveness—were translated into measurable indicators. Based on theoretical foundations and prior empirical observations, SO was categorized into three levels: *Low SO, Moderate SO*, and *High SO.*

These categories were operationalized through five dimensions, as summarized in Table 2.

Table 2: Dimensions of SO

Dimension	Low (Centralized)	Moderate	High (Self-Organized)
Decision Autonomy	Decisions made centrally; minimal local flexibility	Some local input, but key decisions require upper approval	Local teams make decisions independently within defined boundaries
Knowledge Flow Direction	Top-down; knowledge is siloed or hoarded	Mostly hierarchical; limited two-way communication	Lateral and bottom-up flows; open sharing across units
Emergence	No spontaneous process change; only top-down mandates	Occasional local adjustments with limited impact	Processes evolve from local interaction and systemic feedback
Responsiveness	Reactive; changes occur only after disruptions	Somewhat adaptive; slower response to signals	Proactive and adaptive; continuous sensing and adjustment
Dependence on key individuals	High dependence on a few experts or managers	Partial role overlap; some redundancy	Low; distributed roles and peer-based operational resilience

Each dimension was assessed using a Likert-type scale, with experts rating system behaviour based on a structured questionnaire. Ratings were collected from multiple IT domain experts who supervised or directly participated in the ERP simulation and disruption response exercises. These responses were then aggregated to calculate the SO Score using the following formula:

$$\text{SO-Score} = \frac{1}{m}\sum_{j=1}^{m}\left(\sum_{i=1}^{n} w_i \cdot \text{Item}_{ij}\right)$$

Where: m = number of expert respondents, n= number of measurement dimensions, w_i = weight assigned to the i^{th} dimension and $Item_{ij}$= score assigned by expert j to item i

The final SO-Score is calculated as:

$$\text{SO-Score} = w_1\text{*Autonomy} + w_2\text{*Knowledge Flow} + w_3\text{*Emergence} + w_4\cdot\text{Responsiveness} + w_5\text{*Key individual dependence}$$

This structured measurement approach provides a replicable method for evaluating how autonomously and adaptively the ERP system behaves in the face of disruption.

3.4.2 Measurement of AD

To evaluate the adaptive capacity of the system—defined in this study as its ability to adjust, learn, and structurally evolve in response to disruptions—an operational framework was developed based on three levels of organizational adaptation: *Static AD, Responsive AD*, and *Transformative AD.*

These levels were decomposed into five measurable dimensions, each representing a distinct aspect of organizational adaptation according to Table 3:

Table 3: Dimensions of AD

Dimension	Static	Responsive	Transformative
Process updates	Rarely updated	Updated after issues	Proactively and frequently updated
Learning mechanism	Absent	After-action reviews only	Embedded, proactive feedback-driven learning loops
Innovation trigger	Only when forced	After failures	Initiated before failures, driven by foresight
Structural change	Never	Minimal	Radical or systemic changes in structure and processes
Knowledge integration	Poor	Local or isolated	Organization-wide and cross-functional knowledge sharing

The measurement of AD-Score was conducted in the same way as the SO-Score, using the following formula:

$$\text{Adaptation Score} = \frac{1}{m}\sum_{j=1}^{m}\left(\sum_{i=1}^{n} w_i \cdot \text{Item}_{ij}\right)$$

Where m, n, w_i and $Item_{ij}$ are the same as in the So-Score. The weighted AD score can be simplified as:

Adaption score=

w_1*Learning mechanism+w_2*Process updates+
w_3*Innovation trigger+w_4*Structural change+w_5*Knowledge integration

4. Results

ERP systems play a foundational role in operational continuity. However, the kernel upgrade scenario revealed that even minor version mismatches can cause portal system crashes and inter-module failures. Without a pre-defined recovery plan, organizations risk exceeding RTO/RPO thresholds. Downtimes of more than a few hours led to significant productivity losses, missed Service, and compromised decision-making (Prihandono et al., 2024). These risks underscore the need for ERP systems that are not only resilient but also capable of adapting and improving through adversity. The measurement approach provides a replicable framework for evaluating how dynamically an ERP-based knowledge system can learn and evolve in response to disruptions. Based on structured simulations and expert evaluations, the following results were observed:

- *SO-Score* increased from 2.2 out of 5 (Moderate) in Round 1 to 4.1 out of 5 (High) in Round 2.
- *AD-Score* rose from 2.3 out of 5 (Responsive) to 4.0 out of 5 (Transformative).
- *RTO* decreased significantly from 13 days to 90 minutes.
- *RPO* remained constant at 0, indicating complete data retention.

In the first round, despite having all relevant documentation and upgrade procedures in place, the technical team encountered unforeseen complications. As a result, the complete kernel upgrade, along with post-upgrade data validation, took approximately 13 days to complete. While no data was lost (RPO = 0), the system downtime significantly exceeded the defined RTO target. During this extended period, all observed bugs, failures, and corresponding resolutions were systematically documented in the runbook.

In the second round, the lessons learned from the initial attempt were fully incorporated. The team reviewed all server parameters and configurations using a checklist derived from the first round. The upgrade was then performed again, this time utilizing the updated runbook and AI-generated recommendations. The team's responsiveness to unexpected issues significantly improved. Without requiring direct managerial intervention, the technical team completed the kernel upgrade and validation process in 90 minutes, entirely within the RTO target, and again with zero data loss. This progression reflects not only improved recovery but also the operationalization of antifragility, as the ERP system transformed disruption into embedded learning, enabling faster, autonomous responses through iterative learning, AI-supported knowledge codification, and scenario planning.

5. Discussion

5.1 Antifragility and Organizational Resilience: Learning From Stress in Practice

The study highlights the value of adopting an antifragile approach to ERP-related KM. Unlike traditional resilience models that aim to avoid failure, antifragility embraces controlled disruptions as opportunities for learning and improvement (Rane et al., 2024). Capturing insights from these events strengthens organizational capabilities and reduces future vulnerabilities. Integrating AI with KM transforms static knowledge repositories into adaptive systems that evolve through experience (Jarrahi et al., 2023). AI analyzes past incidents, suggests new testing scenarios, and turns failures into structured learning moments. AI-powered analytics also enhance the feedback loop between ERP systems and technical teams by automating runbook generation and improving incident response. This leads to more efficient decision-making, faster recovery, and reduced RTO, ultimately minimizing the operational impact of disruptions.

The key takeaway from the stress testing simulations was that the ERP system not only withstood the changes but also improved as a result. By introducing controlled disruptions, the system was able to identify weak points and, over time, refine its processes and responses. Each iteration of the test increased the system's ability to handle future incidents, which is the core concept of antifragility—systems becoming stronger under stress. This iterative learning process, facilitated by AI, enabled the documentation of new, previously undetected failure modes, thereby enriching the runbook with actionable insights. This approach proved more effective than merely adhering to static recovery protocols, as it integrated knowledge from each event into the overall system architecture, thereby contributing to the organization's antifragility. Through this antifragile KM approach, ERP disruptions were transformed into opportunities for systematic learning, process optimization, and continuous preparedness, converting potential weaknesses into organizational strengths.

5.2 Challenges and Limitations

Despite its potential, implementing AI and antifragility in ERP systems presents several challenges. First, integrating AI into existing ERP infrastructures can be resource-intensive, requiring adequate technical and human capacity. Second, effective AI depends on robust data governance—poor data quality can compromise predictions and hinder antifragile outcomes. Lastly, while AI enhances recovery and learning, over-reliance on automation poses risks. Human oversight remains essential, especially when AI outputs conflict with strategic or operational goals.

5.3 Future Directions

The future of KM lies in evolving into an adaptive system powered by AI and principles of antifragility. Research should examine how KM can autonomously detect weak signals, adapt to disruptions, and scale experiential learning. Beyond ERP, antifragile KM should be explored in areas like supply chains, cybersecurity, and organizational change. Advancing AI tools to contextualize knowledge across languages, platforms, and timelines will support strategic intelligence. Additionally, addressing ethical, governance, and explainability concerns is essential for building trust and ensuring sustainable learning. Future studies should also include diverse testing scenarios to explore the potential of antifragility fully.

6. Conclusion

This study presents a novel approach to KM by embedding it within an antifragile framework powered by AI and tested through ERP disruption simulations. Rather than treating knowledge as a static asset to be preserved, the proposed methodology reframes KM as a dynamic system that grows stronger when exposed to stress. By simulating disruptions and learning from them, organizations enhance the adaptability, responsiveness, and decentralization of their knowledge processes. AI technologies play a critical role by automating knowledge capture, generating procedural content such as runbooks, and suggesting new failure scenarios based on historical data. These capabilities significantly enhance the evolution of organizational knowledge, enabling faster decision-making, improved preparedness, and an institutional memory that improves with each iteration. As businesses continue to navigate increasingly volatile and complex environments, fostering antifragile KM systems will be essential. This research demonstrates that by integrating AI with KM, organizations can establish self-reinforcing learning ecosystems that not only recover from disruptions but also learn and evolve through them, ensuring long-term resilience and innovation readiness.

Ethical and AI declaration: Ethical clearance was not required for the research conducted in this study, as it did not involve personal data or sensitive content necessitating formal ethical approval. AI was employed as part of the research, as the topic of the paper is directly related to AI. However, AI tools were not used for drafting, writing, or generating the text of this paper.

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