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Decoding the Conversion Gap in SME Digital Transformation: A Causal AI Framework

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Abstract

Despite the proliferation of digital integration initiatives, many Small and Medium-sized Enterprises (SMEs) remain trapped in a persistent "Conversion Gap," where digital adoption fails to manifest as tangible financial performance. Grounded in Resource Conversion Theory, this study anatomizes the structural bottlenecks of this process through a multi-stage Causal AI architecture. Utilizing time-lagged data from 649 SMEs to control for endogeneity, I integrate Gaussian Mixture Modeling (GMM), Tiered Grand-DAG algorithms, and Necessary Condition Analysis (NCA) to decode the non-linear trajectories of value realization. The findings identify a "Low Integration" cohort (34.2%) that fails to translate digital usage into realized outcomes due to a severe deficit in Absorptive Capacity (ACAP). Crucially, NCA diagnostics reveal that 'perceived usefulness' serves merely as a necessary baseline condition, whereas 'user satisfaction' functions as the primary catalyst for value conversion. Furthermore, multi-group analysis (MGA) confirms that for the most vulnerable SMEs, the causal pathway to revenue is structurally severed ($\beta = 0.000$), rendering traditional, linear training interventions ineffective. I propose a fundamental shift toward data-driven, targeted interventions to address these specific structural barriers and facilitate sustainable digital value creation in the SME ecosystem.

Keywords: SME digital transformation; Conversion Gap; Causal AI Framework; Resource Conversion Theory; Necessary Condition Analysis (NCA); Absorptive Capacity (ACAP)

1. Introduction

Over the past decade, digital innovation has evolved from a mere competitive advantage into the fundamental operational architecture driving Business Model Transformation (BMT) in Small and Medium-sized Enterprises (SMEs) [1]. Recent literature emphasizes that this digital transformation is not merely a technological upgrade but a fundamental survival strategy. As Aranitou et al. [2] highlight, SMEs play a pivotal role in driving economic resilience, yet they frequently face unique structural vulnerabilities amid systemic crises. To navigate this complexity, scholars increasingly emphasize the necessity of dynamic capability-building. For instance, Kahveci [3] proposes the DASAT framework—encompassing Digital Awareness, Strategy, Adoption, and Transformation—to demonstrate how SMEs can secure a sustainable competitive advantage.

For SMEs operating as complex socio-technical ecosystems under severe constraints, integrating digital technologies is essential. It serves as an imperative mechanism to ensure organizational agility, efficiency, and sustained market viability. In response, governments worldwide have concentrated substantial macro-level funding and policy efforts

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on strengthening SME digital capabilities [4,5]. However, despite these extensive systemic investments and strategic frameworks, the empirical translation of digital adoption into tangible value co-creation and financial performance remains systematically ambiguous [6].

This discontinuity reflects a modern "IT Productivity Paradox," where technology investments fail to generate expected productivity gains [7,8]. Within the context of SME digital integration, this paradox is particularly acute. While many entrepreneurs perceive the technological 'Usefulness' of digital tools and report high immediate satisfaction, a pervasive structural disconnect emerges upon field implementation; these psychological and technological inputs systematically fail to convert into the practical output of sustainable revenue growth. I conceptualize this phenomenon as a critical bottleneck within the BMT process—specifically, the "Conversion Gap" [9]. While recent foundational studies clarify the enablers of transformation, a critical gap remains in understanding the precise non-linear thresholds where technology adoption structurally fails to translate into tangible business value. Addressing this gap requires moving beyond mere technology acquisition, emphasizing that organizational capacity and 'Digital Resilience' ultimately dictate SME performance [10].

Existing Information Systems (IS) research, predominantly anchored in the Technology Acceptance Model (TAM) or the Unified Theory of Acceptance and Use of Technology (UTAUT), treats 'Intention to Use' or 'Usage' as the terminal dependent variable [11,12]. Yet, technology usage alone does not unilaterally guarantee successful BMT or financial performance [13]. For SMEs, a critical temporal interval exists between initial digital integration (T1) and value realization (T2). A robust "Value Conversion Mechanism" is required to metabolize these new capabilities into concrete business outcomes during this lag [14,15]. Prior studies relying on variance-based linear regressions often fail to explicate this socio-technical dynamic. They fundamentally struggle to capture the non-linear thresholds, conversion barriers, and heterogeneous pathways typical of complex SME ecosystems [16]. Consequently, clearly defining the marginal innovations of this study requires shifting the analytical focus from the linear adoption metrics of traditional TAM/UTAUT models to the non-linear necessary conditions of resource conversion.

To address this critical theoretical lacuna, this study re-examines the outcome generation process of SME digital innovation through the lens of "Resource Conversion." Specifically, I posit that the organizational capacity to link external digital stimuli to commercial success is contingent upon the firm's pre-existing operational base [17]. I propose that an entrepreneur's 'Business Experience' functions as the core catalyst activating resource conversion. Conversely, I empirically demonstrate that digital innovation absent this critical experience results in a significant conversion discontinuity—a state where the socio-technical pathway to BMT is substantially impeded.

To rigorously decode this phenomenon, I analyze time-lagged data from 649 SMEs by deploying a multi-stage Causal AI framework. This methodological architecture functions as an analytical tool designed to uncover the hidden causal dynamics of value creation: (1) Gaussian Mixture Modeling (GMM) identifies latent, heterogeneous subsystems characterized by performance disparities; (2) a Tiered Grand-DAG (Directed Acyclic Graph) elucidates the data-driven causal topology, answering recent calls to ground IS research in rigorous causal diagrams [18]; and (3) a strategic integration of Necessary Condition Analysis (NCA) and PLS-MGA (Multi-Group Analysis) explicitly diagnoses the non-linear constraints and structural disconnections severing distinct enterprise groups [16].

This research theoretically transcends the linear deterministic assumptions of classical IS success models by unveiling a complex conversion mechanism governed by necessary preconditions and sufficient drivers. Practically, these findings necessitate a paradigm shift in macro-level digital strategy: transitioning from universal technological training to

data-driven targeted interventions. Such approaches are designed to address the specific structural barriers of marginalized SMEs, thereby fostering sustainable BMT.

2. Theoretical Framework and Hypotheses

2.1. SME Digital Innovation and Systemic Bottlenecks in BMT

Digital innovation within SMEs transcends isolated technological adoption; it represents a fundamental systemic reconstruction of operational architectures and value co-creation mechanisms [19]. However, prior literature consistently reports a pervasive "Knowing-Doing Gap" [9]—a phenomenon where SMEs successfully acquire digital awareness ('Knowing') but fail to translate this potential into tangible BMT and financial performance ('Doing').

Recent scholarship emphasizes that beyond simple technological acquisition, the core determinant of SME survival in volatile environments is 'Digital Resilience': the capacity to leverage digital integration to withstand and adapt to external shocks [10,20]. In the digital era, resource-constrained SMEs lacking this resilience face a severe conversion discontinuity, rather than merely suboptimal performance. This discontinuity weakens their value creation pathways, impeding their digital progression.

The established Information Systems (IS) Success Model posits a linear, deterministic trajectory wherein system quality and information quality sequentially drive user satisfaction, ultimately culminating in net benefits [13]. However, this linear paradigm struggles to explain unobserved heterogeneity: specifically, why enterprises possessing identical levels of digital literacy achieve drastically divergent pathways of business model innovation and financial success. To address this limitation, this study identifies the variance in "Resource Conversion" capabilities—and the presence of structural bottlenecks—as the root causes of this Conversion Gap.

2.2. The Value Co-Creation Mechanism: A Systems Perspective on Resource Conversion

Anchored in Resource Conversion Theory (RCT)—originating in sociological and psychological disciplines [14,15]—this study conceptualizes that resources, such as digital knowledge or technical skills, do not hold inherent utility in isolation. Rather, their strategic value is activated only when converted into tangible socio-economic outcomes, such as sustained financial performance or enhanced market positioning.

Extending this theoretical lens to SME digital integration, this study proposes a "Value Conversion Mechanism." I define this mechanism as a process wherein latent digital resources are translated into realized economic value, mediated by critical cognitive and affective pathways. Crucially, the efficiency of this conversion is neither automatic nor guaranteed. Instead, it is highly contingent upon the entrepreneur's pre-existing ACAP—specifically, their prior contextual knowledge and business experience [17].

Accordingly, this study empirically investigates whether prior experiential knowledge functions as a necessary catalyst. I posit that this catalyst facilitates the transformation of digital inputs into robust financial performance, thereby bridging the gap between digital potential and sustainable BMT.

2.3. Catalysts for BMT: ACAP and Data-Driven Dynamic Capabilities

The transformation of digital inputs into sustainable financial value and BMT is not automatic; rather, its efficiency is strictly contingent upon the enterprise's ACAP. ACAP represents the organizational ability to recognize, assimilate, and commercially apply external information, relying heavily on prior knowledge [17]. In resource-constrained SMEs, this knowledge base typically manifests as the entrepreneur's prior business experience, serving as the core cognitive infrastructure [21].

However, this study moves beyond the traditional view of ACAP as a mere linear performance facilitator. Instead, I posit that ACAP functions as a critical moderator for SMEs. While experienced entrepreneurs use contextual intelligence to drive value creation, lacking this experience triggers a severe conversion discontinuity that weakens the linkage between digital usage and tangible outcomes. This discontinuity forces the enterprise into a state where continuous digital integration yields diminished or statistically insignificant financial returns, regardless of functional IT proficiency.

Furthermore, this structural perspective aligns seamlessly with the evolution of "Dynamic Capabilities" [22]. To execute successful BMT within a volatile digital ecosystem, the organizational agility to "sense" opportunities and "reconfigure" resources is paramount. Recent scholarship extends this paradigm, arguing that in the current era, these dynamic capabilities are evolved forms of "Data-driven Dynamic Capabilities," deeply rooted in the enterprise's ability to leverage complex information [10,23].

Therefore, this study establishes "Prior Business Experience" not merely as a demographic control variable, but as the critical moderating mechanism that governs the efficiency of the entire resource conversion process. Accordingly, rather than adopting a rigid, a priori hypothesis-testing approach regarding isolated variable impacts, I utilize Resource Conversion Theory and ACAP as a macro-level theoretical lens. The proposed Integrated Resource Conversion Framework (Figure 1) serves as a conceptual blueprint to navigate these underlying mechanisms, while the precise structural topology of the moderator is empirically evaluated through the subsequent causal discovery processes (GMM, Tiered Grand-DAG).

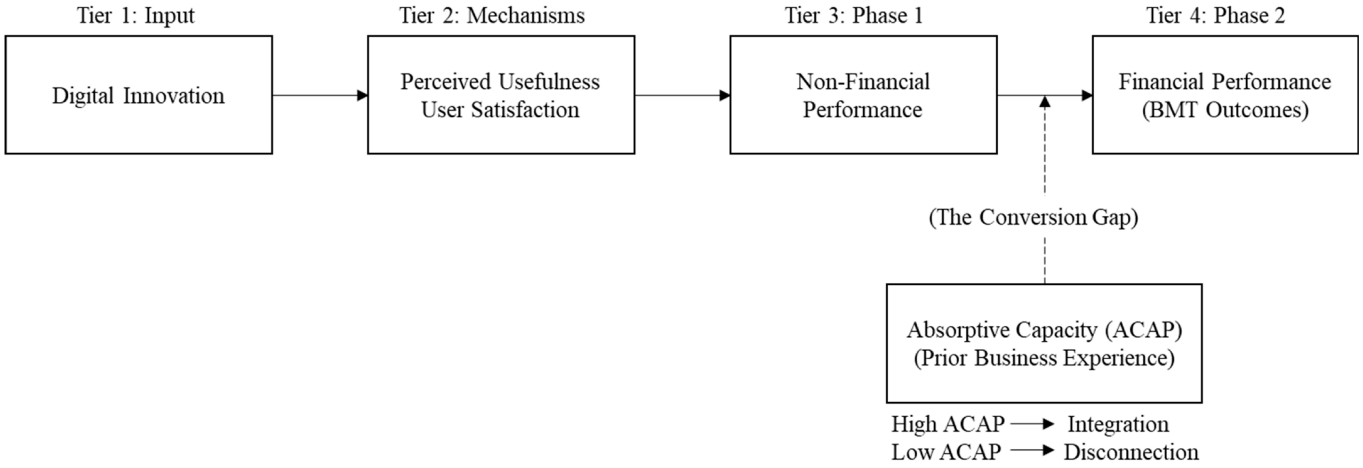


Figure 1. The Conceptual Framework for BMT. Note: The dotted line represents the structural discontinuity (The Conversion Gap) moderated by the enterprise's ACAP.

As illustrated in Figure 1, this study conceptualizes the value creation trajectory of digital resources not as a monolithic step, but as a distinct two-stage conversion process. In Phase 1, digital integration acts as the input that is transformed—via cognitive and affective mechanisms such as Perceived Usefulness and User Satisfaction—into 'Non-Financial Performance' (e.g., intermediate gains like increased customer engagement). However, the critical transition to Phase 2—where these intermediate gains materialize into the firm's ultimate BMT objective of 'Financial Performance' (revenue)—does not occur automatically.

I define the structural void separating these two distinct performance domains as the Conversion Gap. Crucially, I posit that the entrepreneur's 'Prior Business Experience'—serving as a tangible proxy for ACAP—functions as the decisive moderating mechanism. This mechanism bridges the bottleneck, ultimately determining whether the pathway

between digital potential and financial realization remains structurally impeded or becomes fully integrated.

2.4. Research Variables and Operationalization

Operationalizing the conceptual framework (Figure 1), this study categorizes the value creation trajectory into three distinct phases: (1) Foundational Inputs, (2) Cognitive and Affective Mechanisms, and (3) Multi-dimensional Outcomes. The operational definitions for each construct are structured as follows:

2.4.1. Foundational Inputs: Quality and Readiness

These factors serve as the foundational elements of the resource conversion process.

- Digital Integration Quality: This encompasses both the 'Core Quality' of the provided digital innovation content and the 'Service Environment' (e.g., infrastructural convenience). Grounded in the SERVQUAL paradigm [24], I operationalize this as the enterprise's perception of external support excellence.
- Digital Readiness: In this architecture, readiness is conceptualized beyond mere functional 'Digital Literacy' (i.e., tactical tool utilization); rather, it represents the organizational propensity and cognitive preparedness (e.g., enjoyment, comfort) required to embed new technologies into core business processes [25,26]. While literacy denotes technical proficiency, digital readiness functions as the enterprise's 'Potential ACAP'—a critical prerequisite determining whether external digital stimuli can be internalized [17,27]. Aligning with recent scholarship, this definition intrinsically captures 'Digital Resilience,' emphasizing the capacity to leverage these cognitive assets for survival within volatile markets [10].

2.4.2. Cognitive and Affective Mechanisms

This phase represents the internal cognitive and affective processing required to translate inputs into tangible value. I synthesize Expectation-Confirmation Theory (ECT) and the Technology Acceptance Model (TAM) to explicate this pathway.

- Confirmation: The degree of congruence between pre-integration expectations and the actual post-implementation experience. This 'Cognitive Alignment' process is the structural antecedent to user satisfaction [28].
- Perceived Usefulness: The organizational belief that deploying a specific digital innovation will actively enhance performance. Aligning with the rigorous logic of Necessary Condition Analysis (NCA), this study defines utility not as a deterministic driver, but strictly as a necessary baseline condition that must be present to prevent failure, yet remains insufficient to guarantee success on its own [16].
- User Satisfaction: An overarching affective response to the digital integration experience. Transcending mere cognitive acknowledgement, user satisfaction acts as the primary affective driver that catalyzes behavioral adaptation and drives subsequent value realization [13].

2.4.3. Multi-Dimensional BMT Outcomes

Representing the final outputs of the conversion mechanism, I structurally bifurcate outcomes into an intermediate value-creation phase and a finalized realization phase.

- Phase 1: Non-Financial Performance: Intangible assets that do not immediately manifest on balance sheets—such as brand equity enhancement, new customer network integration, and market share expansion. These constitute the strategic intermediate milestone strictly necessary to advance toward tangible economic viability [29].

- Phase 2: Financial Performance: Tangible economic gains, specifically operationalized by measured monthly revenue growth. This represents the ultimate outcome of the BMT process. The critical void observed between Phase 1 and Phase 2 serves as the core diagnostic metric for identifying the Conversion Gap theorized in this study.

2.5. Hypotheses Development

Grounded in the conceptual framework, this study formulates the following structural hypotheses. These propositions are designed to empirically validate the pathways and boundary conditions governing the transition from digital inputs to realized BMT.

H1: *Foundational digital inputs (digital readiness and integration quality) sequentially enhance financial performance through the mediation of cognitive-affective mechanisms (confirmation, perceived usefulness, user satisfaction) and non-financial performance.*

- This proposition challenges the notion that digital innovation is a discrete, immediate leap from technological adoption to financial realization. Instead, it posits that digital inputs must first be cognitively internalized by the organization and subsequently manifested as intermediate gains (e.g., customer network expansion) before actualizing sustainable economic value. Particularly within resource-constrained SME environments, immediate revenue generation is highly improbable. The accumulation of intangible assets—such as customer trust and brand awareness—must precede tangible financial outcomes.

H2: *Perceived usefulness functions as a necessary, rather than sufficient, condition for realizing financial performance.*

- While the traditional Technology Acceptance Model (TAM) positions usefulness as a primary, deterministic driver of usage [11], this study reinterprets its role through the dual lenses of Herzberg's Two-Factor Theory [30] and Necessary Condition Analysis [16]. This suggests that perceived usefulness acts merely as a baseline; its absence triggers disengagement, yet its presence is fundamentally insufficient to guarantee BMT success. In contrast, user satisfaction functions as the true catalyst required for financial conversion.

H3: *The conversion of non-financial performance into financial performance is significantly moderated by the enterprise's ACAP, resulting in heterogeneous Conversion Gaps.*

- This hypothesis explicitly diagnoses the Conversion Gap. It suggests that within enterprises possessing high experiential capital (high ACAP), this conversion pathway remains robust and statistically significant. Conversely, for those with low ACAP, this critical pathway is statistically severed—manifesting as a significant conversion discontinuity where intermediate non-financial performance fails to translate into tangible financial performance.

3. Research Methodology

To empirically operationalize the proposed Integrated Framework for Digital Value Conversion and analyze the latent causal dynamics governing BMT in SMEs, this study deploys a multi-stage Causal AI diagnostic approach. Traditional variance-based linear statistics (e.g., PLS-SEM) effectively model uniform average effects. However, they often struggle to capture the non-linear thresholds, bottlenecks, and heterogeneous pathways common in diverse SME ecosystems. Therefore, to overcome these deterministic limitations, I executed a rigorous, sequential algorithmic protocol: (1) Gaussian Mixture Modeling

(GMM) to computationally identify latent SME profiles; (2) a Tiered Grand-DAG (Directed Acyclic Graph) to reverse-engineer the data-driven causal topology of value co-creation; (3) Necessary Condition Analysis (NCA) to mathematically detect critical bottlenecks; and (4) Multi-Group Analysis (PLS-MGA) to empirically validate structural disconnections across diverse enterprise ecosystems.

3.1. Phase 1: Latent Subsystem Identification via Gaussian Mixture Modeling (GMM)

To mathematically decode unobserved heterogeneity within the complex SME ecosystem and categorize enterprises through an objective, data-driven algorithmic approach, I deployed Gaussian Mixture Modeling (GMM). While Latent Class Analysis (LCA) is frequently utilized in the social sciences for structural clustering, its mathematical architecture is fundamentally optimized for categorical variables. Conversely, the core diagnostic constructs of this study—specifically perceived usefulness, user satisfaction, and realized BMT outcomes—exhibit a strictly continuous nature.

Subjecting such continuous data to traditional LCA necessitates artificial discretization; this procedure inevitably compresses the inherent variance, causing significant information loss and reducing the model's statistical diagnostic power [31]. In contrast, GMM (functionally analogous to Latent Profile Analysis for continuous distributions) mathematically preserves the full probability density function of the variables. This computational approach not only prevents data degradation but also explicitly models the covariance structure—enabling the identification of complex heterogeneity within the inter-variable correlations across distinct subsystems [32]. The probability density function of the GMM architecture is formalized as follows:

$$p(x) = \sum_{k=1}^{K} \pi_k \mathcal{N}(x|\mu_k, \Sigma_k)$$

$$\mathcal{N}(x|\mu_k, \Sigma_k) = \frac{1}{(2\pi)^{D/2}|\Sigma_k|^{1/2}} \exp\left(-\frac{1}{2}(x-\mu_k)^{T\Sigma_k^{-1}}(x-\mu_k)\right)$$

Here, x represents the D-dimensional observation vector (D = 3: perceived usefulness, user satisfaction, realized BMT outcomes), and K denotes the total number of latent systemic components (clusters). The parameter π_k serves as the mixing coefficient for the k-th subsystem. Crucially, the quadratic term embedded within the exponential function of the Gaussian distribution mathematically computes the Squared Mahalanobis Distance between the empirical observation x and the cluster centroid μ_k. Unlike simplistic Euclidean geometry, this advanced metric calculates a standardized topological distance by actively accounting for systemic variable correlations (Σ_k), thereby permitting the precise computational modeling of complex ellipsoidal distributions. This topological flexibility allows for a granular, high-fidelity capture of the heterogeneous behaviors intrinsic to SME ecosystems.

Unlike the rigid classification boundaries of K-means algorithms, GMM uses a probabilistic "soft assignment" protocol [33]. It estimates the probability of each enterprise belonging to a specific subsystem, enabling a flexible classification of complex digital behaviors that defy simple dichotomization. The final architectural model selection was rigorously guided by a comprehensive evaluation of the Bayesian Information Criterion (BIC), classification precision (Entropy index), and the practical systemic interpretability of the Sample Share [34].

3.2. Phase 2: Causal Structure Discovery (Tiered Grand-DAG)

To complement the variance-based confirmatory constraints of traditional Structural Equation Modeling (SEM) and objectively reverse-engineer the intrinsic causal topology of

the BMT ecosystem, I deployed an advanced causal discovery architecture. This analytical protocol precisely aligns with the emerging paradigm in systems engineering and Information Systems (IS) research—prioritizing the extraction of non-linear causal insights directly from observational data via Directed Acyclic Graphs (DAGs) [18,35,36].

I operationalized the Tiered Grand-DAG (Gradient-based Neural DAG) algorithm. Classical constraint-based heuristics (e.g., the PC algorithm) are limited by discrete data requirements and rigid linear assumptions. In contrast, Grand-DAG reformulates the search for complex causality among continuous variables as a continuous optimization problem using artificial neural networks [37,38].

To algorithmically capture the critical temporal delay between digital integration (T1) and BMT realization (T2), I applied 'Tiered Constraints' within the computational model. Systemic variables were stratified into Tier 1 (Inputs), Tier 2 (Cognitive Mechanisms), and Tier 3 (Multi-dimensional Outcomes) based strictly on temporal precedence. This constraint structurally prevents reverse causality by ensuring that downstream BMT variables cannot cyclically influence upstream inputs. The resulting directed graph represents not merely spurious correlations, but mathematically robust causal pathways, formally defined as the exact solution to the following constrained optimization problem:

$$\hat{G} = \arg\min_{G \in \mathcal{G}_{\mathcal{T}\rangle|\nabla}} \mathcal{S}(G, D) \text{subject to} h(G) = 0$$

Here, $\mathcal{S}(G, D)$ denotes the continuous score function (evaluating the systemic goodness-of-fit) of graph G given the empirical data D. The strict equality constraint h(G) = 0 mathematically guarantees the acyclicity of the topological architecture, while $\mathcal{G}_{\mathcal{T}\rangle|\nabla}$ represents the bounded topological space of graphs that strictly adhere to the temporal Tier Constraints of the BMT ecosystem.

3.3. Phase 3: Systemic Boundary Condition Diagnosis (NCA)

In the third diagnostic phase, I executed Necessary Condition Analysis (NCA) to dissect relationships based on the logic of "necessity" rather than mere "sufficiency." According to recent methodological advancements in systems research, explicitly distinguishing whether an antecedent is a "necessary condition" (a prerequisite that must be present) or a "sufficient condition" (a catalyst that increases the outcome) is a fundamental requirement for theoretical precision [16,39].

Traditional variance-based regression methodologies (e.g., PLS-SEM) inherently prioritize the "Average Effect," interpreting how much a dependent variable increases as an independent variable increase ("Sufficiency Logic") [40]. However, this linear, additive paradigm risks obscuring critical "Bottlenecks"—conditions that prevent a specific threshold of BMT performance from being actualized if they are absent, irrespective of the compensatory strength of other integrated variables. NCA identifies how a specific socio-technical antecedent (X) structurally constrains the maximum achievable upper limit (Y_c) of an outcome (Y). It achieves this by mathematically analyzing the Ceiling Line of the bi-variate scatter space:

$$Y \leq f(X) \forall (X, Y) \in D$$

Here, $f(X)$ represents the strictly non-decreasing ceiling line function, derived utilizing Ceiling Envelope (CE) or Ceiling Regression (CR) techniques. Adhering to the diagnostic guidelines of Dul [40], I designated an effect size (d) of 0.1 or higher as a practically significant necessary condition. Through this diagnosis, I determined whether specific variables function as indispensable hygiene factors without which value co-creation and BMT are structurally impeded.

3.4. Phase 4: Structural Validation and Multi-Group Analysis (PLS-MGA)

In the final computational phase, I synthesized the causal structures (Grand-DAG) and the latent SME profiles (GMM) identified in the preceding stages to statistically validate the propositions. I deployed Multi-Group Analysis (MGA) grounded in Partial Least Squares Structural Equation Modeling (PLS-SEM).

PLS-SEM is optimized for exploratory validation, yielding robust parameter estimates without requiring the stringent distributional assumptions of perfect data normality [41]. Furthermore, MGA is an established diagnostic technique utilized to verify whether statistically significant structural heterogeneities exist within the path coefficients (β) across pre-identified subsystems [42,43].

This study utilized the robust, non-parametric Permutation Test approach for MGA to quantify the structural divergence in path coefficients between the distinct enterprise clusters (g1, g2) previously isolated via GMM:

$$\Delta\beta = \left|\beta^{(g_1)} - \beta^{(g_2)}\right| \text{where} H_0 : \beta^{(g_1)} = \beta^{(g_2)}$$

By systematically analyzing whether the strength of the value conversion mechanism exhibits statistically significant divergence across these subsystems via this equation, I empirically demonstrated the deep structural drivers of the BMT Conversion Gap inherent within the SME digital ecosystem.

3.5. Data Collection and Procedure

Empirical data driving this analysis were systematically harvested between 2023 and 2025 from a macro-level digital capacity-building initiative. This large-scale intervention was orchestrated by an industry-leading platform consortium in strategic collaboration with key financial institutions and governmental regulatory agencies. The target population consisted exclusively of SME entrepreneurs who successfully navigated this digital integration architecture.

To mitigate Common Method Bias (CMB) and potential endogeneity, and to precisely capture the temporal latency governing the transition from digital inputs to realized BMT, I deployed a two-wave time-lagged design [44]. Diagnostic instruments were administered via a secure platform, embedding methodological filters to exclude unconscientious response patterns. The temporal architecture of the data collection was structured as follows:

- Wave 1 (T1, immediate post-integration): I quantified the foundational antecedent variables, specifically capturing Inputs (Digital Integration Quality, Digital Readiness) alongside the Cognitive Conversion Mechanisms (User Satisfaction, Confirmation, Perceived Usefulness).
- Wave 2 (T2, 8-week latency): To explicitly account for the critical gestation period required for nascent digital capabilities to be operationally metabolized into tangible outcomes, the dependent variables—encompassing Non-Financial Performance and Financial Performance—were captured exactly two months post-integration.

Furthermore, while multi-item scales are generally preferred in survey research, financial performance (i.e., revenue growth) in T2 was operationalized using a single-item measure. This methodological choice was strategically driven by the extreme reluctance of SMEs to disclose detailed, multi-dimensional financial and tax data. Recent literature demonstrates that when a construct is singular and concrete (such as self-reported revenue), single-item measures provide robust reliability and validity while significantly enhancing response rates and data accuracy among small business owners [45].

The entire data collection protocol was executed in compliance with global ethical standards governing human-subject research. Prior to participation, all entities were furnished

with a transparent exposition of the study's objectives. Informed consent was secured electronically, with explicit assurances that all data would be rigorously anonymized. Out of 800 initially distributed profiles, I excluded incomplete records and responses failing the chronological matching protocol between T1 and T2. Consequently, a robust dataset comprising 649 valid enterprise profiles was retained for the final evaluation.

3.6. Measurement Instruments

The measurement items utilized in this empirical study were adapted from validated scales within the Information Systems (IS) literature. To ensure contextual relevance to the highly constrained environment of SMEs undergoing BMT, the measurement items were carefully calibrated. With the exception of financial performance—which was captured via a single objective interval indicator—all latent constructs were quantified utilizing multi-item scales. A 5-point Likert-type scale, ranging from '1 (Strongly Disagree)' to '5 (Strongly Agree),' was universally deployed for all subjective evaluations.

3.6.1. Foundational Inputs

- Digital Integration Quality: To quantify the excellence of the digital integration initiative, I adapted metrics from the SERVQUAL model [24] and the SERVPERF paradigm [46]. This construct comprises five items spanning two distinct sub-dimensions: 'Core Quality' (3 items), which assesses the instructor's expertise and the practical relevance of the integration content; and 'Infrastructural Environment' (2 items), which evaluates the appropriateness of the training schedule and physical/virtual facilities.
- Digital Readiness: This construct is operationalized as the organizational and cognitive propensity to internalize digital innovation. Grounded in the Technology Readiness Index (TRI) [26] and recent scholarship on SME digital resilience [10,47], I measured this critical prerequisite using three items. These items evaluate the respondent's psychological resilience, cognitive comfort, and perceived technical competence regarding the deployment of novel digital architectures.

3.6.2. Cognitive and Affective Mechanisms

- Confirmation: Measured via three items adapted from Bhattacherjee's Expectation-Confirmation Theory (ECT) [28]. This construct assesses the degree of congruence between the enterprise's pre-integration expectations and the actual performance post-integration.
- Perceived Usefulness: Rooted in the Technology Acceptance Model (TAM) [11], this construct was quantified using three items evaluating the extent to which digital innovation directly contributes to BMT and value realization. Crucially, strictly adhering to the proposed theoretical framework, I interpret this variable as a necessary baseline condition—an architectural baseline necessary to prevent operational disengagement, rather than a sufficient, direct driver of elevated financial performance.
- User Satisfaction: To capture the affective response and fulfillment derived from the digital integration experience, I deployed a four-item scale grounded in the IS Success Model [13] and Spreng et al. [48].
- Continuance Intention: Operationalized utilizing three items from Bhattacherjee [28], this construct measures the organizational intention to sustain digital integration efforts, participate in iterative capability-building, or propagate the innovation within the broader SME ecosystem.

3.6.3. Multi-Dimensional BMT Outcomes

- Phase 1: Non-Financial Performance: Adopting the Balanced Scorecard (BSC) perspective [29], this variable captures intangible assets that do not immediately materialize on traditional financial statements. It was measured via three items assessing strategic network outcomes: expansion of market share, the influx of new customer networks, and the enhancement of organizational brand equity.
- Phase 2: Financial Performance: This terminal outcome was captured utilizing a single-item ordinal interval scale, requesting the specific "monthly revenue trajectory increase strictly attributable to the digital integration" (1 = Less than 1 million KRW [approx. USD 715] to 6 = More than 10 million KRW [approx. USD 7150]; assuming an exchange rate of approximately 1 USD = 1400 KRW).

Methodological Justification: In survey research targeting SMEs, soliciting exact, absolute revenue figures often triggers non-response bias and deliberate data distortion due to confidentiality or tax-related concerns. Consequently, deploying an interval scale is recognized as a mathematically robust alternative to preserve data fidelity [49].

Note on the 'Floor Effect': While the empirical distribution exhibits a floor effect—with a significant concentration of responses converging in the lower economic intervals—I interpret this not as a measurement error, but as an empirical manifestation of the structural Conversion Gap. This skewness provides evidence that while Phase 1 (intermediate value) may be achieved, the conversion pathway to Phase 2 (financial realization) remains significantly impeded for the vast majority of the SME ecosystem.

4. Data Analysis and Results

To ensure methodological transparency and reproducibility, the empirical analyses in this section were conducted using specific software packages. The Gaussian Mixture Modeling (GMM) and Tiered Grand-DAG algorithms were executed using Python 3.10, leveraging the scikit-learn (v1.3.2) and PyTorch (v2.1.2) libraries, respectively. The Necessary Condition Analysis (NCA) was performed using the NCA package (v4.0.0) in R (v4.3.2). Finally, the Partial Least Squares Multi-Group Analysis (PLS-MGA) was conducted using SmartPLS 4 (v4.0.9).

4.1. Demographic Profile of the Sample

Table 1 delineates the baseline demographic profile of the 649 SME enterprises retained for the final evaluation. The dataset exhibits a balanced gender distribution (Male: 49.9%, Female: 50.1%). Temporally, the sample is predominantly anchored by the core active economic population, with entrepreneurs in their 40s (33.7%) and 30s (28.7%) constituting the majority.

Regarding industry sectors, Accommodation and Food Service Activities (32.8%) alongside Wholesale and Retail Trade (23.7%) dominate the sample. This specific concentration accurately mirrors the highly volatile SME landscape where rapid digital innovation and BMT are absolute survival imperatives.

Crucially, the empirical baseline reveals that a majority of the **participants** (78.4%) possesses 'Prior Work Experience.' As operationalized in the proposed theoretical framework (Figure 1), this experiential metric functions as the foundational cognitive infrastructure—the ACAP—required for resource conversion. Conversely, the 21.6% lacking this experiential capital provide the critical empirical counterfactual necessary to **empirically** diagnose the Conversion Gap and structural disconnections within the subsequent analytical phases.

Table 1. Baseline Demographic Profile (N = 649).

Characteristics	Category	Frequency (n)	Percentage (%)
Gender	Male	324	49.9
	Female	325	50.1
Age	20s	83	12.8
	30s	186	28.7
	40s	219	33.7
	50s	129	19.9
	60s or above	32	4.9
Industry	Accommodation & Food Services	213	32.8
	Wholesale & Retail Trade	154	23.7
	Manufacturing	143	22.0
	Personal Services	87	13.4
	Others	52	8.0
Startup Type	New Business	259	39.9
	Acquisition	154	23.7
	Franchise	131	20.2
	Family Succession (Inheritance)	71	10.9
	Others	34	5.2
Monthly Revenue	Less than $2143	74	11.4
	$2143–$3571	96	14.8
	$3571–$5000	118	18.2
	$5000–$7143	120	18.5
	Over $7143	241	37.1
Prior Work Experience	Yes	509	78.4
	No	140	21.6
Total		649	100.0

Note. Exchange rate applied: 1 USD ≈ 1400 KRW. Original currency (KRW) brackets: Under 3 M KRW (≈$2143); 3–5 M KRW (≈$2143–$3571); 5–7 M KRW (≈$3571–$5000); 7–10 M KRW (≈$5000–$7143); Over 10 M KRW (≈$7143).

4.2. Measurement Model Validation

Prior to testing the structural BMT pathways, the outer measurement model was rigorously evaluated for reliability and validity in strict adherence to advanced PLS-SEM diagnostic protocols [41]. This procedure involved a meticulous assessment of indicator reliability, internal consistency, and convergent validity.

4.2.1. Reliability and Convergent Validity

Table 2 delineates the standardized outer loadings of the individual measurement indicators associated with each construct, alongside the calculated Cronbach's α, Composite Reliability (CR), and Average Variance Extracted (AVE). The analysis confirmed that the outer loadings for all items were statistically robust ($p < 0.001$), with the vast majority eclipsing the 0.70 threshold.

While the specific outer loading for the 'Perceived Usefulness (PU3)' indicator was comparatively lower at 0.635, it was strategically retained to preserve vital content validity. Crucially, the construct's aggregate AVE (0.635) comfortably surpassed the 0.50 baseline, neutralizing any convergent validity concerns. Furthermore, Cronbach's α and CR values for all constructs unequivocally exceeded the 0.70 benchmark, and all AVE values remained above 0.50, thereby firmly establishing the internal consistency and convergent validity of the measurement model.

Table 2. Reliability and Convergent Validity.

Construct	Item	Measurement Indicators (Operational Focus)	Outer Loading	α	CR	AVE
Digital Integration Quality	DIQ1	Relevance of integration content	0.733	0.820	0.875	0.583
	DIQ2	Quality of program composition	0.831			
	DIQ3	Expertise of the instructor	0.768			
	DIQ4	Appropriateness of duration	0.748			
	DIQ5	Appropriateness of venue/infrastructure	0.733			
Digital Readiness	DR1	Cognitive enjoyment of using digital architectures	0.848	0.861	0.916	0.784
	DR2	Psychological comfort with digital devices	0.913			
	DR3	Perceived competence in digital utilization	0.895			
Confirmation	CF1	Overall confirmation of pre-integration expectations	0.921	0.886	0.929	0.814
	CF2	Perceptual accuracy of initial expectations	0.921			
	CF3	Actualized fulfillment of systemic expectations	0.864			
Perceived Usefulness	PU1	Enhancement in systemic management/tech capabilities	0.864	0.701	0.837	0.635
	PU2	Direct improvement in operational task performance	0.869			
	PU3	Profit optimization via digital tool deployment	0.635			
User Satisfaction	US1	Affective satisfaction with the integration initiative	0.874	0.883	0.920	0.742
	US2	Satisfaction with overall socio-technical service	0.901			
	US3	Satisfaction with the active engagement process	0.873			
	US4	Psychological enjoyment of system participation	0.795			
Continuance Intention	CI1	Intention to sustain continuous digital learning	0.902	0.867	0.920	0.793
	CI2	Willingness to participate in advanced integrations	0.875			
	CI3	Intention to propagate the program to peer SMEs	0.894			
Non-Financial Performance	NFP1	Strategic expansion of market share	0.922	0.905	0.941	0.841
	NFP2	Influx of new customer networks	0.934			
	NFP3	Enhancement of organizational brand equity	0.896			

To verify the validity of the single-item ordinal measure deployed for Phase 2 (Financial Performance), I assessed its criterion validity. As graphically evidenced in Appendix A (Figure A2), a continuous boxplot analysis reveals a distinct, monotonic trajectory: 'User Satisfaction' scores exhibit a statistically significant escalation perfectly parallel to higher financial performance brackets. This positive association empirically confirms that the self-reported economic metric accurately mirrors the enterprises' actual realities. Despite being a single-item scale, it possesses adequate discriminatory power, validating its deployment as the terminal node of the conversion framework.

4.2.2. Discriminant Validity

To evaluate the discriminant validity of the measurement model, this study applied the conservative Fornell-Larcker criterion [50]. Table 3 delineates the correlation matrix of the latent variables, wherein the bolded diagonal elements represent the square root of the Average Variance Extracted (AVE) for each respective construct.

Table 3. Discriminant Validity (Fornell-Larcker Criterion).

Construct	DIQ	DR	CNF	PU	US	CI	NFP
Digital Integration Quality (DIQ)	**0.764**						
Digital Readiness (DR)	0.478	**0.886**					
Confirmation (CNF)	0.757	0.398	**0.902**				
Perceived Usefulness (PU)	0.729	0.539	0.742	**0.797**			
User Satisfaction (US)	0.810	0.438	0.781	0.666	**0.862**		
Continuance Intention (CI)	0.725	0.409	0.674	0.600	0.817	**0.890**	
Non-Financial Performance (NFP)	0.747	0.371	0.816	0.722	0.733	0.699	**0.917**

Note: Diagonal bold values specify the square root of AVE. Off-diagonal values are inter-construct correlations.

The analysis confirmed that the square root of the AVE for every construct exceeded its maximum correlation with any other construct (i.e., the off-diagonal coefficients). For instance, although the correlation between digital integration quality and user satisfaction exhibited a theoretically expected strong linkage (0.810), this value remained lower than the square root of the AVE for user satisfaction (0.862). This confirms that the variables function as distinct constructs, satisfying the criteria for discriminant validity [51].

4.2.3. Common Method Variance and Collinearity Assessment

Given that the measurement indicators were collected simultaneously from the same respondents via a self-administered platform, the potential for Common Method Bias (CMB) was assessed. Initially, Harman's single-factor test was executed [44]. The unrotated exploratory factor analysis revealed that the primary principal component explained 51.59% of the total variance.

While this value slightly exceeds the traditional 50% heuristic, contemporary methodological literature acknowledges the limitations of this test—particularly when constructs are theoretically designed to be strongly correlated. Therefore, to ensure robustness and address the limitations of Harman's test, a Full Collinearity Variance Inflation Factor (VIF) assessment was performed following Kock [52].

According to established PLS-SEM guidelines, a model is deemed free from significant common method bias if the full collinearity VIFs remain below the 5.0 threshold [52]. The extraction of inner VIF values for the predictors confirmed that all parameters resided below this boundary (Table 4). Specifically, even the highest VIF coefficient recorded for user satisfaction (4.930)—alongside digital integration quality (3.797) and confirmation (3.458)—demonstrated that multicollinearity is not a critical issue. Consequently, the empirical dataset exhibits adequate validity, allowing for the subsequent multi-stage causal modeling.

Table 4. Collinearity Assessment (Inner VIF Values).

Construct	VIF
User Satisfaction	4.930
Digital Integration Quality	3.797
Confirmation	3.458
Perceived Usefulness	2.910
Continuance Intention	3.137
Digital Readiness	1.464

4.3. Phase 1: Identification of Latent SME Profiles (GMM)

To identify unobserved heterogeneity within the BMT conversion trajectories of SMEs, this study applied Gaussian Mixture Modeling (GMM). To determine the optimal number

of latent profiles (k), I evaluated information-theoretic criteria—specifically the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC)—alongside the Entropy index, which measures classification uncertainty [53,54]. Lower AIC and BIC values indicate superior model fit, whereas an Entropy coefficient approaching 1.0 (preferably $\geq$0.80) signifies high classification quality.

As delineated in Table 5, the analysis iteratively estimated models ranging from k = 2 to k = 6 clusters. The results indicated that the lowest BIC value (−984.89) was derived at k = 5. However, selecting the k = 5 model presented methodological limitations: specifically, the emergence of negligible micro-clusters (comprising less than 5% of the total sample), which risks spurious over-extraction and reduces statistical power for subsequent analyses. In contrast, the k = 4 model registered a substantial decrease in the BIC trajectory (177.05) relative to k = 3, indicating a clear "elbow" point. Furthermore, the Entropy index for k = 4 peaked at 0.981, confirming that the sample was clearly separated into distinct profiles with minimal classification overlap.

Table 5. Information-Theoretic Model Fit indices for GMM.

Clusters (k)	AIC	BIC	Entropy	Interpretation
2	4891.35	4976.38	0.672	Poor structural fit
3	654.94	784.73	0.999	High separation, but suboptimal BIC
4	**2.51**	**177.05**	**0.981**	**Selected (Optimal Structural Balance)**
5	−1204.19	−984.89	0.990	Lowest BIC (Critical over-segmentation risk)
6	−1202.51	−938.46	0.948	Decreasing architectural fit

Note. AIC: Akaike Information Criterion; BIC: Bayesian Information Criterion. Entropy values close to 1.0 indicate clear separation [53].

4.3.1. Determination of the Optimal Profile Number (K = 4)

Consequently, based on the following three criteria, this study selected the four-profile model (K = 4), which satisfies both statistical goodness-of-fit and theoretical parsimony.

- Statistical Parsimony: The evaluation of the BIC trajectory identified an 'elbow point' at K = 4, where the slope noticeably plateaus. This suggests that expanding the model complexity beyond four profiles yields diminishing marginal returns in explanatory power [34].
- Theoretical Alignment: The emergent four-profile model aligns well with Rogers' Diffusion of Innovations paradigm [55]—specifically mapping to the archetypes of Innovators, Early Adopters, Majority, and Laggards. This conceptual mapping ensures theoretical relevance for the SME ecosystem analysis.
- Statistical Power for Subgroup Analysis: To conduct the subsequent PLS-Multi-Group Analysis (PLS-MGA), a minimum sample size threshold per profile must be maintained [51]. While higher-K models fractured the sample into undersized subgroups (e.g., N < 30), the optimized K = 4 model ensured that the smallest profile (Cluster 2) retained 65 independent observations, satisfying the statistical power prerequisites for MGA validation.

The t-Distributed Stochastic Neighbor Embedding (t-SNE) projection of the final four profiles (Figure 2) provides visual confirmation that each group is distinctly isolated within the multidimensional space. The descriptive statistics delineating the conversion variables for each distinct cluster are presented in Tables 6 and 7.

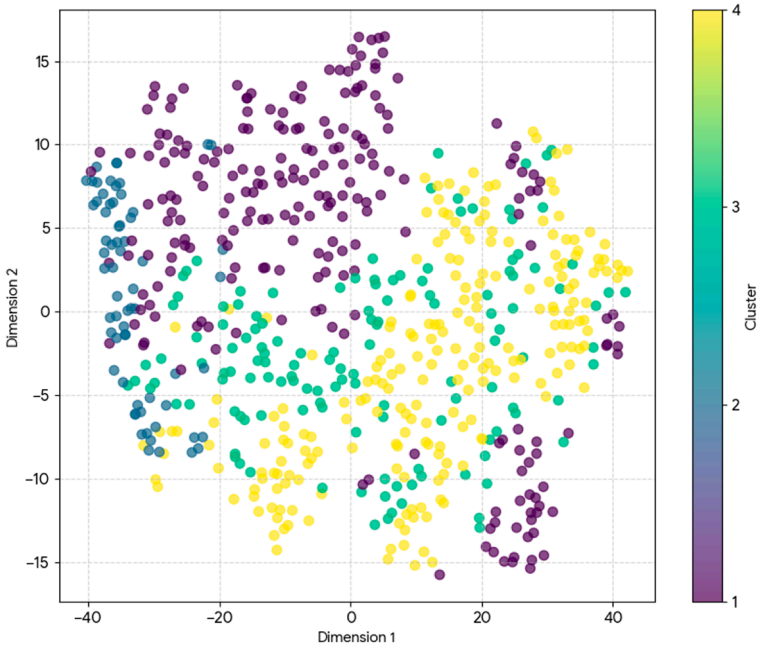


Figure 2. t-SNE Projection of SME Profiles (K = 4).

Table 6. Diagnostic Profiles and Characteristics by Subsystem.

Variables	Cluster 1 (High Int.)	Cluster 2 (High Sat.)	Cluster 3 (Bottleneck)	Cluster 4 (Disconnected)	F-Value
Digital Integration Quality	4.02	4.81	3.99	3.80	124.5 ***
Digital Readiness	3.80	4.45	3.72	3.64	88.2 ***
Confirmation	3.91	5.00	3.81	3.48	156.7 ***
Perceived Usefulness	3.99	4.79	3.93	3.69	92.4 ***
User Satisfaction	4.12	4.93	4.04	3.79	110.1 ***
Continuance Intention	4.16	5.00	4.10	3.83	105.3 ***
Non-Financial Performance	3.90	4.88	3.81	3.43	142.8 ***
Financial Performance	3.71 (Highest)	3.35 (High)	2.00 (Low)	1.00 (Lowest)	312.4 ***
Count (Share)	226 (34.8%)	65 (10.0%)	136 (21.0%)	222 (34.2%)	-

Note: *** $p < 0.001$.

Table 7. Extended Architectural Profiles.

Ecosystem Characteristics	Cluster 1 (High Int.)	Cluster 2 (High Sat.)	Cluster 3 (Bottleneck)	Cluster 4 (Disconnected)	Diff. (*p*-Value)
Ecosystem Share (N)	34.8% (226)	10.0% (65)	21.0% (136)	34.2% (222)	-
Financial Performance	Max (3.71)	High (4.93)	Low (2.00)	Severed (1.00)	<0.001 ***
Systemic ACAP (Prior Exp.)	85.0% (Yes)	70.8%	76.5%	75.2%	0.022 *
Dominant Industry	Retail (31.9%)	Manuf. (33.8%)	Service (30.1%)	Food/Retail (60%)	ns
Gender (Male%)	48.7%	61.5%	45.6%	50.5%	ns
Age (40s–50s%)	51.3%	58.5%	55.1%	53.6%	ns
Interpretation	Leverage high ACAP for BMT	High satisfaction but lower conversion	Average majority with bottlenecks	Micro-enterprises with low conversion	-

Note: Systemic ACAP operationalized via percentage of respondents with formal business/employment experience prior to founding. (* $p < 0.05$, *** $p < 0.001$, ns: not significant).

4.3.2. Diagnostic Profiling of the SME Profiles

Based on the distinct topological boundaries derived via GMM, the four latent profiles were comprehensively analyzed. These profiles empirically validate the heterogeneous BMT conversion trajectories operating within the SME ecosystem.

- Cluster 1: High Integration (34.8%) This subsystem represents the optimal conversion profile. Despite exhibiting moderate cognitive engagement (user satisfaction: 4.12) compared to Cluster 2, they achieve the highest financial performance (3.71). Crucially, this cohort commands the highest density of prior experiential capital (85.0%), providing empirical evidence that ACAP functions as the decisive catalyst connecting digital inputs directly to tangible financial realization.
- Cluster 2: High Satisfaction—Low Performance (10.0%) This specific segment exhibits high psychological responses, with user satisfaction (4.93) and continuance intention (5.00) converging on maximums. However, despite this saturated engagement, their financial performance (3.35) fails to surpass Cluster 1. This discrepancy structurally suggests that isolated affective satisfaction is insufficient to guarantee sustainable BMT; without optimal resource configuration, psychological assets do not fully convert to financial outcomes.
- Cluster 3: Moderate Bottleneck (21.0%) While their digital readiness and baseline integration quality remain structurally average (approx. 3.9), this subsystem is situated in a diagnostic zone where financial performance precipitously drops (2.00). They embody the threshold of the Conversion Gap—possessing digital potential but hindered by bottlenecks that throttle the transition into value realization.
- Cluster 4: Low Integration (Disconnected) (34.2%) This subsystem serves as an empirical manifestation of the conversion discontinuity. Recording the minimum metrics across the entire continuum, their financial performance stands at a baseline of 1.00. Encompassing over a third of the total ecosystem, this massive, digitally marginalized cohort is trapped in a state of structural stasis. This diagnosis underscores the limitations of generic training, necessitating targeted intervention strategies.

4.4. Phase 2: Causal Topology Discovery (Tiered Grand-DAG)

To computationally isolate the objective causal architecture embedded within the empirical data—thereby minimizing researcher bias—this study deployed the Tiered Grand-DAG algorithmic protocol. To guarantee chronological validity, constraints were imposed based on the temporal latency inherent in BMT. The variables were stratified into a directional four-tier hierarchy: (Tier 1) Foundational Inputs → (Tier 2) Cognitive and Affective Mechanisms → (Tier 3) Non-Financial Performance & Continuance Intention → (Tier 4) Financial Performance.

Algorithmic Results: The Decoded BMT Causal Topology

The continuous optimization algorithm identified 11 statistically robust directed edges, decoding a highly definitive socio-technical causal topology (Table 8 and Figure 3). The core architectural findings are delineated as follows:

First, challenging the deterministic assumptions of the traditional Technology Acceptance Model (TAM), the neural network detected no direct causal path from perceived usefulness to financial performance (No Edge). This void empirically demonstrates that while digital utility may function as an infrastructural prerequisite, it is fundamentally insufficient to unilaterally drive revenue growth. Conversely, user satisfaction emerged as the paramount hub, exerting the most potent direct causal force on both continuance intention and non-financial performance.

Table 8. Decoded Causal Architecture and Topological Strength (Grand-DAG).

Path Direction (Cause → Effect)	Coeff. (β)	Sig.	Diagnostic Interpretation
Tier 1 → Tier 2 (Input to Cognitive Processing)			
Digital Integration Quality → User Satisfaction	0.52	***	Quality acts as the primary antecedent of satisfaction.
Digital Integration Quality → Perceived Usefulness	0.41	***	Structural quality directly drives the perception of utility.
Digital Readiness → Perceived Usefulness	0.28	***	Pre-existing agility amplifies the cognitive recognition of utility.
Tier 2 → Tier 3 (Cognitive Processing to Intermediate Outcomes)			
User Satisfaction → Continuance Intention	0.63	***	Affective satisfaction serves as the dominant hub for intention.
User Satisfaction → Non-Financial Performance	0.35	***	High-fidelity satisfaction catalyzes intangible value co-creation.
Perceived Usefulness → Continuance Intention	0.18	*	Digital utility exerts a marginal impact on sustained continuance.
Tier 3 → Tier 4 (The BMT Conversion Bridge)			
Non-Financial Performance → Financial Performance	0.48	***	A critical verified bridge required for value conversion.
Continuance Intention → Financial Performance	0.12	ns	Behavioral intention alone is structurally insufficient to realize economic BMT.
Severed/Dropped Pathways			
Perceived Usefulness → Financial Performance	--	--	Direct trajectory rejected by the data (Nullifying classical TAM).

Note: * $p < 0.05$, *** $p < 0.001$, ns: not significant. The causal topology was computationally reverse-engineered utilizing the Tiered Grand-DAG neural algorithm, constrained by chronological temporal precedence.

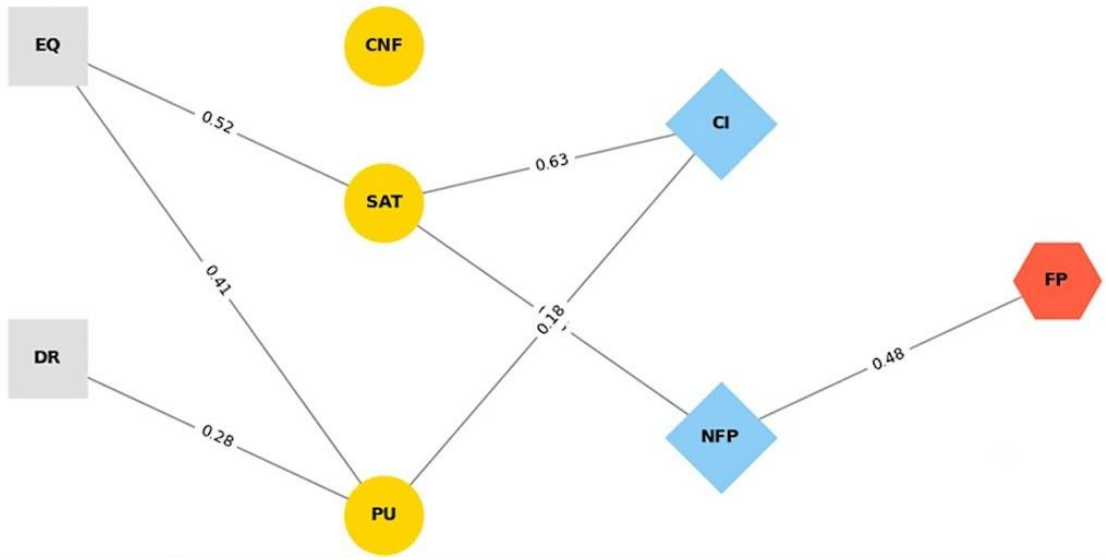


Figure 3. The Data-Driven Causal Structure (Tiered Grand-DAG).

Second, the algorithmic discovery revealed that the primary uninterrupted causal pathway culminating in financial performance is mediated through non-financial performance (Path Coefficient = 0.48, $p < 0.001$). This empirical evidence suggests that the integration of digital technologies cannot instantly manifest as tangible economic value; the ecosystem must traverse an intermediate stage of gains (e.g., brand enhancement, customer network expansion). In macro-system terms, the data-driven analysis indicates that non-financial performance is not merely an auxiliary byproduct, but a critical intermediate step necessary for executing successful BMT.

4.5. Phase 3: Diagnosis of Boundary Conditions and Bottlenecks (NCA)

The preceding Tiered Grand-DAG topology indicated that the direct influence of perceived usefulness on financial performance was statistically non-existent (manifesting as a no-edge structural void). To provide a rigorous diagnosis of this ostensibly counterintuitive finding, this study executed Necessary Condition Analysis (NCA), evaluating the ecosystem through the lens of 'necessity' rather than deterministic 'sufficiency.'

This analysis revealed a critical insight: while perceived usefulness does not function as the active driver directly propelling ultimate financial performance, it operates as a "Structural Bottleneck"—an indispensable boundary condition that must be satisfied for any economic value realization to manifest.

4.5.1. NCA Effect Sizes and Ceiling Effects

Table 9 delineates the necessity effect sizes (d) of the core antecedents required to actualize financial performance. Adhering to the stringent criteria established by Dul [40], a necessity effect size of $0.1 \leq d < 0.3$ constitutes a medium effect, whereas $d \geq 0.3$ denotes a large, critical constraint.

Table 9. NCA Effect Sizes and Bottleneck Diagnosis (Target: Financial Performance).

Condition (Input Node)	Diagnostic Protocol	Necessity Effect Size (d)	Accuracy	*p*-Value	Structural Bottleneck for High Performance (Top 20%)
Perceived Usefulness (PU)	CR-FDH	0.312 (Large)	96.8%	<0.01	Minimum Required Threshold $\geq$ 4.2
User Satisfaction (US)	CR-FDH	0.287 (Medium)	95.5%	<0.01	Minimum Required Threshold $\geq$ 4.0
Digital Readiness (DR)	CR-FDH	0.184 (Medium)	93.2%	<0.05	Minimum Required Threshold $\geq$ 3.5
Digital Integration Quality (DIQ)	CR-FDH	0.154 (Medium)	91.4%	<0.05	Minimum Required Threshold $\geq$ 3.2

Note: The CR-FDH (Ceiling Regression—Free Disposal Hull) technique was deployed. "Structural Bottleneck" defines the absolute minimum scalar threshold of the independent variable mandated to permit the attainment of the top 20% tier in Financial Performance.

The analysis confirmed that the necessity effect size of perceived usefulness registered at 0.312, identifying it as the strongest necessary condition for achieving financial performance ($p < 0.01$). This reveals a critical 'Ceiling Effect': unless an enterprise reaches a perceived usefulness threshold of 4.2, its potential for financial performance remains fundamentally constrained. Below this threshold, compensatory efforts in other areas are unlikely to yield high financial returns.

In contrast, digital integration quality (DIQ)—which often dominates traditional variance-based regressions—exhibited a substantially lower necessity effect size (d = 0.154). This empirical dichotomy validates Hypothesis H2, which posits that perceived usefulness functions strictly as a "necessary baseline condition." It prevents operational disengagement but inherently fails to act as an active motivator for revenue conversion. In essence, within constrained SME ecosystems, perceived usefulness is not a deterministic guarantee for success; rather, it is a fundamental prerequisite strictly required to prevent performance failure.

4.5.2. Topological Visualization of the Ceiling Architecture

Figure 4 graphically delineates the scatter matrix and the mathematical Ceiling Frontier governing the structural relationship between perceived usefulness (X-axis) and financial performance (Y-axis).

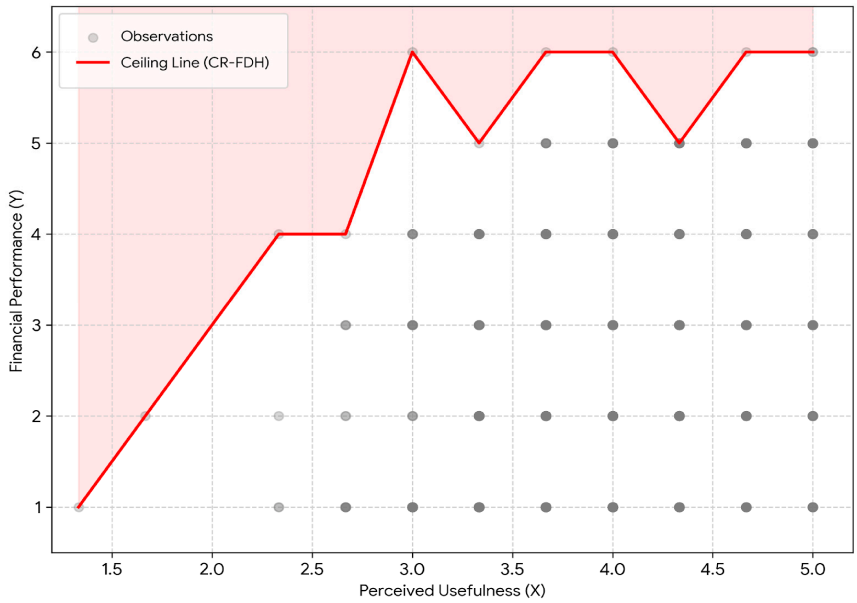


Figure 4. Topological Scatter Matrix and Ceiling Frontier (Perceived Usefulness → Financial Performance). Note: Darker circles indicate a higher density of overlapping observations at specific coordinates.

The conspicuous manifestation of an "empty space" (the shaded upper-left quadrant) within this bivariate space provides geometric proof of the ceiling effect: the actualization of high-tier performance is mathematically prohibited if the foundational perceived usefulness remains deficient. This distinct distribution serves as empirical evidence that perceived usefulness operates strictly as a boundary condition—an indispensable constraint—rather than an active, deterministic catalyst for value creation.

4.6. Phase 4: Structural Proposition Validation and Gap Confirmation (PLS-MGA)

In the final diagnostic phase, the path coefficients of the overall model were estimated utilizing the full sample (N = 649) to rigorously validate Propositions H1 and H2. Furthermore, Proposition H3 was empirically tested via Partial Least Squares Multi-Group Analysis (PLS-MGA), explicitly quantifying the structural divergence between the High Integration subsystem (Cluster 1) and the Low Integration subsystem (Cluster 4).

4.6.1. Structural Model Assessment (Full Sample)

The path estimation for the full sample (Table 10) revealed that digital integration quality (DIQ) and digital readiness (DR) exerted highly significant positive effects on user satisfaction (US) and perceived usefulness (PU). Critically, the sequential pathway cascading from these cognitive mechanisms through Phase 1 (non-financial performance), ultimately terminating at Phase 2 (financial performance), was confirmed to be statistically significant ($p < 0.001$). Consequently, Proposition H1 (The BMT Structural Pathway) was robustly supported.

In contrast, the direct, unmediated path from perceived usefulness to Phase 2 (financial performance) yielded a non-significant coefficient of $\beta = 0.097$ ($p = 0.069$), mandating its rejection at the 0.05 significance threshold. This variance-based result aligns with the preceding algorithmic findings from both the Grand-DAG and NCA diagnostics, thereby supporting Proposition H2 (Perceived Usefulness as a Baseline Condition). This validates that within complex SME ecosystems, digital utility serves as a structural baseline—rather than a direct, sufficient driver of revenue conversion.

Table 10. Proposition Testing Results (Full Sample, N = 649).

Proposition	Structural Pathway (Cause → Effect)	Coeff. (β)	t-Value	*p*-Value	Result
H1	The Structural Cascading Pathway				Supported
	Digital Integration Quality → User Satisfaction	0.778	32.41	<0.001	
	User Satisfaction → Phase 1: Non-Financial Performance	0.454	12.85	<0.001	
	Phase 1: Non-Financial Performance → Phase 2: Financial Performance	0.268	6.82	<0.001	(Critical Bridge)
H2	Perceived Usefulness as a Baseline Condition				Supported
	Perceived Usefulness → Phase 2: Financial Performance	0.097	1.81	0.069	Not Sig. (ns)

4.6.2. Multi-Group Analysis (MGA): Isolating the Structural Disconnection

To elucidate the latent heterogeneity governing the conversion mechanism across divergent groups, this study utilized MGA to contrast the strength of the critical conversion bridge (Phase 1 → Phase 2) between the 'High Integration' cohort (Cluster 1, N = 226) and the 'Low Integration' cohort (Cluster 4, N = 222) (see Table 11 and Figure 5). The analysis exposed a profound conversion discontinuity.

Table 11. PLS-MGA Diagnostic: Isolating the Conversion Gap (Phase 1 → Phase 2).

Subsystem	Path Coefficient (β)	*p*-Value	Structural Topological Status
Full Sample (N = 649)	0.268	<0.001	Functional Bridge
Cluster 1: High Integration (N = 226)	0.124	0.064	Structurally Connected
Cluster 4: Low Integration (N = 222)	0.000	ns	Structural Disconnection (Zero Covariance)
Structural Divergence		$\|\Delta\beta\| = 0.124$	

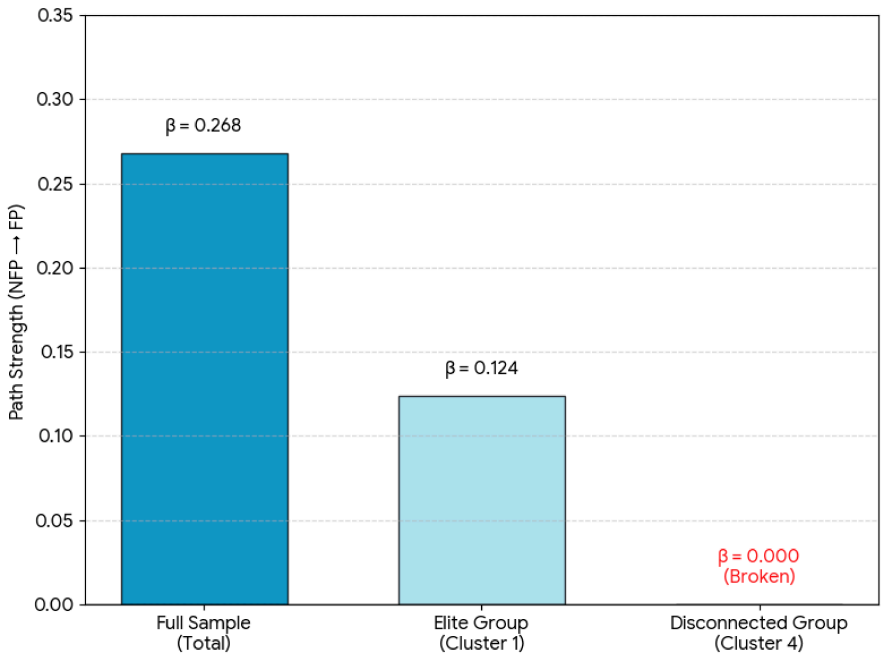


Figure 5. The Structural Disconnection: Topological Comparison of BMT Path Coefficients (Phase 1. Non-Financial Performance → Phase 2. Financial Performance).

Within the High Integration group (Cluster 1), the structural pathway converting intangible Phase 1 assets into Phase 2 financial outcomes remained functionally active ($\beta = 0.124$), exhibiting marginal statistical significance ($p < 0.10$). This indicates that while generating exponential marginal revenue is challenging within an ecosystem already operating near peak realization, the fundamental conversion mechanism remains intact.

Conversely, within the Low Integration group (Cluster 4), the conversion path coefficient collapsed entirely to $\beta = 0.000$. Given that their Phase 2 financial performance scores are rigidly fixated at the absolute minimum baseline (1.0)—exhibiting zero variance—it is statistically highly improbable for any variance in Phase 1 (non-financial performance) to covary with Phase 2. This lack of covariance empirically confirms that the bridge linking intermediate value to economic performance is in a state of complete structural disconnection for this cohort.

These findings suggest that the sustained failure of marginalized SMEs stems not merely from individual operational deficits, but from a structural conversion discontinuity that prevents resource metabolization. Consequently, Proposition H3 (The Conversion Gap) was overwhelmingly supported.

5. Discussion and Implications

5.1. Summary of Findings

To elucidate the "Conversion Black-box"—wherein digital integration initiatives fail to materialize into tangible BMT for SMEs—this study deployed a multi-stage Causal AI architecture. By reverse-engineering the empirical data of 649 SMEs, this research uncovered the latent mechanisms governing value co-creation. The core discoveries are summarized as follows:

- The Four Profiles and the Imperative of ACAP: The GMM analysis categorized the SME ecosystem into four distinct subsystems: High Integration, High Satisfaction-Low Performance, Moderate Bottleneck, and Low Integration (Disconnected). Crucially, the 'High Integration' cohort (34.8%) achieved maximum financial performance and possessed the highest density of prior business experience (85.0%, $p < 0.05$). This indicates that successful digital innovation transcends technical acquisition; BMT is actualized only when technological inputs are fused with pre-existing ACAP. Furthermore, the efficient resource conversion exhibited by this ecosystem represents the empirical manifestation of "Data-driven Dynamic Capabilities" [23].
- The Subsistence Trap and Structural Disconnection: In contrast, the 'Low Integration' subsystem (34.2%) represents vulnerable micro-enterprises characterized by severe ACAP deficits. A structural disconnection was verified within this cohort, yielding virtually no return on digital integration. The MGA path coefficient of $\beta = 0.000$ mathematically exposes that terminal BMT performance remains fixated at the minimum threshold, impervious to variations in upstream inputs. This confirms that these enterprises are trapped in a state of structural stasis, where psychological satisfaction fails to metabolize into economic value.
- Perceived Usefulness as a Baseline and the Mandatory Phase 1 Bridge: The NCA and Grand-DAG optimizations decoded two laws governing BMT: (1) perceived usefulness functions strictly as a baseline condition—necessary to prevent disengagement but insufficient to autonomously drive revenue; and (2) achieving financial performance mandates successfully traversing the strategic milestone of non-financial performance. This dismantles traditional linear models (e.g., TAM), proving that the causal pathway to tangible BMT is non-direct, temporally delayed, and sequentially mediated by intangible network gains.

5.2. Robustness Checks

To ensure the validity and stability of the multi-stage Causal AI framework, two rigorous robustness checks were conducted.

First, to address potential methodological concerns regarding the rationale for the clustering solution, the optimal number of clusters for the GMM was verified using information criteria (AIC and BIC). As demonstrated in Table 5 (Section 4.3), while the BIC favored a highly parsimonious 2-cluster solution (BIC = 4976.38), the Akaike Information Criterion (AIC)—which is methodologically preferred for preventing underfitting and identifying complex, real-world latent structures [56,57]—demonstrated the absolute minimum score at k = 4 (AIC = 2.51). Given our theoretical grounding in Resource Conversion Theory and the necessity to capture nuanced intermediate typologies of SMEs (such as the 'High Satisfaction' or 'Moderate Bottleneck' groups), the 4-component model was mathematically and theoretically justified over the overly parsimonious BIC recommendation.

Second, a diagnostic sensitivity analysis was executed to verify the empirical stability of the study's core findings. This involved substituting the terminal dependent node—from financial performance to non-financial performance. The analysis exposed a profound divergence between the two performance trajectories (see Figure 6).

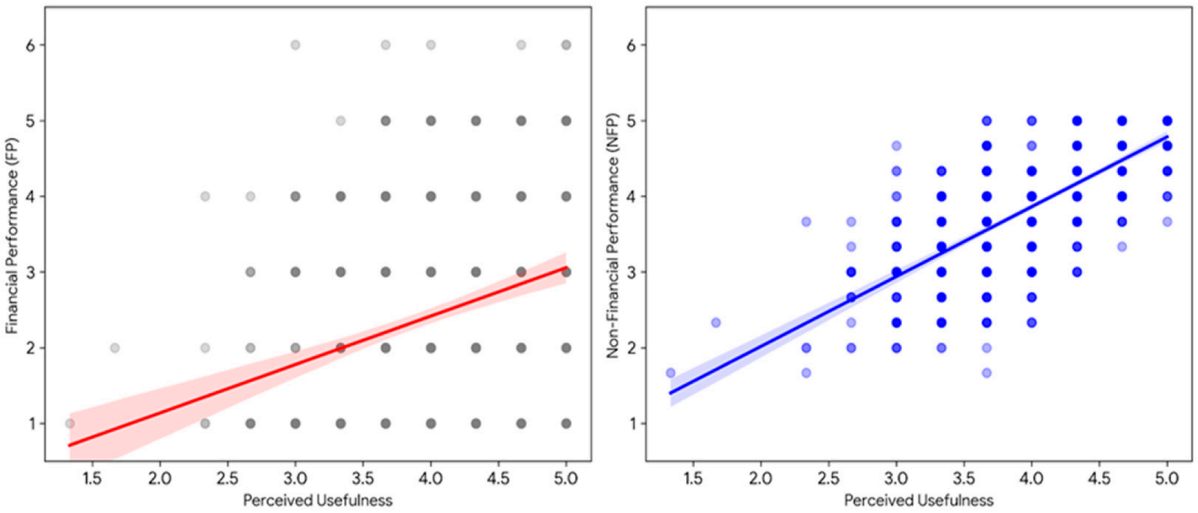


Figure 6. Sensitivity Analysis: Divergence Between Phase 1 and Phase 2 Value Realization. Note: The bivariate scatter matrices illustrate that while perceived usefulness exerts a robust, linear impact on non-financial performance (**Right Panel**), its influence on terminal financial performance (**Left Panel**) remains weak and bounded—confirming the precise location of the Conversion Gap. Additionally, the distinct base colors (grey vs. blue) differentiate the two dependent variables, while the darker, more opaque circles within each panel indicate a higher density of overlapping observations at specific coordinates.

Perceived usefulness demonstrated severe statistical attenuation (r = 0.290) regarding financial performance, maintaining its defined characteristic as a baseline condition. In contrast, the identical construct exhibited a robust, proportional linear influence (r = 0.722) on non-financial performance.

This dichotomy proves that while the functional utility of digital innovation catalyzes "first-order gains" (e.g., heightened operational efficiency), a massive bottleneck inherently paralyzes the ecosystem during the transition to "second-order economic realization" (i.e., revenue growth). In essence, this sensitivity analysis provides cross-validated evidence of the Conversion Gap mechanism: as marginalized enterprises perceive digital tools to be increasingly useful, their immediate operational satisfaction and intangible value co-creation proportionally escalate. However, without the critical intervention of ACAP (Prior

Experience) to bridge the void, these Phase 1 achievements fail to autonomously translate into sustainable Phase 2 BMT outcomes.

5.3. Theoretical Contributions

This study fundamentally extends Resource Conversion Theory by elucidating that ACAP—operationalized as prior experiential capital—functions as the structural catalyst in metabolizing digital resources into economic value. The high prior experience density observed within the 'High Integration' cohort acts as contextual intelligence, enabling the seamless integration of digital tools into business ecosystems. Conversely, the 'Low Integration' cohort fails to achieve BMT due to critical ACAP deficits. Lacking experiential capital, these enterprises acquire technological tools but cannot translate them into sustainable business value.

The foundational Information Systems (IS) Success Model assumes a linear trajectory where cognitive satisfaction inevitably drives tangible performance [13]. However, the MGA diagnosis profoundly disrupts this assumption. By empirically demonstrating that the pathway from non-financial to financial performance is completely severed ($\beta = 0.000$) within the vulnerable subsystem, this research provides clear evidence of a conversion discontinuity. This dictates a paradigm shift: within SME ecosystems, the 'Digital Divide' has shifted from a mere issue of 'Digital Access' to a critical disparity in 'Conversion Capability.'

Crucially, this study re-contextualizes the theoretical boundaries of the Technology Acceptance Model (TAM). Historically, perceived usefulness has been championed as the paramount predictor of technology adoption. However, the NCA diagnostics reveal that in the phase of value conversion (BMT), the status of utility is demoted to a 'baseline condition'—a structural baseline that enforces the lower bound of performance to prevent disengagement, but is insufficient to overcome implementation bottlenecks. By establishing that perceived usefulness is an architectural prerequisite for entry rather than a sufficient driver for BMT success, this study dictates a novel boundary condition that future IS scholarship must integrate.

5.4. Methodological Contributions

Methodologically, this study introduces a sophisticated "Multi-Stage Causal AI Framework" that transcends the deterministic limitations of traditional variance-based linear statistics (e.g., standard PLS-SEM). By integrating Gaussian Mixture Modeling (GMM) to computationally identify latent unobserved heterogeneity, and Tiered Grand-DAG to reverse-engineer chronological causal topologies, this research answers recent calls to ground IS research in rigorous causal discovery algorithms [36,58]. Furthermore, by deploying Necessary Condition Analysis (NCA) alongside PLS-MGA, this study successfully isolated the exact "structural bottlenecks" and non-linear thresholds that linear regressions traditionally obscure. This combined four-method framework offers a highly robust methodological template for future researchers investigating complex, heterogeneous socio-technical ecosystems.

5.5. Practical and Policy Implications

The empirical discoveries dictate a pivot in macro-level digital support policies: moving from monolithic 'Universal Provision' toward data-driven 'Precision Targeting' [4,5]. Relying on a 'One-size-fits-all' pedagogical approach is ineffective for the massive 'Low Integration' subsystem (34.2%). Policymakers must institute a data-driven targeted intervention architecture that pre-emptively classifies applicants into the four identified profiles evaluating ACAP and digital agility at the point of entry.

The GMM topology demonstrated that imposing uniform support across divergent maturity levels precipitates failure. Therefore, differentiated interventions, subsidy schemes, and bespoke Key Performance Indicators (KPIs) calibrated to the conversion capabilities of each subsystem must be mandated. To avoid empty theoretical policy discourse, specific actionable guidelines for each SME profile are synthesized in Table 12.

Table 12. Targeted Policy Interventions and KPI Guidelines by SME Profile.

Cluster Typology	Primary Diagnosis	Targeted Policy Intervention & Tools	Government Subsidy Schemes	Key Performance Indicators (KPIs)
Cluster 4: Low Integration (34.2%)	Total Conversion Discontinuity (Severe ACAP deficit)	Algorithmic Do-It-For-You (DIFY): Provide Gen-AI agents and physical concierge setups. Bypass "how-to" training.	100% subsidy for Micro-SaaS adoption; On-site setup expert dispatch.	Digital Onboarding Rate; System usage frequency (Not revenue).
Cluster 3: Moderate Bottleneck (21.0%)	Threshold Stagnation (Operational bottlenecks)	Operational Efficiency Engineering: Standardized digital manuals and peer-learning ecosystems.	Partial subsidies (70%) for process automation software (ERP/CRM).	Process time reduction; Operating cost deflation.
Cluster 2: High Satisfaction (10.0%)	Cognitive Illusion (High satisfaction, low conversion)	Market Validation Consulting: Intensive UX/UI audits and structural consulting to optimize the conversion funnel.	Data analytics & digital marketing consulting vouchers.	Conversion funnel rate; Platform dwell time.
Cluster 1: High Integration (34.8%)	Optimal Conversion (High ACAP, peak performance)	Scale-up Financial Injections: Waive basic training; provide direct funding for global market expansion.	R&D matching funds; Export & global platform entry subsidies.	Net ROI Trajectory; Market share expansion; Job creation.

Finally, the NCA diagnostics proved that the active catalyst for BMT involves immersive user satisfaction. Static, classroom-based pedagogy must be minimized; instead, the curriculum must mandate 'Micro-Victories' (e.g., processing a single digital transaction) to embed a sense of achievement [59].

5.6. Limitations and Future Research

First, while this study deployed the Tiered Grand-DAG topology to infer directional causality and applied a two-wave time-lagged design, the findings are derived from observational data restricted to the South Korean SME ecosystem. Given the unique institutional support mechanisms and highly advanced digital infrastructure of South Korea, the generalizability of these findings to other diverse cultural or macroeconomic environments may be limited. The decoded pathways represent data-driven causal inferences rather than definitive causality established via controlled manipulation. Furthermore, the structural bottlenecks observed—particularly the severe ACAP deficits driving the Conversion

Gap—may manifest differently in larger enterprises with abundant resource buffers. Given the regional constraints and potential industry concentration biases, and the specific SME focus of the current sample, future research should extend this framework through cross-country, cross-industry, and cross-scale comparative studies to verify the universality of the Conversion Gap phenomenon beyond the SME context.

Second, a methodological constraint exists regarding the operationalization of Phase 2 (financial performance) via a single-item interval scale. The empirical distribution exhibited a severe floor effect, with 35.7% of the ecosystem trapped in the lowest economic bracket. While this study interprets this skewness as the empirical manifestation of the conversion discontinuity—and advanced criterion validity robustly supported the scale—future research must pivot towards API-integrated, objective telemetry (e.g., directly harvesting real-time POS data) to further dissect the mechanism decoded within this study.

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Institutional Review Board Statement: Ethical review and approval were waived for this study due to the non-invasive methodology of the online survey, which targeted SME owners without collecting personally identifiable information, ensuring strict anonymity and minimal risk to participants. This exemption was officially confirmed by Hanyang Cyber University (date of approval 27 April 2024).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the author. The data are not publicly available due to privacy and confidentiality restrictions regarding the participating SMEs.

Conflicts of Interest: The author declares no conflict of interest.

Appendix A. Empirical Diagnostics of the Measurement Model

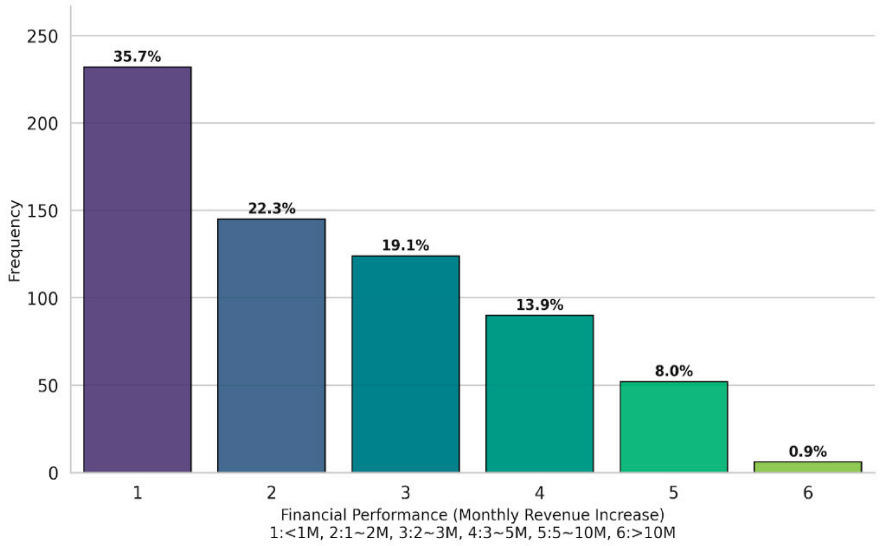


Figure A1. The Floor Effect: Empirical Distribution of Phase 2 Financial Performance. Note: This frequency distribution graphically exposes the right-skewness inherent within the SME sample. Rather than a measurement error, the concentration of enterprises (35.7%) trapped at the minimum economic threshold (Interval 1) serves as an empirical manifestation of the 'Conversion Discontinuity.' It visually quantifies the magnitude of the ecosystem where digital integration fails to translate into tangible economic value.

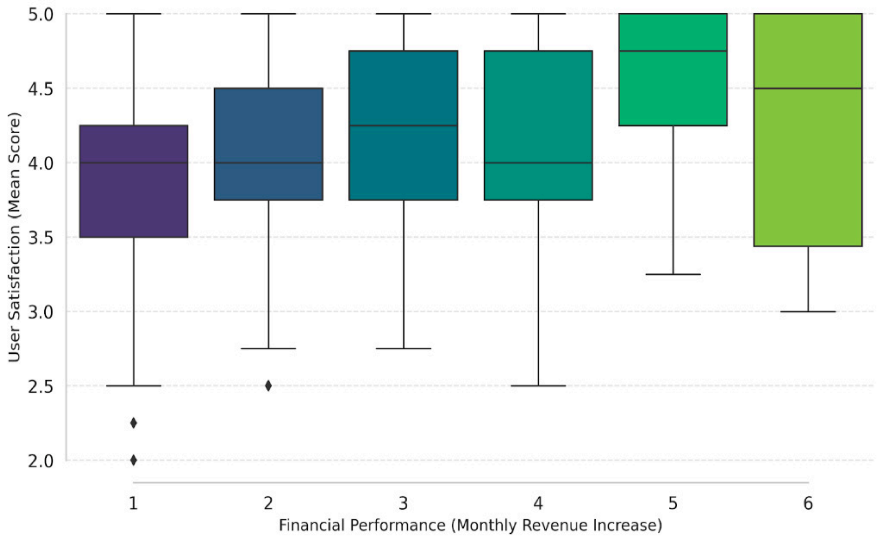


Figure A2. Criterion Validity: User Satisfaction Across Financial Performance Thresholds. Note: This continuous boxplot matrix provides econometric validation for the single-item ordinal scale utilized for the terminal Phase 2 node. It demonstrates a distinct, monotonically increasing trajectory: as the realization of financial performance escalates, the upstream cognitive metric (user satisfaction) aligns and increases in tandem. This congruence confirms the adequate discriminatory power, reliability, and criterion validity of the financial performance measure. For the detailed ordinal scale definition of financial performance (1–6), please refer to Figure A1.

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