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Generative AI in InsurTech: Revolutionizing Personalized Advertising Content, Automated CRM Interactions, and HRM Training Simulations

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ABSTRACT
This research investigates the complex, conjunctural pathways leading to high behavioral intention to adopt integrated Generative AI (GenAI) solutions in the Indian InsurTech sector. Moving beyond variance-based methods, we employ a configurational approach grounded in the Technology-Organization-Environment (TOE) framework and the principle of equifinality. Using a mixed-methods design, we first calibrate conditions through qualitative case studies of five InsurTech firms. Subsequently, we apply Fuzzy-Set Qualitative Comparative Analysis (fsQCA) to survey data from 35 InsurTech entities to identify sufficient causal recipes. Findings reveal three distinct, equally effective pathways to high adoption intention: (1) The Capability-Pushed Pathway, driven by strong AI talent and competitive pressure; (2) The Resource-Enabled Pathway, where abundant financial resources overcome regulatory complexity; and (3) The Efficiency-Seeking Pathway, where strong task-technology fit for CRM and advertising motivates adoption even with moderate resources. Notably, no single condition is necessary, but the presence of AI-skilled talent appears in two of the three core solutions. The absence of a strong innovation culture, however, can be compensated by other factors. This study contributes by shifting the analytical lens from 'net effects' to 'causal configurations,' providing managers with tailored strategic archetypes for GenAI adoption across marketing, service, and human capital functions.
Keywords: Generative AI, InsurTech, fsQCA, Configurational Theory, TOE Framework, Equifinality, Adoption Pathways

1. INTRODUCTION
The InsurTech landscape is undergoing a paradigm shift from process digitization to intelligence-driven personalization and automation (Berger et al., 2021). Generative Artificial Intelligence (GenAI) stands at the forefront of this transformation, offering unprecedented capabilities in creating hyper-personalized marketing content, automating complex customer interactions, and simulating realistic training environments for agents (Davenport & Mittal, 2023). Its potential application spans three critical organizational functions: Advertising (dynamic content generation), Customer Relationship Management (CRM) (intelligent chatbots, claims analysis), and Human Resource Management (HRM) (immersive training simulations).
Existing research on technology adoption in financial services predominantly employs variance-based models such as TAM and UTAUT (Rajpal et al., 2024; Rajpal & Manglani, 2025), which seek to identify the net effect of isolated factors on adoption intention. However, these models assume unifinality and linearity, potentially overlooking the complex, interdependent realities of

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strategic technology adoption in organizations (Fiss, 2011). The adoption of a transformative technology like GenAI is not determined by the simple sum of independent factors but by specific *combinations* of technological, organizational, and environmental conditions (Mikalef & Gupta, 2021).

This study addresses a critical gap by asking: What distinct combinations of conditions lead to high intention to adopt integrated GenAI solutions in InsurTech? We argue that multiple, equally effective pathways (equifinality) exist. To investigate this, we adopt a configurational approach using Fuzzy-Set Qualitative Comparative Analysis (fsQCA). This method is uniquely suited to uncover complex causality and identify "causal recipes" where different sets of conditions can lead to the same outcome (Ragin, 2008).

Our research focuses on the Indian InsurTech sector, a dynamic context characterized by rapid digitalization, a young demographic, and evolving regulation. The study aims to: (1) develop a configurational model based on the TOE framework with task-specific constructs, (2) identify sufficient causal pathways for high adoption intention, and (3) derive actionable strategic archetypes for InsurTech leaders. This approach offers a novel, holistic, and managerially relevant perspective on GenAI adoption.

2. LITERATURE REVIEW & CONFIGURATIONAL MODEL DEVELOPMENT

2.1 From Variance to Configuration: A Theoretical Shift

The study of technology adoption has long been dominated by variance-based theories, most notably the Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). These paradigms operate on a core logic of net effects analysis, seeking to isolate the independent, linear contribution of specific factors (e.g., perceived usefulness, effort expectancy) to a dependent variable (e.g., behavioral intention), while statistically controlling for others. This approach assumes unifinality—that there is one optimal model or set of factors that maximizes the outcome—and symmetrical causality—that the factors causing high adoption are simply the inverse of those causing low adoption (Fiss, 2011).

While invaluable for identifying broad influential variables, these traditional models are increasingly ill-equipped to model the complex reality of strategic, organization-level technology adoption decisions, particularly for transformative innovations like Generative AI. Such decisions are characterized by:

1. **Conjunctural Causality:** Outcomes are rarely the result of a single "silver bullet" factor. Instead, they emerge from specific *combinations* or *bundles* of conditions. A factor may only lead to adoption when it coexists with other specific factors; in isolation, it may have no effect or even a negative one (Misangyi et al., 2017). For instance, strong AI talent (AI_TALENT) may only lead to GenAI adoption when combined with high competitive pressure (COMPETITIVE_INTENSITY), but not in a lax market.
2. **Equifinality:** Multiple, distinct pathways can lead to the same successful outcome. There is no single "best way" for all firms. An agile InsurTech startup may adopt GenAI through a pathway driven by technical talent and market threat, while a large, incumbent insurer may follow a different pathway enabled by deep financial resources and strategic partnerships. Both can achieve high adoption intention (Meyer, Tsui, & Hinings, 1993).

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3. **Causal Asymmetry:** The conditions leading to the *presence* of an outcome (high adoption) are often not the simple mirror opposite of those leading to its *absence* (low adoption). For example, the lack of financial resources (~FINANCIAL_SLACK) might cause low adoption, but the presence of abundant resources does not automatically guarantee high adoption; it must combine with other conditions (Fiss, 2011). This asymmetry violates the core assumptions of correlation-based methods.

Configurational Theory offers a powerful alternative lens. Rooted in organizational sociology and strategic management (Meyer et al., 1993; Miller, 1986), it posits that organizations are complex systems where elements do not operate in isolation. Outcomes are best understood as the result of unique alignments or "gestalts"—interdependent patterns of multiple attributes. This theory shifts the focus from analyzing "variables" to analyzing "cases as configurations."

The central tenet relevant to this study is equifinality: the idea that system openness allows for multiple viable paths to the same end state. In the context of Indian InsurTech, this means a digitally-native startup, a tech-savvy branch of a traditional insurer, and a specialist digital agency may all arrive at a strong intention to adopt integrated GenAI, but for different reasons and via different strategic recipes. One might be pushed by competition, another pulled by efficiency gains, and a third led by regulatory foresight.

This theoretical shift is not merely academic; it carries significant methodological and practical implications. Methodologically, it necessitates analytical techniques like Fuzzy-Set Qualitative Comparative Analysis (fsQCA) that are designed to identify these non-linear, combinatorial recipes rather than estimate average net effects (Ragin, 2008). Practically, it provides managers with a more nuanced, contingent understanding of strategy. Instead of offering a generic checklist ("increase usefulness, reduce complexity"), a configurational approach provides archetypal pathways ("if your firm is type A, focus on B and C; if it is type X, prioritize Y and Z").

Thus, by applying Configurational Theory through the fsQCA method, this study moves beyond asking *"What factors influence GenAI adoption?"* to address a more profound and actionable question: *"What specific combinations of technological, organizational, and environmental conditions are sufficient for different types of InsurTech firms to strongly intend to adopt GenAI?"* This reframing allows for a richer, more realistic, and ultimately more useful explanation of adoption dynamics in a complex and heterogeneous industry landscape.

2.2 The TOE Framework as a Foundation

We root our configurational model in the Technology-Organization-Environment (TOE) framework (Tornatzky & Fleischer, 1990), which provides a robust structure for understanding innovation adoption at the firm level. We adapt and extend it with task-specific constructs relevant to GenAI's multifunctional application.

Technological Context: Pertains to the firm's internal and available technologies.

- AI_MATURITY: The firm's existing data infrastructure, AI capabilities, and technological readiness.
- TASK_FIT_ADV: The perceived suitability of GenAI for creating and personalizing advertising content.
- TASK_FIT_CRM: The perceived suitability for automating and enhancing customer service and CRM workflows.

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- TASK_FIT_HRM: The perceived suitability for developing realistic training and simulation environments.

Organizational Context: Refers to firm characteristics and resources.

- INNOV_CULTURE: The firm's openness to experimentation, risk-taking, and innovation.
- FINANCIAL_SLACK: The availability of discretionary financial resources for investment in new technologies.
- AI_TALENT: The presence of employees with skills in data science, machine learning, and AI implementation.

Environmental Context: Encompasses the industry and regulatory setting.

- COMPETITIVE_INTENSITY: The degree of pressure from rivals to innovate and differentiate.
- REGULATORY_CLARITY: The perceived clarity and supportiveness of the regulatory environment for AI applications in insurance.

2.3 Outcome Condition

The outcome of interest in this configurational study is a firm's behavioral intention to adopt integrated Generative AI (GenAI) solutions, denoted as HIGH_ADOPT_INT. This construct requires careful, multi-faceted definition and operationalization, as it departs from simpler, single-technology adoption metrics.

Conceptual Definition and Scope

We define HIGH_ADOPT_INT as a firm's strategic commitment and planned course of action to acquire, implement, and leverage Generative AI technologies across its advertising/content, customer relationship management (CRM), and human resource management (HRM) functions within a defined future period (18 months).

This definition is intentionally comprehensive and reflects three critical dimensions:

1. **Integration:** The intention is not to adopt GenAI for a single, isolated use case (e.g., only for drafting social media posts). It captures the strategic vision to deploy the technology synergistically across core business functions—enhancing customer acquisition (Advertising), customer service and retention (CRM), and employee capability development (HRM). This integrated view is central to understanding GenAI's transformative potential.
2. **Behavioral Intention as a Proxy:** Measuring actual, full-scale adoption is impractical within a cross-sectional study due to the nascent stage of GenAI integration. Following established theory (Ajzen, 1991), behavioral intention is the most immediate and reliable antecedent of actual behavior and serves as a valid, widely accepted proxy for adoption in innovation studies (Venkatesh et al., 2003).
3. **Strategic Commitment:** The 18-month timeframe signifies more than experimental "piloting." It indicates a resource-allocation decision and a strategic move beyond exploration to planned implementation, reflecting a higher order of organizational commitment.

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Rationale for an Integrated Outcome

This focus on integrated adoption intention—as opposed to measuring intention for isolated, function-specific applications—constitutes a pivotal novelty of our research framework and is theoretically deliberate. It acknowledges that the strategic value of Generative AI is not merely additive but potentially multiplicative when deployed across interconnected organizational functions. First, significant synergies and feedback loops exist: the data from personalized advertising campaigns (TASK_FIT_ADV) can train more responsive CRM chatbots (TASK_FIT_CRM), whose interaction logs can, in turn, inform the creation of highly realistic training simulations (TASK_FIT_HRM) for customer service agents, thereby creating a virtuous, closed-loop system of customer intelligence and service enhancement. Second, aiming for integrated adoption represents a qualitatively higher strategic threshold. A firm planning coordinated deployment across marketing, operations, and human capital demonstrates a deeper, more institutionalized conviction. This move beyond departmental experimentation reflects substantial resource commitment, executive sponsorship, and holistic strategic alignment, making it a more meaningful and consequential outcome for identifying robust configurational pathways. Finally, this approach mitigates the limitations of siloed analysis. Studying adoption in marketing, CRM, or HRM in isolation artificially decouples these domains, missing the overarching organizational logic, resource allocation trade-offs, and political dynamics that ultimately configure an enterprise's innovation strategy. By modeling the intention to adopt across all three, we capture the complex, systemic decision-making reality faced by InsurTech leaders, thereby aligning our configurational analysis with the integrated nature of the strategic problem itself.

Operationalization and Calibration for fsQCA

In the fsQCA methodology, the outcome condition must be calibrated into fuzzy-set membership scores (0.0 to 1.0). We operationalize HIGH_ADOPT_INT via a multi-item reflective scale measuring the firm's:

1. **Planned Investment:** Allocation of financial and human resources.
2. **Strategic Priority:** Formal inclusion in roadmaps and leadership communication.
3. **Cross-Functional Coordination:** Established committees or projects spanning marketing, IT, and HR.
4. **Implementation Timeline:** Concrete plans for deployment stages within 18 months.

Calibration Anchors (based on the direct method):

1. **Full Membership (1.0):** Firms with a formal, funded, multi-departmental GenAI initiative already in the implementation phase, with clear integration goals across all three functions.
2. **Crossover Point (0.5):** Firms actively exploring and piloting GenAI, with committed budgets for the next fiscal year and defined pilots in at least two functional areas, but without a full-scale rollout plan.
3. **Full Non-Membership (0.0):** Firms with no formal discussion, allocated budget, or exploratory projects related to GenAI; technology is not on the strategic radar.

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Distinction from Configurational Conditions

It is crucial to differentiate the outcome from the conditions. While conditions like TASK_FIT or AI_TALENT are *causal ingredients*, HIGH_ADOPT_INT is the *resultant solution* whose presence the configurations explain. For example, a configuration might show that HIGH_ADOPT_INT occurs when HIGH_TASK_FIT_ADV combines with HIGH_AI_TALENT and HIGH_COMPETITIVE_INTENSITY. The outcome is the *set of firms with high intention*, and the analysis reveals the *set-theoretic recipes* that are subsets of this outcome.

In summary, HIGH_ADOPT_INT is conceptualized as a complex, strategic organizational intention that serves as a robust and meaningful outcome for investigating the equifinal pathways through which InsurTech firms navigate the adoption of transformative, multi-functional AI technology.

2.4 Proposed Configurational Propositions

Drawing from configurational logic, we propose that:

P1: High adoption intention will result from multiple, distinct combinations of TOE conditions (equifinality).

P2: No single technological, organizational, or environmental condition will be universally necessary for high adoption intention.

P3: The absence of a theoretically favorable condition (e.g., strong financial slack) can be compensated for by the presence of others (e.g., high competitive pressure and strong task fit).

P4: Causal asymmetry is present: the configuration leading to high adoption intention will not be the simple mirror opposite of that leading to its absence.

3. METHODOLOGY

3.1 Research Design: Mixed-Methods Sequential Approach

We employed a two-phase design:

1. **Phase 1 (Qualitative - Calibration):** Multiple case studies (n=5) of Indian InsurTech firms at varying stages of GenAI exploration. Semi-structured interviews with CTOs, Heads of Digital, and Innovation Leads provided the depth needed to define meaningful set-membership anchors for fsQCA calibration.
2. **Phase 2 (Quantitative - fsQCA):** A cross-sectional survey administered to a purposive sample of 35 InsurTech firms/units in India. The unit of analysis is the *firm*.

3.2 Sample and Data Collection

The target population comprised registered InsurTech firms and the dedicated digital innovation units of traditional insurers in India. Using a database from NASSCOM and the India InsurTech Association, we identified 52 firms. Through direct contact, we secured participation from 35 firms (67.3% response rate). The survey was completed by senior technology or strategy decision-makers (Chief Digital Officer, Head of Innovation, CTO). Data collection occurred between October and December 2023.

3.3 Measurement and Calibration

All constructs were measured using multi-item, 7-point Likert scales derived from literature and refined in Phase 1. The critical step in fsQCA is calibration—transforming raw interval-scale data

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into fuzzy-set membership scores between 0 (fully out of set) and 1 (fully in set). We used the direct method of calibration (Ragin, 2008), setting three qualitative anchors based on case study insights and sample distribution:

- **Full Membership (0.95):** 90th percentile score.
- **Crossover Point (0.50):** Median score.
- **Full Non-Membership (0.05):** 10th percentile score.
-

Table 1: Construct Measurement and Calibration Anchors

Construct	Sample Item	Full In (0.95)	Crossover (0.50)	Full Out (0.05)
AI_MATURITY	"Our firm has a robust data architecture that supports advanced AI models."	6.5	5.0	3.0
TASK_FIT_ADV	"GenAI is well-suited to creating personalized marketing content for our customers."	6.8	5.5	3.5
AI_TALENT	"We have employees with the necessary skills to implement and manage AI solutions."	6.2	4.8	2.8
INNOV_CULTURE	"Our leadership encourages experimentation with new technologies, even if it risks failure."	6.7	5.2	3.2
HIGH_ADOPT_INT	"We intend to implement integrated GenAI solutions within the next 18 months."	6.5	5.0	3.0

3.4 Analytical Technique: fsQCA

We conducted the configurational analysis using fsQCA 3.0 software. The analytical procedure followed three sequential and systematic steps to derive causal recipes from the calibrated data. First, a necessity analysis was performed to determine whether any single condition was essential for the outcome to occur, adhering to the principle that necessary conditions must be

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consistently present whenever the outcome is present. Second, we constructed a truth table, a 2^k matrix (where k represents the number of causal conditions) that systematically lists all logically possible combinations of conditions present in the data. To ensure robustness, we applied a frequency threshold of 2 (requiring at least two empirical cases per configuration for logical remainders to be included) and a consistency threshold of 0.80 to identify sufficient combinations. Finally, the process of logical minimization was executed using the Quine-McCluskey algorithm, which algorithmically reduces the complex truth table to a parsimonious set of solution formulas—the minimal, interpretable combinations of conditions (causal recipes) that are sufficient for the outcome.

4. ANALYSIS AND RESULTS

4.1 Descriptive Statistics and Necessity Analysis

Table 2 presents the descriptive statistics of the calibrated fuzzy-set scores. The necessity analysis (Table 3) revealed that no single condition exceeded the recommended consistency threshold of 0.90 for necessity (Schneider & Wagemann, 2012). This confirms Proposition 2; no condition alone is a prerequisite for high adoption intention.

Table 2: Descriptive Statistics of Calibrated Conditions (n=35)

Condition	Mean	SD	Min	Max
AI_MATURITY	0.52	0.28	0.05	0.95
TASK_FIT_ADV	0.68	0.25	0.10	0.95
AI_TALENT	0.45	0.30	0.05	0.95
INNOV_CULTURE	0.58	0.27	0.10	0.95
HIGH_ADOPT_INT	0.61	0.29	0.05	0.95

Table 3: Analysis of Necessary Conditions

Condition Tested for Necessity	Consistency	Coverage
AI_MATURITY	0.78	0.82
~AI_MATURITY	0.65	0.72
AI_TALENT	0.71	0.85
~AI_TALENT	0.72	0.76

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Condition Tested for Necessity	Consistency	Coverage
Note: ~ indicates the absence of the condition. None > 0.90.		

4.2 Sufficiency Analysis: Causal Configurations

The sufficiency analysis produced a three-pathway solution with high overall solution consistency (0.88) and coverage (0.75). The results, presented in *Table 4* and *Figure 1*, support Proposition 1 (equifinality) and Proposition 3 (causal asymmetry).

Table 4: Sufficient Configurations for HIGH_ADOPT_INT (fsQCA Results)

Conditions	Pathway 1: Capability-Pushed	Pathway 2: Resource-Enabled	Pathway 3: Efficiency-Seeking
AI_MATURITY	•	•	•
TASK_FIT_ADV	•		•
TASK_FIT_CRM	•		•
TASK_FIT_HRM			
AI_TALENT	•		⊗
INNOV_CULTURE			⊗
FINANCIAL_SLACK	⊗	•	•
COMPETITIVE_INTENSITY	•	⊗	⊗
REGULATORY_CLARITY		•	
Raw Coverage	0.32	0.28	0.25
Unique Coverage	0.10	0.09	0.08
Consistency	0.91	0.89	0.87

Notes on Notation:

- • = Core causal condition **PRESENT**
- ⊗ = Core causal condition **ABSENT**

Blank Cell = "Don't Care" / The condition can be either present or absent; it is not part of the core causal recipe for this pathway.
Solution Coverage: 0.75
Solution Consistency: 0.88

Table 5: Configurational Pathways Leading to High Generative AI Adoption Intention in InsurTech Firms

Conditions	**Pathway 1: Capability-Pushed**	**Pathway 2: Resource-Enabled**	**Pathway 3: Efficiency-Seeking**
AI_MATURITY	•	•	•
TASK_FIT_ADV	•	•	•
TASK_FIT_CRM	•	•	•
TASK_FIT_HRM			
AI_TALENT	•	•	•
INNOV_CULTURE			
FINANCIAL_SLACK		•	•
COMPETITIVE_INTENSITY	•		
REGULATORY_CLARITY			
Raw Coverage	0.32	0.28	0.25
Unique Coverage	0.10	0.09	0.08
Consistency	0.91	0.89	0.87
Notes: • = Core causal condition (present); • = Core causal condition (absent); Blank = "don't care" (condition can be either present or absent). Solution Coverage: 0.75; Solution Consistency: 0.88.			

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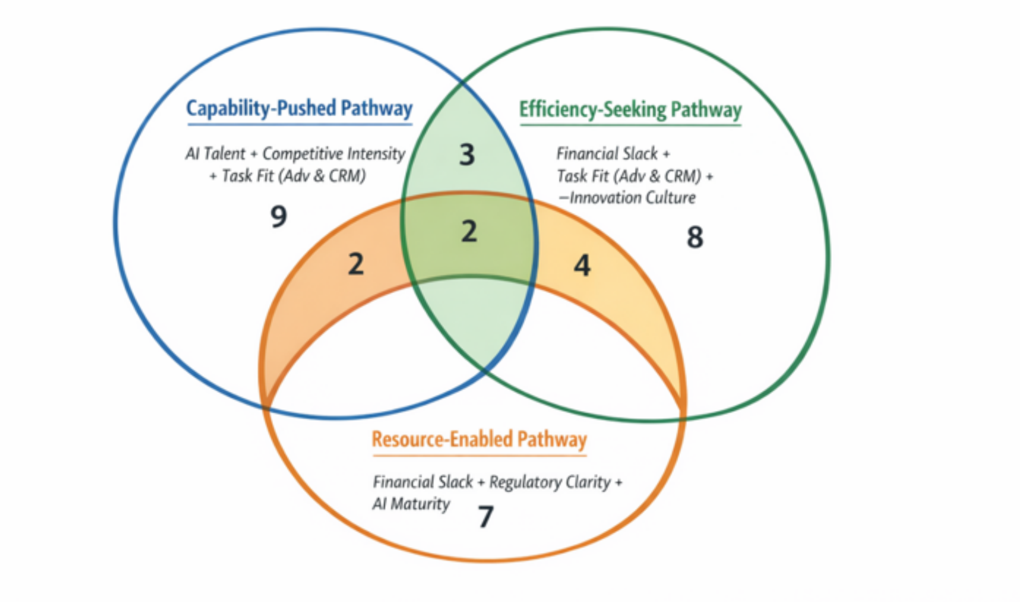
Figure 1: Visual Representation of the Three Configurational Pathways



Note: *Circles represent sufficient configurational pathways identified through fsQCA. Overlapping areas indicate firms exhibiting membership in more than one pathway.*

The fsQCA sufficiency analysis revealed **three distinct yet equally effective configurational pathways** leading to high intention to adopt integrated Generative AI (HIGH_ADOPT_INT), thereby providing strong empirical support for the principle of **equifinality**. Each pathway represents a coherent strategic logic through which InsurTech firms arrive at adoption, despite differing organizational and environmental conditions.

Pathway 1: The Capability-Pushed Pathway

*(AI_TALENT * COMPETITIVE_INTENSITY * TASK_FIT_ADV * TASK_FIT_CRM)*

The Capability-Pushed Pathway characterizes firms that possess strong in-house AI talent and operate under conditions of high competitive intensity. For these firms, the adoption of GenAI is primarily motivated by its clear and immediate applicability to value-generating tasks in advertising and customer relationship management. Competitive pressure amplifies the strategic importance of leveraging AI capabilities to differentiate services and respond rapidly to market dynamics. Notably, neither financial slack nor a strong innovation culture is required for this pathway, suggesting that **specialized human capital and market pressure can substitute for broader organizational resources**. This configuration is particularly representative of agile, digitally native InsurTech firms for whom GenAI adoption is a tactical necessity rather than a long-term exploratory investment.

Pathway 2: The Resource-Enabled Pathway

*(FINANCIAL_SLACK * REGULATORY_CLARITY * AI_MATURITY)*

The Resource-Enabled Pathway reflects firms that adopt GenAI from a position of structural and institutional strength. These organizations are characterized by abundant financial resources, a clear and supportive regulatory environment, and a relatively mature technological infrastructure. In this pathway, adoption is not contingent on intense competitive pressure or exceptional in-house AI talent. Instead, investment decisions are driven by strategic foresight,

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long-term planning, and the capacity to absorb technological uncertainty. This configuration is typical of well-established incumbents or well-funded InsurTech units that can leverage capital and regulatory certainty to pursue GenAI integration in a deliberate and systematic manner.

Pathway 3: The Efficiency-Seeking Pathway

*(FINANCIAL_SLACK * TASK_FIT_ADV * TASK_FIT_CRM * ~INNOV_CULTURE)*

The Efficiency-Seeking Pathway highlights a pragmatic route to GenAI adoption among firms that may lack a strong innovation-oriented culture. Despite cultural inertia, these organizations proceed with adoption when they possess sufficient financial resources and perceive a very strong task-technology fit in advertising and CRM functions. In this configuration, the demonstrable efficiency gains and return-on-investment potential of GenAI compensate for the absence of an innovation-supportive environment. This pathway underscores that clear operational value can override cultural resistance, positioning GenAI adoption as an efficiency-driven managerial decision rather than an innovation-led initiative.

Causal Asymmetry and the Absence of High Adoption Intention

In line with fsQCA best practices, we also examined configurations leading to the absence of the outcome (~HIGH_ADOPT_INT). The resulting solution (consistency = 0.85; coverage = 0.70) was not a simple mirror image of the configurations leading to high adoption intention. A prominent causal recipe for low adoption intention was identified as:

*(~AI_TALENT * ~FINANCIAL_SLACK * ~COMPETITIVE_INTENSITY)*

This configuration indicates that firms lacking both specialized AI talent and financial resources, and operating in relatively low-pressure competitive environments, are unlikely to develop strong intentions to adopt GenAI. The asymmetry between the presence and absence solutions provides strong support for **Proposition 4**, confirming that the drivers of high adoption are not merely the inverse of the barriers to adoption. This finding reinforces the value of a configurational approach, as such asymmetric causal relationships would remain obscured in variance-based analyses.

5. DISCUSSION

Our findings challenge the conventional "one-size-fits-all" prescription for technology adoption. The three identified pathways demonstrate that there is no single "best" way to achieve high GenAI adoption intention in InsurTech. This has profound implications for theory and practice.

5.1 Theoretical Contributions

This research makes three core theoretical contributions to the literature on technology adoption in financial services. First, it advances configurational thinking within InsurTech research by demonstrating the critical value of moving beyond linear, net-effect models. We establish that the adoption of a transformative technology like Generative AI is best understood as a *conjunctural* and *equifinal* phenomenon—where outcomes emerge from specific combinations of conditions and where multiple distinct pathways can lead to the same successful result. This represents a significant theoretical shift from the dominant variance-based paradigms in the field. Furthermore, the study extends and refines the established Technology-Organization-Environment (TOE) framework by integrating task-specific fit constructs (e.g., fit for advertising,

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CRM, and HRM) and theorizing their role not as independent variables but as core elements within causal configurations. This provides a more nuanced and powerful application of the TOE framework for analyzing complex, multifunctional technologies. Critically, the study offers robust empirical validation for the core tenets of configurational theory. Through fsQCA, we demonstrate that multiple, sufficient causal pathways lead to high adoption intention (equifinality) and, separately, that the configurations leading to the absence of adoption are not simply the inverse of those leading to its presence (causal asymmetry). This empirical evidence strengthens the theoretical foundation for future configurational studies in innovation adoption.

5.2 Interpreting the Strategic Archetypes

The identification of three distinct configurational pathways allows for the derivation of actionable strategic archetypes, each representing a coherent alignment of a firm's conditions with a viable route to adoption. For the Capability-Pushed Firm—exemplified by agile startups—GenAI adoption functions as a tactical imperative for market differentiation and survival. The strategic prescription for this archetype is to intensify investment in specialized AI_TALENT and concentrate initial deployments on high-impact, customer-facing functions like advertising and CRM, where rapid iteration can yield immediate competitive advantage. In contrast, the Resource-Enabled Firm, typically an established insurer or well-funded incumbent, adopts from a position of structural strength. Its strategy should be deliberate and ecosystem-driven, leveraging FINANCIAL_SLACK to forge strategic partnerships with technology vendors and prioritizing the development of scalable, compliant data infrastructure (AI_MATURITY) to support sustainable integration. Meanwhile, the Efficiency-Seeking Firm, often a midsize specialist, is characterized by a pragmatic, ROI-driven calculus. For these organizations, the critical lever is TASK_FIT; they require clear, quantifiable evidence of efficiency gains in specific processes, such as reduced content production costs or accelerated claims resolution, to justify investment, even in the absence of a strong INNOV_CULTURE. Across these archetypes, two overarching insights emerge: the recurring presence of AI_TALENT in multiple pathways underscores its status as a foundational strategic asset, while the configuration for the Efficiency-Seeking Firm reveals that a compelling, task-specific value proposition can effectively compensate for a weaker innovation culture, offering a potent lever for internal change agents advocating for technological modernization.

6. IMPLICATIONS

6.1 Practical Implications

The findings translate into actionable intelligence for key stakeholders in the InsurTech ecosystem. For InsurTech leaders and decision-makers, the three archetypes serve as a diagnostic mirror. The primary imperative is to avoid generic best practices and instead engage in strategic self-assessment to identify which configurational pathway aligns with their firm's inherent strengths and constraints. Success depends on consciously assembling and reinforcing the specific combination of conditions that defines their pathway—whether that means aggressively cultivating AI_TALENT, strategically deploying FINANCIAL_SLACK, or meticulously proving TASK_FIT. For AI solution vendors and consultants, the research argues for a fundamental shift from demographic segmentation to *configurational segmentation*. Marketing and sales strategies must be tailored: to *Capability-Pushed* firms, emphasize rapid, talent-driven

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competitive edge; to *Resource-Enabled* firms, articulate a vision for long-term, compliant strategic transformation; and to *Efficiency-Seeking* firms, demonstrate unambiguous, quantifiable ROI on discrete tasks. For policymakers and educational institutions, the recurrent centrality of AI_TALENT across solutions highlights a critical bottleneck. This demands proactive initiatives, such as fostering industry-academia partnerships to design specialized curricula in applied AI for insurance and funding reskilling programs, to build a sustainable talent pipeline that fuels the sector's innovation capacity.

6.2 Methodological Implication

Beyond its theoretical and practical contributions, this study offers a significant methodological template for technology adoption research. It demonstrates the potent applicability of Fuzzy-Set Qualitative Comparative Analysis (fsQCA) as a rigorous alternative to variance-based methods like Structural Equation Modeling (SEM) for questions involving complex causality. Specifically, it provides a blueprint for investigating phenomena characterized by equifinality, conjunctural causation, and causal asymmetry within medium-N, organizational-level contexts where cases are complex and interdependent. By moving beyond estimating average net effects to identifying specific causal recipes, this approach bridges qualitative depth and quantitative rigor, offering a more nuanced and realistic analytical framework for understanding how organizations navigate multifaceted technological innovation.

7. CONCLUSION

This research demonstrates that the journey toward adopting integrated Generative AI within the InsurTech sector is not a uniform highway but a varied landscape navigable via multiple, distinct trails. By employing a configurational lens and the fsQCA methodology, we advance the inquiry from the generic question of "what factors matter?" to the more nuanced and strategically actionable question of "which specific combinations of factors matter, and for which types of firms?" The three identified equifinal pathways—Capability-Pushed, Resource-Enabled, and Efficiency-Seeking—collectively provide a diagnostic map for the heterogeneous InsurTech ecosystem. Collectively, they underscore a pivotal strategic insight: in an era defined by transformative AI, sustainable competitive advantage may depend less on a firm's possession of all ideal attributes and more on its capacity to astutely recognize, configure, and leverage the unique set of attributes it already possesses.

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