Resilient strategies for reducing decision-making uncertainty in generative AI and LLM integration*

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Abstract
Generative AI (GenAI) and Large Language Models (LLMs) are transforming industries through automation, content generation, and advanced decision-making. However, many organizations struggle to move beyond pilot projects due to fragmented infrastructure, capability gaps, ethical concerns, and evolving regulations, leading to persistent decision-making uncertainty. This study investigates how resilient technological strategies can address these uncertainties and enable responsible, scalable GenAI adoption. Drawing on a multi-case analysis of sixteen organizations across six industries and seven countries, it identifies recurring barriers, including workforce resistance, leadership misalignment, and lack of governance clarity. Thematic analysis reveals three critical enablers: strategic leadership, cross-functional collaboration, and ethical alignment. To support long-term integration, the study proposes a practical framework combining readiness assessment, capacity-building, and governance planning. This framework guides organizations from experimentation to operational maturity, ensuring that GenAI systems deliver value while remaining ethical, inclusive, and adaptable. The findings emphasize regenerative AI adoption as a future-oriented, iterative and adaptive approach, which prioritizes continuous learning, ethical integration, and long-term resilience. It ensures that AI systems evolve with organizational needs while aligning with broader societal and sustainable goals.

Keywords
Generative AI, Resilient Decision-Making, Regenerative adoption, Organizational Transformation

1. Introduction

The rapid rise of Generative AI and LLMs is fundamentally reshaping how businesses and industries operate. From content creation and process automation to decision-making support, these technologies are unlocking new modes of working. Tools like ChatGPT have significantly accelerated this shift, prompting organizations across sectors, such as healthcare, finance, education, and marketing, to explore Gen AI's transformative potential [1, 2].

However, while the excitement is real, so are the challenges. Many organizations are still struggling to integrate Gen AI beyond isolated experiments or pilot projects. Obstacles such as outdated legacy systems, the absence of a clear strategy, employee resistance, and concerns about privacy and regulation complicate adoption efforts and introduce uncertainty into AI-related decision-making [3].

This is where the concept of regenerative AI becomes valuable. Unlike traditional adoption models that emphasize automation or short-term gains, regenerative AI emphasizes long-term, sustainable value creation. It refers to an approach where AI systems are designed to continuously

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learn, adapt, and evolve in response to real-world feedback, while also supporting ethical, inclusive, and resource-efficient practices. [4, 5].

Reaching organizational maturity in AI adoption involves more than just implementing new technologies; it requires resilient strategies built on thoughtful planning, strong data infrastructure, and continuous learning. Such approaches reduce risk and uncertainty by helping systems withstand ethical, technical, and operational pressures over time [6].

Despite increased interest, a significant gap remains in connecting the technological, ethical, leadership, and strategic dimensions of GenAI adoption into a unified, actionable framework. Existing literature often treats these elements in isolation, overlooking their interaction in practice. This study addresses that gap by asking: How can resilient technological strategies reduce decision-making uncertainty and enable regenerative AI adoption? Based on insights from 16 organizations across six industries and seven countries, it identifies key adoption barriers and highlights practical approaches for developing ethical, adaptive, and sustainable AI strategies beyond the hype.

2. Background

While the potential of regenerative AI is clear, realizing it in practice requires a deep understanding of both human and organizational behavior, as well as the technical and ethical systems that shape adoption. To explore these dimensions, it is essential to understand foundational theories and frameworks that inform how Gen AI and LLMs are evaluated, accepted, and deployed within organizations.

Adoption doesn't happen in isolation. It’s shaped by user perceptions, organizational readiness, and the ability of systems to support or resist change. This section introduces key frameworks that explain these behaviors, beginning with user acceptance.

Two foundational models the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) highlight how perceived usefulness, ease of use, social influence, and organizational support affect technology adoption [7, 8]. An extended version, Unified Theory of Acceptance and Use of Technology (UTAUT2), adds deeper behavioral insights by including hedonic motivation (enjoyment), price value, and habit formation, making it more relevant for GenAI adoption [9]. Beyond individual perceptions, social and organizational factors play a major role in AI adoption. Support from peers and leaders, along with trust in technology, strongly influences users’ willingness to engage with AI especially in areas involving privacy, fairness, and job security [10]. Behavioral intention is shaped by training, user experience, and organizational culture. Companies that promote AI literacy and provide a supportive environment tend to achieve higher and more sustained adoption. According to UTAUT2, frequent and positive use can turn new technologies into habits, boosting long-term integration [9].

To understand broader adoption trends, the Diffusion of Innovations (DOI) theory [11] provides valuable insight. It identifies five key factors: relative advantage, compatibility, complexity, trialability, and observability. These help explain why organizations adopt Gen AI when its benefits are clear, it integrates well with existing systems, and its impact is visible. Trial runs and pilot projects also reduce uncertainty and help stakeholders build confidence [12].

Complementing this, the Trust in Specific Technology Theory (TSTT) highlights the importance of explainability, reliability, and user-centric design in fostering trust in AI [13]. Human-AI interaction is another key aspect. Drawing from Human-Computer Interaction (HCI), and Hybrid AI, successful systems have be easy to use and not cognitively overwhelming [14].

On the technical front, the Task-Technology Fit (TTF) model suggests that technology is most effective when it aligns closely with the tasks it supports [15]. Poor alignment can reduce efficiency, especially in roles that require creativity or complex reasoning. Technical debt is another concern when organizations choose quick fixes over sustainable solutions; they often face higher long-term costs and integration issues [16]. Continuous Integration and Continuous Deployment (CI/CD) practices support the sustainable implementation of Gen AI by allowing organizations to update systems frequently and reliably [17]. Together with TTF and proactive technical debt management, these practices create scalable and resilient systems.

Ethics and governance are foundational to responsible AI deployment. The Accountability and Credibility Theory (ACT) and AI Explainability frameworks highlight the importance of making AI decisions transparent and understandable [18]. Issues of bias, data privacy, and fairness are particularly critical when using large datasets. GDPR and related data regulations offer guidelines that organizations should follow to protect user rights and build trust [19]. Security is another key pillar. With Gen AI systems increasingly targeted for cyber threats, robust cybersecurity strategies, including encryption, role-based access, and regular audits, are vital to maintaining system integrity [20].

Organizational readiness depends on AI literacy, available resources, and a culture that supports innovation. Strong training programs and leadership backing improve preparedness for AI integration [21]. Socio-technical systems theory highlights the need to balance technology with human elements like workflows, incentives, and communication [22]. Resistance to change often driven by job security fears can be eased through phased rollouts, transparent communication, and upskilling efforts, all of which support smoother adoption [23].

The recent studies offer further insights into sector-specific adoption. Holmström and Carroll [24] explore how GenAI fits into organizational innovation strategies, while Gupta et al. [25] and Javaid et al. [26] examine its application and limitations in marketing, healthcare, and model efficiency. Previous, studies from Russo [27], Hacker et al. [28] and Fui-Hoon Nah et al. [29] provide frameworks and governance models to support more ethical, effective, and transparent use of AI across contexts.

3. Methodology

This study adopts an exploratory multiple-case study approach to investigate the real-world barriers organizations face when adopting GenAI. Given the dynamic evolution of these technologies and the socio-technical complexity of enterprise domains, a qualitative research design was chosen to explore the how and why behind adoption barriers [30]. We applied a holistic case study method, positioning the organization as the primary unit of analysis. This approach supports a deep, contextual understanding of organizational readiness, alignment, and governance structures, areas where conventional metrics might fall short.

The study examined 16 organizational cases through 18 interviews across seven countries, including Finland, the Netherlands, USA, India, Australia, Sri Lanka, and UAE. These organizations span nine industries, from healthcare and cybersecurity to software, IT services, telecommunications and consulting. Interviewees held roles in R&D, operations, project leadership, quality assurance, and technical strategy, providing a well-rounded perspective on AI integration across levels and functions. We used maximum variation sampling to ensure diversity in organization type, industry, and AI maturity level. Interviews were semi-structured, conducted remotely via Microsoft Teams, and lasted between 40 minutes to one hour. This format provided enough flexibility to explore emerging themes while remaining focused on the core research questions. Conversations centered around readiness, leadership alignment, infrastructure gaps, ethical considerations, and real-world experiences of implementing GenAI. All interviews were transcribed and anonymized to ensure participant confidentiality.

We employed thematic analysis to extract key patterns from the interview data, following Braun and Clarke’s [30] framework, using NVivo software to systematically code and analyze the transcripts, which were iteratively refined. The process began with familiarization and initial coding to identify first-order concepts directly from participant narratives. These were then grouped and abstracted into second-order themes and aggregated dimensions. Abductive reasoning helped bridge raw empirical observations with existing theoretical constructs, allowing iterative refinement of the themes. Thematic interconnections were further examined to map relationships and dependencies, providing a holistic view of the barriers organisations face. The analysis followed an iterative, inductive-abductive process, as summarized in Table 1.

Table 1
Methodological approach in thematic analysis

Description	Analysis Focus	Methodological Approach
Documenting evidence from interviews	Identify data relevant to study	Inductive
Classifying Key Aspects	Filter common knowledge to focus coding on evidence that generates new understanding	Abductive
Identify first-order concepts	Combine relevant evidence into cohesive themes	Inductive
Identify second-order themes and form aggregate dimensions or main themes	Abstract and synthesize first-order themes into second-order themes, which are then combined to form aggregated dimensions	Inductive
Analyzing core cause-and-effect within aggregate dimensions and Mapping Thematic Interconnections	Correlate aggregate dimensions with between dimensions on thematic findings and map casual relations	Abductive Reasoning

To ensure construct validity, we triangulated data sources with multiple interviews and aligned findings with prior literature. Internal validity was enhanced via pattern-matching and explanation-building across cases. External validity was addressed through purposeful sampling and framing the research for transferability across organizational contexts. Reliability was supported by a detailed case study protocol and a centralized database documenting each step of the research process.

4. Results

This chapter presents the study's findings based on data from semi-structured interviews, the research identified five key themes that highlight the barriers to adopting Gen AI technologies in organizations. The thematic analysis findings are illustrated in Table 2.

4.1. Resilient Adoption Strategies for Decision-Making Uncertainties

The first theme focused on how resilient adoption strategies help reduce decision-making uncertainties. The findings emphasized that the rapid adoption of Gen AI brings both opportunities and challenges for organizations. Decision-making uncertainties frequently emerged due to evolving technologies, shifting business landscapes, and the necessity for strategic alignment. To develop resilience in Gen AI adoption, it is fundamental to address Decision-Making elements that influence the implementation, customization, and trust in AI solutions.

The rapid expansion of AI technologies has led to an overwhelming number of choices, making it difficult for organizations to select suitable tools. A key challenge is aligning these technologies with business growth strategies to ensure they provide tangible benefits. Evaluating the effectiveness and cost of AI tools is essential for long-term viability, with organizations prioritizing practical value over hype. The complexity of decision-making required ongoing assessment of new technologies to ensure alignment with business needs. As one discussion pointed out, “*We will not put AI for the sake of adding AI, so it should have a proper use case and it should be the suitable technology to, you know, achieve value... what we are after is adding value to our customers.*”

AI adoption varies across domains and use cases. Many organizations struggled with customizing AI tools, especially in subjective fields where decision-making relies on human expertise. Fragmentation across AI platforms creates integration challenges, requiring companies to navigate interoperability issues. Technical complexity further complicates adoption, as AI solutions often demand extensive modifications to fit into existing workflows. Data integration remains a major obstacle, with many organizations lacking the necessary infrastructure to leverage AI effectively. The ability to tailor AI applications while maintaining operational consistency is essential for sustainable adoption.

Building trust in AI remains a fundamental challenge. While there is urgency to adopt AI, skepticism persists regarding its reliability and long-term impact. Organizations often hesitate due to the "*black-box*" nature of deep learning models, which limits transparency and interpretability. Awareness plays a key role in addressing these concerns. Employees and decision-makers have to understand AI’s capabilities and limitations to create a culture of informed adoption. Without clear communication and explainability, skepticism may hinder AI integration at both strategic and operational levels.

Table 2
Thematic Analysis

Theme	Sub-Theme	First-Order Concepts
Resilient Adoption Strategies for Decision-Making Uncertainties	Navigating AI Tool Selection & Growth Alignment	Difficulty in Choosing Suitable AI Tools Due to Overwhelming Options, Evaluating AI Tools for Effectiveness and Cost Before Continued Adoption, Cautiously Adopting Gen AI by Prioritizing Practical Value Over Hype, Navigating the Complexity of Widespread AI Solutions Rapid Growth and Overwhelming Popularity, Use Case Readiness and Task Suitability of AI
	Customization & Adaptability	Challenges in Using AI for Subjective Fields, Fragmentation and Lack of Interoperability Across AI Tools and Platforms, Technical Complexity and Data Integration Challenges
	Trust & Transparency	Awareness and Trust in AI Influence of Urgency and Skepticism, Black-Box Nature and Lack of Transparency in Deep Learning Models
	Complexity & Commitment	Abstract concept and complex Scenario translation, Incremental Refinement and Long-term commitment, Technological Novelty and Familiarity Gap in Gen AI Applications
Multi-Stakeholder Collaboration & Organizational Readiness	Business Impact & Ethics	Balancing Client Expectations with AI Limitations and Application Feasibility, Business Growth Versus Job Displacement Concerns
	Organizational Culture & Resistance to Change	Hierarchical Structure and Traditional Industry Practices, User Resistance to Change and Technology Adoption, Societal and Cultural Misalignment in Adopting AI Technologies, Mixed Acceptance of Generative AI Tools within Teams, Variability in AI Adoption Across Different Departments and Roles
	Governance and Stakeholder Collaboration	Preference for Human Interaction Despite AI Advancements, Stakeholder Alignment and Concerns Regarding AI Integration, Absence of Unified AI Regulatory Frameworks Creating Inconsistencies, Legal and Compliance Complexity Influence in AI Adoption Process
Ethical, Regulatory, & Trust Considerations	AI Ethics, Trust, & Reliability Concerns	Comprehensive Regulatory Compliance and Ethical Standards, AI Tools' Inaccuracies and Reliability Hinder Adoption, Lack of Trust in AI Tools Due to Inaccuracies and Immaturity
	Privacy & Data Security Risks	Confidentiality in Handling Sensitive and Private Data, Customer Reluctance Stemming from Data Privacy and Consent Concerns in AI Adoption, Privacy and Security in the Use of AI Tools and Implementations, Strict Access Control and Data Security Constraints in Generative AI Adoption.
	Data Governance & Compliance	Data Privacy and Comprehensive Data Protection Challenges, Restrict Data Accessibility and User Content Utilization in AI Adoption
Technical & Operational Challenges in AI Deployment	Performance Optimization & Alignment	Challenges in Aligning Multiple LLMs Due to Contradictory Outputs, System Misalignment Challenges in Achieving Desired AI Outputs
	Integration Barriers	Challenges Integrating AI into Legacy Systems, Challenges Integrating LLM Technologies Due to Limited Data and Industry Isolation, Guidelines and Standards for Integrating AI Systems into Workflows, Integrating Across Complex Multi-System Ecosystems with Usability and Interoperability
	Simplified Adoption	Complexity in understanding the underlying technology with Simplified Usability in Adoption, Content Overload While Ensuring Human Oversight and Value Integration
	Usability, Scalability & Context Retention	AI Tools Struggle with Context Retention and Follow-Up Questions Inconsistency, Scalability and Usability Limitations of AI-Generated Solutions
	Data Bias & Model Generalization	AI Model Generalizability and the Need for Diverse, Comprehensive Training Data, Bias in AI Models Due to Non-Generalized Training Data; Challenges in Data Acquisition for AI Model Training; Language Barriers in AI Adoption and Utilization
	Financial & Infrastructure Constraints	High Costs of AI Tools, Training Infrastructure, and Financial Investment, High Licensing Costs and Rigid Subscriptions Deter AI Tool Adoption, Resource Constraints and Lack of Expertise Hinder AI Implementation, Time and Financial Resource Investment in Data Preparation for Model Customization
Sustainable & Regenerative Aspects: Identifying Capability Gaps	Value-Driven Adoption	Awareness and Understanding of Gen AI Among Management, Region-Specific Preferences and Customer-Specific Requirements, Viewing AI as a Tool, Not Strategy a Strategic Asset
	Data and Information Gaps	Lack of Structured Learning and Knowledge Sharing, Outdated AI Data and Lack of Problem-Specific Direction
	Knowledge & Skill Gaps	Learning Curve and Knowledge Dissemination, Resource Scarcity for Learning and Knowledge Gaps, User Understanding and Effective Prompting in AI-assisted coding, Non-Technical Users Struggle in Understanding and Adopting
	Operational Scalability & Resource Readiness	Iterative Development Process with Uncertain Outcomes, Keeping Up with Rapidly Evolving AI Technologies and Market Dynamics, Readiness and Operational Limitations of AI Tools in Practical Use, Budget Constraints Limiting Technical Integration and Implementation Capabilities, Dependence on External Expertise Due to Resource Limitations
	Customization & Fine-Tuning	Caution Using AI in Coding Due to Inefficient or Complex Outputs, Customizing and Fine-Tuning AI Models for Complex or Existing Systems
	Resource Constraints & Expertise	Interdisciplinary Knowledge Gaps and Communication Barriers, Lack of Internal Expertise in AI, Requiring External Assistance and Specialized Teams

The adoption of Gen AI requires a long-term commitment. Its abstract decision-making makes translating complex scenarios into actionable insights difficult. Organizations had taken an incremental approach, refining implementations over time to align with evolving needs. Technological novelty introduces a learning curve, particularly for non-technical employees. Many found that familiarity gaps hinder seamless integration into operations. As one respondent noted, "*The organization has only recently begun adopting generative AI technologies and is still exploring them. Many employees in business processes, not just development, require guidance and a significant learning curve to use it effectively.*"

Participants emphasized that generative AI would become a key part of business operations, transforming strategy, marketing, sales, and customer service. They expressed strong interest in adoption, aligning it with long-term goals. However, they stressed that successful implementation requires organizations to handle complexity, invest in continuous learning, and ensure stakeholder collaboration and readiness. Resilient adoption strategies not only reduce uncertainty but also enable organizational alignment and cross-functional readiness for broader AI adoption.

4.2. Multi-Stakeholder Collaboration & Organizational Readiness

Successful Gen AI adoption required strong collaboration across teams, operational units, and leadership. Balancing socio-technical factors, ethics, and stakeholder expectations while managing resistance to change was vital. Yet, achieving alignment across these areas remains challenging. Resilient adoption strategies and informed decisions help reduce uncertainty, improve coordination, and build organizational readiness.

A key concern identified was the mismatch between client expectations and the practical limitations of AI. Organizations often feel pressured to integrate AI, even when it may not be the right solution. Concerns also arise around business growth and potential job displacement. Many decision-makers struggled to identify where AI truly adds value without creating unrealistic expectations. As one participant noted, "*We have to be very, very careful… we don't apply it just for the sake of using AI. The biggest challenge will be turning down clients asking for AI solutions when we have to say this is not the right case for AI application.*"

Resistance to change was among the most cited barriers. Hierarchies and traditional practices slow down tech integration. Employees accustomed to established workflows may hesitate to adopt AI tools, even when they offer benefits. This resistance varies across departments; some embrace AI, others remain skeptical. As one participant shared, *"It's not that they dislike generative AI, but they have a familiar way of working and are comfortable with existing tools. When introducing tools like GitHub Copilot, the resistance often stems from interface changes rather than the tool itself.*"

Stakeholder alignment is another key challenge. Views on AI vary, with some underestimating its impact and others seeing its potential disruption. "*They think that generative AI and AI will not harm them. But this is not the case. If automation happens, it will impact all.*" Achieving harmony is difficult, especially without clear regulations. As another participant stated, "*Before doing anything, I had to take everyone on board, especially the directors.*" Varied requirements across domains and regions add further complexity.

Addressing these challenges requires both cultural and structural readiness, continuous dialogue, and a strong commitment to ethical and regulatory constraints in AI practices. By adopting a collaborative environment, cross-functional coordination and aligning stakeholder interests, organizations can enhance their preparedness and streamline the process of shaping ethical and regulatory policies.

4.3. Ethical, Regulatory, and Trust Considerations

Ethical, regulatory, and trust constraints strongly influence organizational decision-making. Successful AI implementation requires stakeholder alignment on ethics, data security, and compliance. Ongoing concerns about trust, privacy, and governance highlight the need for clear guidelines and robust regulation.

A key challenge is ensuring trust and reliability in AI systems. Despite advancements, tools still exhibit inaccuracies that hinder adoption. Model immaturity and a lack of robust regulations contribute to hesitation, especially when dealing with sensitive data and critical tasks. As one participant stated, *"We need to wait until privacy frameworks and cultural concerns are better addressed. Until then, AI cannot be fully trusted for corporate environments."*

Concerns extend to AI's performance on complex, high-value tasks, with participants citing inconsistent results and limited explainability. Data privacy and security risks are also major barriers. Organizations should manage sensitive data while ensuring compliance, but uncertainties around data handling raise skepticism. As one participant shared, "*AI needs data, but we still don't know how data is being collected by these companies. Most of the time, we have no idea.*"

Strict access controls and protection measures are essential. The fear of misuse or breaches limits trust, particularly in regulated sectors like healthcare and cybersecurity. Many companies restrict AI access to sensitive data and enforce governance policies to align with regulations. Yet, navigating diverse regional and sector-specific compliance frameworks adds complexity. One participant highlighted, "*On the corporate and business side, we've received requests from companies not to include any of their data in AI systems. They are concerned about privacy and data protection.*" Organizations face challenges in balancing AI-driven innovation with protecting user data. Regulatory constraints further complicate AI deployment, making compliance a top priority in adoption decisions.

As a result, companies take a cautious approach, prioritizing regulatory and ethical considerations over AI integration. Organizational readiness and stakeholder alignment, along with appropriate technical and operational strategies, are essential for navigating complexity, simplifying AI deployment, and ensuring compliance. These ethical and regulatory concerns directly contributed to decision-making uncertainty, as leaders hesitate to approve AI solutions without clarity on trust, privacy, and compliance.

4.4. Technical & Operational Challenges in AI Deployment

The deployment of AI in organizations presents several technical and operational challenges that impact its effectiveness and adoption. These include performance optimization, integration complexities, usability issues, data biases, and resource constraints. Aligning multiple LLMs to produce consistent and reliable output remains difficult. Inconsistencies in model training and decision logic can result in contradictions and system misalignment. Ensuring AI systems deliver coherent, relevant responses is a persistent hurdle. Integrating AI into legacy systems also poses compatibility issues. Many organizations struggle to embed AI into existing workflows that span multiple platforms and have limited data access. This complexity slows adoption. "*We are moving away from legacy systems, and it's a constant work in progress. There are over 90 integrations to be done, and we've completed about a quarter or a third of them. It's a lot of work.*"

While AI enhances efficiency, usability remains a concern. Many find it difficult to understand the underlying technology, which leads to hesitation. Human oversight and managing content overload are critical for making tools user-friendly. Context retention and consistency in follow-up queries are ongoing limitations. Scalability is another challenge; many AI-generated solutions don't adapt well to changes. "*The generative solution won't be scalable if we need to make changes. We'd have to read and understand everything again, and if we rely on AI itself, it becomes unusable over time.*"

AI models need diverse, representative training data to function well across domains. Outputs may exhibit biases due to limited datasets, leading to fairness issues. Additionally, language diversity presents another challenge, restricting use in multilingual environments. Cost is a major obstacle, especially for smaller organizations. Licensing fees, rigid subscriptions, outsourcing costs, and infrastructure needs all hinder adoption. Limited expertise and resources compound the problem further. *"Generative AI has become subscription-based, so you can use third-party infrastructure for training instead of buying machines with high GPUs. However, even with these options, the cost of training, such as for a code review model, can be substantial."* Another added, "*Copilot or Microsoft 365 is fairly expensive, especially when scaling it across an organization.*"

Addressing performance inconsistencies, integration limitations, usability concerns, biases, and resource barriers requires a strategic and future-oriented approach. This includes prioritizing ethical considerations and compliance. By investing in scalable solutions, enhancing training data diversity, and ensuring seamless integration, organizations can improve AI's effectiveness and adoption. These insights highlighted the importance of regenerative AI adoption where systems evolve over time through continuous learning, ethical alignment, and organizational adaptability.

4.5. Sustainable and Regenerative Aspects: Identifying Capability Gaps

For organizations to adopt Generative AI successfully, they should bridge critical capability gaps that hinder long-term sustainability. These include knowledge limitations, resource constraints, and scalability challenges. Without addressing them, AI adoption remains fragmented and reactive rather than strategic or future-proof.

Leadership awareness is fundamental. Many still viewed AI as a short-term tool instead of a strategic asset. *"I think the management people, the ones making decisions, need to truly see the value of Gen AI,"*. Region-specific needs and case-specific requirements are added to adoption hurdles. A major barrier is the lack of structured learning and knowledge-sharing. Many organizations lacked direction, leading to outdated datasets and inefficiencies. The learning curve is steep, especially for non-technical users. As one participant shared, "*The pain point is, of course, the learning curve. People are not familiar with AI-based development, so it takes time. Once familiar, they adapt, but the challenge remains knowledge dissemination across teams.*"

AI development is iterative and requires ongoing refinement. However, budget constraints, rapid tech changes, and tool limitations posed operational barriers. Limited internal expertise forces many to rely on external help, making scaling difficult. As one noted, "*Training is not straightforward. You get it right and move forward, then find anomalies and have to go back. It's an ongoing process.*" Programming use is cautious due to unpredictable outputs. Customizing AI models demands specialized expertise and investment. Interdisciplinary gaps, especially in fields like medical-AI, slow progress. Technical and non-technical teams often face communication barriers. As one participant explained, "*With the internally available staff, we cannot because we are not into development and things. So, we had to rethink whether to hire someone or outsource.*"

Sustainable AI adoption requires a long-term, value-driven approach. Leadership should support AI as a strategic enabler. Yet, issues like data quality, unstructured learning, and skills shortages persist. Continuous learning and internal capacity-building are key to scaling AI effectively and responsibly. The rapid evolution of AI necessitates flexible strategies for continuous improvement. Organizations should customize AI to meet industry needs but often rely on external expertise due to resource limitations. By investing in internal capabilities, ensuring access to critical infrastructure, and advancing an adaptive learning culture, organizations can create resilient AI adoption strategies that support long-term decision-making and improve scalability. Addressing these capability gaps is vital for regenerative adoption, which emphasized not just implementation but sustained, ethical, and inclusive AI integration.

4.6. Thematic Relationships

Figure 1 illustrates the interrelationships among the extracted themes, highlighting the causal links identified through the analysis.

Resilient adoption strategies for decision-making uncertainties help organizations prepare for AI integration by enabling multi-stakeholder collaboration and strengthening organizational readiness. These strategies focused on developing the necessary capabilities and addressing resource gaps critical for sustainable and regenerative AI adoption. Collaboration and readiness play a key role in shaping ethical, regulatory, and trust frameworks, ensuring AI deployment aligns with stakeholder expectations and ethical standards.

Simultaneously, ethical, regulatory, and trust considerations shape the technical and operational deployment of AI by defining legal and moral boundaries. They influence policies and highlight essential concerns such as privacy, fairness, and security. Insights from technical deployment like system limitations or data risks help refine these frameworks, ensuring governance is responsive to real-world conditions.

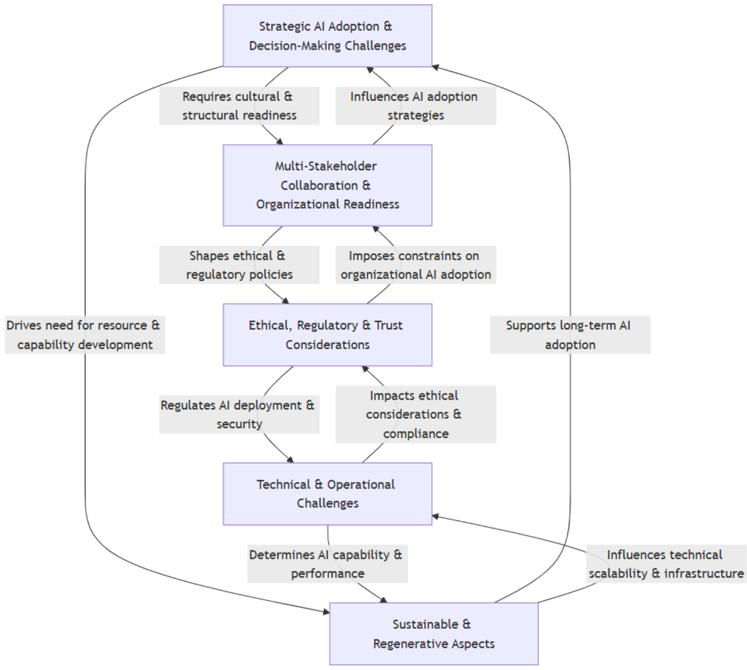

Figure 1: Thematic Relationships Diagram

Addressing technical and operational challenges is vital for identifying infrastructure gaps, performance bottlenecks, and scalability issues. These challenges often expose deeper capability gaps within organizations that must be addressed to ensure successful AI adoption. By closing sustainability and capability gaps, organizations strengthen their ability to scale and adapt. This reinforces the effectiveness of adoption strategies and builds long-term confidence. Together, these interconnected themes create a continuous feedback loop, where strategic, ethical, and technical dimensions evolve in sync supporting resilient, responsible, and future-ready AI adoption.

5. Discussion

This study emphasizes the critical role of resilient technological strategies in managing decision-making uncertainties throughout the GenAI adoption lifecycle. Decision-making, as shown through our integrated framework, is not a singular event but a continuous and evolving process influenced by multiple interrelated factors, such as performance expectations, infrastructure readiness, usability, and ongoing trust. These insights align with principles from the UTAUT2 framework, which views technology adoption as a dynamic interplay between individual motivations, organizational structures, and habitual behaviors.

Resilient adoption begins with aligning GenAI initiatives to organizational goals and stakeholder priorities with broader organizational objectives and stakeholder expectations, confirming earlier insights [29, 30]. This highlights the vital role of purpose-driven leadership, emphasizing the alignment of AI initiatives with meaningful long-term organizational impacts. Our findings indicate that organizations embedding governance and ethical considerations early in decision-making can manage uncertainties more effectively, particularly in areas such as regulatory compliance, transparency, and operational relevance.

A key takeaway from our findings is the necessity of prioritizing long-term strategic value over short-term experimentation or technology-driven hype, mirroring analyses from previous research [26, 27, 28]. This supports the concept of regenerative value creation, emphasizing that truly beneficial AI systems should deliver sustained value beyond immediate operational gains. Additionally, this aligns with our findings advocating sustainable, ethical, and contextually adaptive AI systems. Our research further confirms previous concerns regarding digital inequity and skill gaps [3]. Without structured training programs and inclusive designs, organizations risk impairing internal skill contrasts, emphasizing the need for internal capacity-building and inclusive access as fundamental elements for effective GenAI integration.

Our findings highlight persistent capability gaps as significant barriers, consistent with prior studies [26, 28]. Fragmented knowledge and insufficiently structured learning initiatives hinder strategic adoption. Organizations aiming to scale AI effectively need resilience and adaptability, which emerged as essential qualities during our study. Successful organizations have embraced agile and iterative adjustments in response to ongoing technological and market uncertainties.

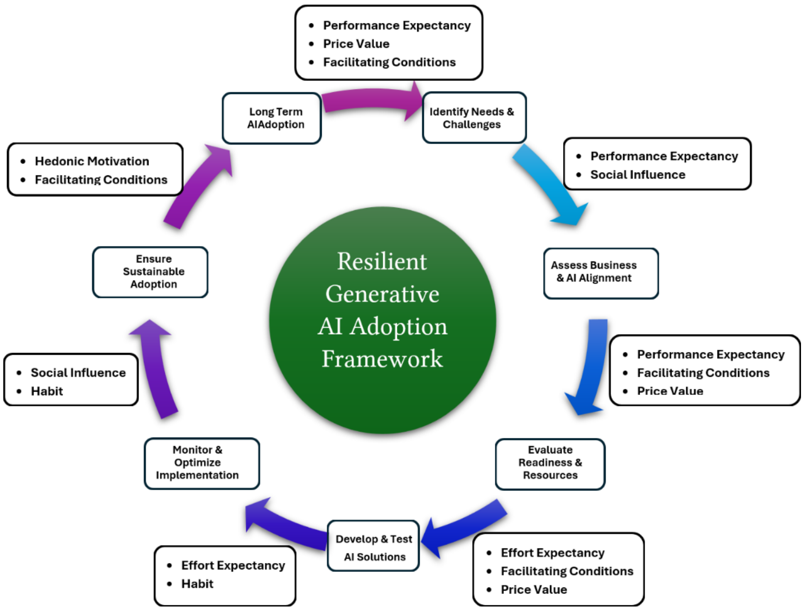

Figure 2: Resilient Generative AI Adoption Framework adapted from UTAUT2

Our empirical observations align closely with UTAUT2 constructs, as demonstrated in Figure 2. During the initial stage of identifying organizational needs and challenges, the constructions of performance expectancy (anticipated benefits) and social influence (stakeholder expectations) significantly drive early decision-making. As organizations progress towards evaluating readiness and resources, facilitating conditions (such as adequate infrastructure and resources) and price value (cost-effectiveness considerations) become prominent factors influencing adoption decisions.

The practical implementation stages, such as developing, testing, and optimizing AI solutions, further reinforce the critical role of effort expectancy (ease of use) and habit (routine integration into workflows) for successful and sustained user adoption. At advanced stages of ensuring sustainable adoption, hedonic motivation (user satisfaction and enjoyment), alongside established habits, play essential roles in long-term engagement. Finally, the iterative feedback loops from long-term adoption back to identifying new challenges highlights ongoing considerations of performance expectancy, facilitating conditions, and cost-effectiveness, reinforcing the continuous and adaptive nature of the adoption process.

Collectively, our findings emphasize a systemic and multi-layered perspective on GenAI adoption, integrating technical capabilities, ethical frameworks, and strategic organizational alignment. Truly regenerative AI systems depend upon continuous feedback loops among decision-makers, users, and technological systems. Rather than eliminating uncertainty, resilient strategies equip organizations with the tools and mindset necessary for managing it, implementing informed, transparent, and adaptive decision-making processes over time.

6. Conclusion

This study emphasizes how resilient technological strategies can reduce decision-making uncertainty and enable the sustainable adoption of Generative AI. Through a multi-case analysis across industries and geographies, we identified key barriers ranging from technical complexity and ethical concerns to organizational readiness and capability gaps. The findings emphasize that long-term success with GenAI requires more than functional implementation; it demands alignment with strategic goals, robust governance, and continuous adaptation. Embedding ethical, scalable, and inclusive practices into AI systems not only builds trust but also fosters long-term, regenerative value creation. By treating AI as a strategic asset rather than a short-term tool, organizations can enhance decision-making processes that are transparent, adaptable, and future-ready.

7. Limitations and future work

This study is limited by its sample size of 16 cases, which, despite their diversity, may not reflect the full range of organizational contexts. The qualitative approach, while rich in insight, introduces subjectivity and limits generalizability. Additionally, the fast-changing nature of AI technologies and regulations means that some barriers identified may evolve quickly. Future research could expand the scope with larger, cross-sector studies and incorporate quantitative methods to strengthen generalizability and track changes over time.

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Declaration on Generative AI

The authors used Grammarly for language support and take full responsibility for the final content.

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