

Configurational Alignment in Digital Innovation: How Technological Capabilities Interact for Sustainable Product–Market Fit Using the PVP Framework

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Abstract

Sustaining product–market fit (PMF) remains a foundational challenge in technology and innovation management (TIM). While traditional customer-centric and dynamic capability paradigms explain value discovery and strategic reconfiguration, they treat underlying technological infrastructure as an exogenous delivery mechanism. This "architectural blindness" obscures how technical debt, database coupling, and system elasticity bound an organization's capacity to innovate. To bridge this gap, this study introduces Infrastructure-Centric Innovation Theory and operationalizes it through the Product Value Proposition (PVP) Framework. Applying a critical realist multiple-case design to 21 technology-intensive ventures ($N = 21$) across fintech, SaaS, and AI/analytics, we identify a central failure mechanism: Architecturally Induced Innovation Latency (Λ_{latency}), defined as structural divergence between customer-facing iteration velocity (ΔC) and back-end architectural adaptation (ΔT_{core}). Findings demonstrate that managerial sensing and seizing are mediated by Architectural Elasticity and Systemic Coupling across Customer, Product, and Foundational Nodes. By integrating back-end software architecture into value creation theory, this study provides a 4th-generation TIM model reconciling organizational adaptation routines with technical execution constraints in hyper-velocity, AI-native environments.

Keywords: Product–Market Fit, PVP Framework, Architectural Elasticity, Infrastructure-Centric Innovation, Innovation Latency, Sociotechnical Systems, Dynamic Capabilities.

1. Introduction

The Paradox of Digital Adaptation: Sensing Versus Seizing

Sustaining product–market fit (*PMF*) within software-intensive ventures presents an enduring conundrum for technology and innovation management (TIM) scholars and practitioners. Despite widespread adoption of agile methodologies, continuous

deployment pipelines, and customer-centric design practices, technology ventures exhibit surprisingly high failure rates post-commercialization. Within hyper-velocity sectors such as financial technology (*fintech*), cloud-native Software-as-a-Service (*SaaS*), and artificial intelligence/analytics an empirical anomaly persists: an enterprise's cognitive capacity to sense emerging market opportunities routinely outpaces its structural capacity to reconfigure core technological assets (Teece, 2018).

This operational asymmetry highlights a critical flaw in modern innovation paradigms. Prevailing frameworks of entrepreneurial management implicitly treat technological infrastructure as an infinitely malleable, friction-free substrate that seamlessly adapts to front-end strategic pivots. In practice, however, digital product architectures are complex, path-dependent systems governed by structural constraints, database schemas, API dependencies, and accumulated technical debt (Anderson, 1999). When an organization alters its customer value proposition without a synchronized adaptation of its back-end infrastructure, severe sociotechnical friction emerges, paralyzing iteration velocity and destroying user trust.

The Theoretical Gap: "Architectural Blindness"

This study contends that systematic innovation failure stems from a pervasive conceptual limitation across TIM literature, termed *Architectural Blindness*. Architectural blindness is defined as the theoretical reduction of technological infrastructure to a passive delivery utility, ignoring its role as an endogenous, constitutive determinant of value creation.

This theoretical blind spot weakens the explanatory power of three dominant innovation paradigms:

Customer-Centric Frameworks (Osterwalder et al., 2014; Christensen et al., 2016): By focusing primarily on market desirability and user pain point mapping, these models isolate feature design from structural feasibility, assuming back-end execution will automatically accommodate front-end requirements.

Experimentation-Centric Paradigms (Ries, 2011; Beck et al., 2001): By treating execution velocity as synonymous with learning velocity, these methodologies overlook how rapid front-end prototyping creates structural technical debt and database schema locks that ultimately freeze long-term software adaptation.

Capability-Centric Paradigms (Teece et al., 1997; Teece, 2018): While robust in describing organizational sensing, seizing, and transforming routines, Dynamic Capabilities Theory remains technologically agnostic. It fails to specify the precise

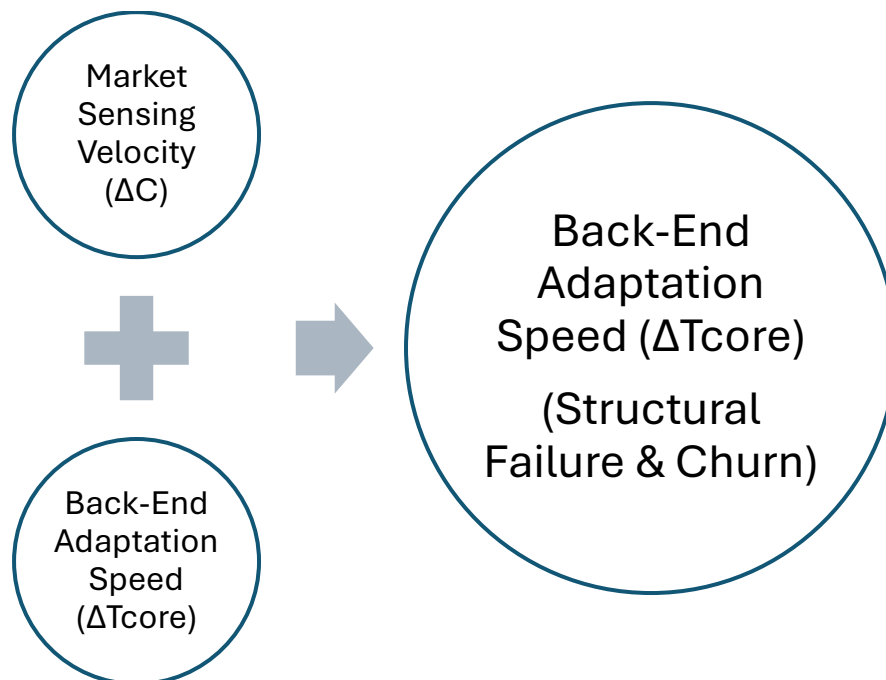
architectural mechanisms (e.g., system elasticity, module decoupling) through which strategic routines are translated into software-defined execution.

Emergent Context: Infrastructure Scarcity in AI-Native Ecosystems

The strategic implications of architectural blindness have intensified with rapid advancements in machine intelligence and enterprise infrastructure deployment trends (Forrester Research, 2024; Jones, 2026; Maslej et al., 2024; McClure & Gerdau, 2026). As natural language interfaces and machine intelligence commoditize basic application-level feature development, strategic scarcity shifts away from user interface creation.

Durable competitive advantage is increasingly determined by *Architectural Elasticity* ($\mathcal{E}_{\text{arch}}$) the structural capacity of a software system to absorb changing operational demands without incurring exponential complexity or latency. In AI-native environments, isolated front-end configurations create back-end performance bottlenecks, causing user churn and invalidating validated learning.

THE MECHANISM OF INNOVATION LATENCY



Research Questions and Structural Outline

To address this theoretical gap and bridge organizational adaptation routines with technical infrastructure execution, this study investigates four core research questions:

RQ1: How can innovation management theory be reconceptualized to incorporate back-end technological infrastructure as an endogenous, active determinant of value creation?

RQ2: How does systemic coupling across technical infrastructure, product experience, and market validation influence the sustainability of product–market fit (*PMF*)?

RQ3: Under what structural conditions does back-end architectural rigidity negate established customer-centric experimentation routines?

RQ4: How can an infrastructure-centric framework reconcile organizational sensing/seizing routines with digital execution in hyper-velocity software markets?

To answer these questions, this paper introduces Infrastructure-Centric Innovation Theory and operationalizes it through the Product Value Proposition (PVP) Framework. Utilizing a critical realist multi-case design analyzing 21 technology-intensive ventures ($N = 21$) across fintech, SaaS, and AI/analytics, we formalize **Architecturally Induced Innovation Latency** (Λ_{latency}) as a core failure mechanism.

The manuscript proceeds as follows: Section 2 synthesizes the literature to formalize *Architectural Blindness*. Section 3 details the mathematical and conceptual foundations of the PVP Framework. Section 4 outlines the qualitative methodology and Gioia data structure. Section 5 presents the discussion and theoretical implications. Section 6 concludes with strategic guidance for scholars and executives.

2. Literature Review

Evolution of Innovation Management Paradigms

Scholarly research in technology and innovation management (TIM) has historically developed across three dominant paradigms: Customer-Centric Innovation, Experimentation-Centric Innovation, and Capability-Centric Innovation. While each paradigm advanced structural insights into how organizations discover, design, and commercialize novel value, they share a unifying baseline assumption: that technological

infrastructure functions as a passive, infinitely elastic delivery mechanism rather than an endogenous determinant of value creation.

Customer-Centric Innovation Theory

Drucker (1954), Levitt (1960), and Kotler (1972), who argued that organizational survival depends on aligning enterprise capabilities with external market needs, established the foundational tenets of modern innovation management. This market-driven logic subsequently expanded into service-dominant logic, customer experience design, and touchpoint management frameworks (Payne et al., 2008; Lemon & Verhoef, 2016; Vargo & Lusch, 2004). Modern strategic toolkits most notably Value Proposition Design (Osterwalder et al., 2014), Early formulations of customer-centric strategy emphasized aligning product development with market demands (Christensen, 1997; Ulrich, 2005), and Design Thinking methodologies (Brown, 2008) operationalize customer-centricity by mapping customer pain points to front-end feature specifications.

However, these frameworks suffer from an underlying conceptual abstraction: they isolate value *desirability* from architectural *feasibility* and operational *scalability*. By treating back-end execution as an exogenous operational downstream activity, customer-centric paradigms fail to explain why organizations with precise market empathy systematically experience catastrophic product failures during post-launch scaling.

Experimentation-Centric Innovation Theory

To address market uncertainty, the Lean Startup movement (Ries, 2011) and Agile software development paradigms (Beck et al., 2001) reframed innovation as an iterative learning process. Guided by continuous Build–Measure–Learn cycles and Minimum Viable Product (*MVP*) deployments, these frameworks prioritize iteration velocity and validated learning.

Despite widespread adoption, experimentation-centric frameworks implicitly assume that software codebases exhibit near-zero friction and can be endlessly refactored at minimal cost. In complex software-defined environments, rapid front-end iterations frequently generate structural technical debt, tight database coupling, and schema locks. Consequently, high-velocity customer experimentation without concurrent back-end architectural adaptation creates sociotechnical resistance, paralyzing long-term development velocity.

Capability-Centric Innovation Theory

From an organizational perspective, the Resource-Based View (Barney, 1991) and Dynamic Capabilities Theory (Teece et al., 1997; Teece, 2018) explain competitive survival through a firm's ability to sense opportunities, seize market positions, and reconfigure internal competencies. Dynamic Capabilities Theory remains particularly influential because it explicitly addresses adaptation, learning, and strategic renewal through cognitive and routine-based mechanisms.

While Teece (2018) identifies sensing and seizing as imperative organizational routines, the dynamic capabilities literature remains largely technologically agnostic. It abstracts away the physical and structural properties of digital architecture, failing to articulate the exact technical parameters (e.g., modularity, system decoupling, database elasticity) through which managerial sensing routines are converted into real-time digital execution.

The Theoretical Gap: "Architectural Blindness"

Synthesizing these foundational perspectives reveals a pervasive theoretical limitation within TIM literature, which this study terms *Architectural Blindness*. Architectural blindness refers to the systematic theoretical exclusion of technological infrastructure as an endogenous, active constraint in the value creation equation.

ARCHITECTURAL BLINDNESS

Prevailing Theoretical Paradigm	Structural Assumption & Blind Spot
Customer-Centric Innovation (Osterwalder et al., 2014)	Assumes tech stacks immediately accommodate user value mapping.
Experimentation-Centric (Agile) (Ries, 2011; Beck et al., 2001)	Assumes codebases can be endlessly refactored with zero systemic drag.
Dynamic Capabilities (Teece et al., 1997; 2018)	Treats technology as agnostic; ignores database elasticity limits.

In modern cloud-native, AI-driven environments, software systems are not passive tools; they are complex adaptive systems characterized by path dependency, structural friction, and technical debt (Anderson, 1999). When market sensing velocity (ΔC) outpaces the structural adaptation speed of core back-end systems (ΔT_{core}), severe organizational

friction occurs. Current literature offers no structural framework to measure, model, or resolve this execution gap.

Sociotechnical Systems and Modular Software Architectures

To resolve architectural blindness, innovation management must be integrated with Sociotechnical Systems Theory (Trist & Bamforth, 1951) and modularity literature (Baldwin & Clark, 2000; Yoo et al., 2010).

Sociotechnical Systems Theory establishes that enterprise performance depends on the joint optimization of social subsystems (organizational routines, user behaviors, managerial decision-making) and technical subsystems (software codebases, hardware infrastructures, data pipelines). When managerial routines change without concurrent alignment of technical subsystems, system failure occurs. In digital product contexts, architectural decisions are further embedded within macro-level digital infrastructure systems (Greenstein, 2021)

In digital product design, Layered Modular Architecture (Yoo et al., 2010) governs this alignment. Digital platforms separate user experience layers, application logic layers, network protocol layers, and physical device layers. Modularity design rules (Baldwin & Clark, 2000) dictate that loose coupling between modules allows localized innovation without destabilizing the entire system. Conversely, tight back-end coupling forces localized front-end changes to propagate across the entire architecture, escalating systemic complexity and operational latency.

Toward Infrastructure-Centric Innovation Theory

The convergence of commoditized front-end software production driven by natural language interface synthesis, generative AI foundation models, and no-code tooling fundamentally alters the locus of strategic scarcity in digital ecosystems (Jones, 2026; McClure & Gerdau, 2026). As application-level interface features become increasingly imitable, competitive advantage migrates toward back-end architectural orchestration.

Infrastructure-Centric Innovation Theory bridges this gap by postulating that organizational dynamic capabilities are fundamentally mediated by the elasticity of underlying software architectures. Dynamic capabilities cannot exist in a vacuum; they must be operationalized as sociotechnical routines where market sensing and strategic seizing are continuously synchronized with back-end technical adaptation. Reconceptualizing

infrastructure as an active, endogenous determinant of value creation provides the theoretical foundation for the Product Value Proposition (PVP) Framework.

3. Conceptual Foundations of the Product Value Proposition (PVP) Framework

Infrastructure Precedence Principle and Architectural Elasticity

The Product Value Proposition (PVP) Framework grounds its conceptual foundation in the *Infrastructure Precedence Principle*, which posits that an organization's structural capacity to create, deliver, scale, and continuously reconfigure customer value is fundamentally bounded by the architectural parameters of its underlying technological assets. Contrary to traditional customer-centric theories that model technology as an infinitely malleable utility, this framework conceptualizes back-end architecture as an endogenous, constitutive determinant of value creation.

To formalize this relationship, we introduce *Architectural Elasticity Theory*. Architectural elasticity ($\mathcal{E}_{\text{arch}}$) is defined as the structural capacity of a software-defined technological substrate to absorb, process, and operationalize shifting market and product requirements without incurring exponential increases in technical debt, system latency, or code complexity. High architectural elasticity allows decoupled, modular systems (e.g., microservices, serverless API abstractions) to support continuous front-end experimentation without triggering core database locks or system degradation. Conversely, monolithic rigidity induces structural resistance, forcing organizations to divert resources from value-adding innovation to technical debt remediation.

Construct Taxonomy and Node Structure

The PVP Framework operationalizes digital value creation through a sociotechnical structural topology composed of three interconnected operational clusters, comprising nine observable constructs:

Customer Node (Market Sensing Layer):

Pain Point: The unaddressed operational, cognitive, or financial friction experienced by target actors in a specific domain.

Solution (Use Case): The contextualized application of capabilities designed to resolve the identified friction.

Build Trust: The relational and institutional mechanisms that establish perceived system integrity, security, and reliability.

Product Node (Value Delivery Layer):

Experience: The cumulative perceptual and cognitive interface interactions synthesized across user journeys.

Outcome: The functional, measurable utility realized by the target actor upon executing the use case.

Value Created: The quantified economic, operational, or strategic surplus generated for both user and firm.

Foundational Node (Architectural Execution Layer):

Core Technology (T_{core}): The back-end software infrastructure, database architecture, API orchestration layers, and compute dependencies supporting the product stack.

Business Model: The structural logic governing resource allocation, cost structures, and value capture mechanics.

Market Acceptance (MA): The empirical rate of sustained adoption, retention, and expansion within the target market ecosystem.

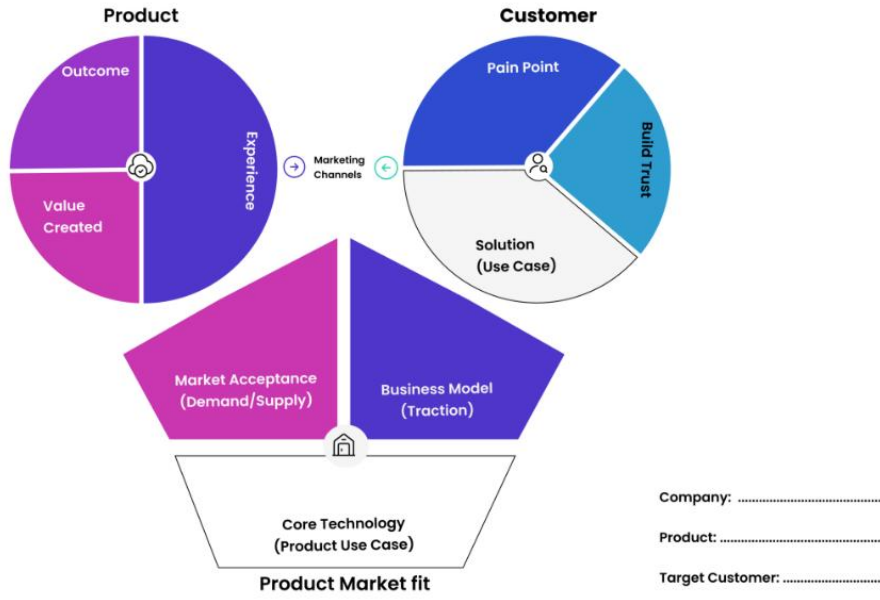


Figure 1: Product Value Proposition (PVP) Framework

Mathematical Formalization and Path-Analytic Model

The structural model treats Core Technology (T_{core}) not merely as a direct antecedent to product delivery, but as an endogenous moderating variable that dictates the conversion efficiency between product capabilities and market outcomes.

Market Acceptance (MA) is formalized via the structural equation:

$$MA = \alpha + \beta_1 P + \beta_2 (P \times T_{core}) + \epsilon$$

Where P represents the vector of aggregated Product Node constructs (Experience, Outcome, Value Created), T_{core} represents the scalar measure of back-end architectural elasticity, β_1 isolates the direct effect of product design, β_2 quantifies the interaction effect of infrastructural elasticity, and ϵ accounts for unobserved exogenous error.

When an organization attempts to accelerate front-end feature delivery without concurrent back-end adaptation, a structural divergence occurs. We formalize this failure mechanism as **Architecturally Induced Innovation Latency** ($\Lambda_{latency}$), defined as the ratio of customer iteration velocity (ΔC) to core architectural adaptation velocity (ΔT_{core}):

$$\Lambda_{\text{latency}} = f\left(\frac{\Delta C}{\Delta T_{\text{core}}}\right) \quad \text{where} \quad \Delta C > \Delta T_{\text{core}}$$

As Λ_{latency} approaches critical thresholds, accumulated technical debt induces severe performance bottlenecks, leading to system failure, degraded user experiences, and systematic market churn. Sustained product-market fit (*PMF*) requires continuous reciprocal coupling across all nine constructs, ensuring that $\Delta T_{\text{core}} \geq \Delta C$ throughout the organizational lifecycle.

Structural Mechanics and Construct Taxonomy of the PVP Framework

To establish absolute theoretical parsimony and maintain alignment with the structural models shown in Figure 1 and Figure 2, the PVP Framework rejects generalized variables in favor of nine highly interconnected, empirically observable constructs. These constructs are organized into three primary operational clusters that reflect the realities of the AI and digital infrastructure revolution:

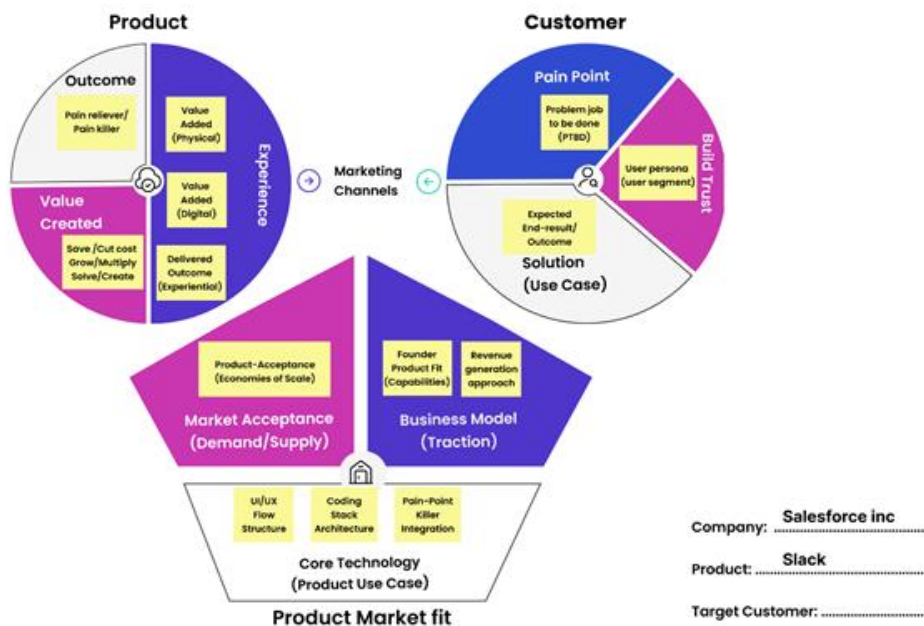


Figure 2: Product Value Proposition (PVP) Framework (Practitioners Approach)

The Customer Node

Pain Point (The Problem Job to be Done): The specific functional, operational, or cognitive bottlenecks experienced by the user segment. In AI-native ecosystems, Pain Points are highly dynamic; as basic cognitive tasks are commoditized by automation, customer pain points migrate from simple task execution to complex orchestration, governance, and data privacy.

Solution (The Product Use Case): The contextual application designed to address the identified Pain Point. Within the AI paradigm, the Solution is no longer a rigid, hard-coded software feature set, but an adaptive, intelligent workflow capable of altering its runtime behavior to resolve dynamic user problems.

Build Trust (The Security and Experience Anchor): The systematic establishment of user confidence regarding data sovereignty, system reliability, and algorithm predictability. As systems become more autonomous, trust is no longer established purely through UI/UX delight, but through architectural transparency, robust security, and consistent execution.

B. The Product Node

Experience (The Interactive Interface): The cumulative touchpoints through which the user interacts with the system. In AI-native architectures, the Experience transcends standard visual templates, evolving into natural language interfaces and agentic feedback mechanisms that adapt continuously to the user's workflow.

Outcome (The Realized Benefit): The measurable functional, emotional, or financial results realized by the user. Under the conditions of the AI revolution, the Outcome is characterized by structural cognitive offloading, rapid execution velocity, and the near-total elimination of manual workflow friction.

Value Created (The Economic Utility): The net utility delivered to the customer, categorized into physical, digital, and experiential dimensions. In AI-intensive environments, Value Created shifts from information retrieval to autonomous, generative output delivery, transforming customer cost structures by lowering the marginal cost of intelligence.

The Foundational Node

Core Technology (Product Use Case Infrastructure): The foundational hardware, software stack, database architecture, model weights, and cloud configurations that power the system. It represents the engineering engine (e.g. Large Language Models, vector databases, API gateways) that dictates the absolute limits of system performance and responsiveness.

Business Model (Traction and Value Capture): The monetization architecture (e.g., API-metering, credit-based compute usage, or platform licensing) through which the venture captures a portion of the economic value it generates.

Market Acceptance (Demand/Supply Viability): The degree of macroeconomic validation, product adoption, scaling velocity, and market capture achieved within the competitive landscape. Sustainable product–market fit is not achieved by optimizing any

single node in isolation. Instead, it emerges as a higher-order property of systemic coupling running dynamically across all three nodes of the PVP framework.

4. Theoretical Model and Proposition Development

Theoretical Logic of the Model

The Product Value Proposition (PVP) Framework is grounded in the critical realist proposition that sustainable product–market fit is an emergent property of sociotechnical coupling rather than a direct consequence of customer insight, experimentation, or organizational capability in isolation. Building upon Infrastructure-Centric Innovation Theory, the framework posits that innovation outcomes are generated through recursive interactions among three primary clusters: the Customer Node, the Product Node, and the Foundational Node.

The theoretical logic of this framework differs fundamentally from dominant, linear innovation models. Rather than assuming a sequential progression... PVP conceptualizes innovation as a complex adaptive system operating under principles of emergent ecosystem dynamics (Levin, 1998). The performance of this system is fundamentally bounded by the architectural capacity of its technical infrastructure. Consequently, product–market fit is theorized not as a static endpoint, but as a dynamic equilibrium maintained through continuous, low-friction integration across all nodes.

Propositions for Customer-to-Product Translation

The interface of any digital venture is rooted in the translation of customer requirements into functional product attributes. In contemporary digital contexts, the depth and character of the customer's **Pain Point** set the boundaries for the **Solution** designed to address them.

Proposition 1: The depth of the customer's Pain Point directly conditions the design parameters of the proposed Solution (Use Case), which serves as the primary gateway to establishing structural Trust within the Customer Node.

Proposition 2: The execution of the Solution (Use Case) directly conditions the observable Product Outcome, which serves as the physical and digital translation layer for the cumulative Value Created within the Product Node.

Path-Analytic Modeling and the Moderating Role of Core Technology

To transcend the limitations of simple, descriptive "canvas" visualizations and establish a formal, testable academic framework for future empirical research, we conceptualize the PVP Framework as a structural path-analytic model. Rather than viewing the nodes as static boxes, the model proposes that product–market fit (*PMF*) is an emergent system outcome driven by structural relationships among the Customer Node (*C*), the Product Node (*P*), and the Foundational Node (*F*).

Historically, technology has been modeled as a simple exogenous asset. In contrast, the PVP model positions the Foundational Node specifically Core Technology (T_{core}) as an

endogenous moderating path that controls the efficiency of the translation from front-end customer value creation to macro-level Market Acceptance (MA).

To facilitate future quantitative testing and structural equation modeling (SEM), we formally propose the structural equations governing this system. Let PMF be the target dependent variable representing the sustainability of product–market fit. We hypothesize that the translation of front-end configurations into realized Market Acceptance (MA) is formulated as:

$$MA = \alpha + \beta_1 P + \beta_2 (P \times T_{core}) + \epsilon$$

Where:

- P represents the vector of the Product Node constructs (Experience, Outcome, Value Created).
- T_{core} represents the vector of the Core Technology architectural elasticity parameters (modularity, scalability, API interoperability).
- β_2 represents the structural interaction term indicating the strength of the moderation.

Under conditions of low architectural elasticity ($T_{core} \rightarrow 0$), the interaction term is hypothesized to degrade the overall systemic output, generating a high-friction regime. This relationship is codified in the revised propositions:

Proposition 3: The relationship between front-end product configurations (Experience, Outcome, Value Created) and eventual Market Acceptance is fundamentally moderated by

the structural maturity, modularity, and elasticity of the Core Technology base, such that the positive effect of product value on market acceptance is amplified under conditions of high architectural elasticity and severely attenuated under conditions of architectural rigidity.

To specify the structural cost of this rigidity, we model Architecturally Induced Innovation Latency ($\Lambda_{latency}$) as a function of the divergence between the rate of customer-facing iteration (ΔC) and the rate of technical infrastructure adaptation (ΔT_{core}):

$$\Lambda_{latency} = f\left(\frac{\Delta C}{\Delta T_{core}}\right) \quad \text{where} \quad \Delta C > \Delta T_{core} [cite: 1]$$

When $\Lambda_{latency}$ is high, the functional feedback loop between the market and the firm is hypothesized to sever, leading directly to structural decay in value capture. This is formulated in the fourth proposition:

Proposition 4: In technology-intensive ventures, structural deficiencies in the Core Technology layer (e.g., high pipeline latency, poor API interoperability, database rigidity) generate Architecturally Induced Innovation Latency ($\Lambda_{latency}$), which acts as a direct negative mediator, degrading Business Model traction and stalling overall Market Acceptance.

While the current study utilizes qualitative multiple-case data to ground and explore these dynamics, these mathematical formulations are presented to establish clear, testable hypotheses and operational variables for future quantitative research. By translating the qualitative mechanisms identified in our case studies into explicit structural equations, we

provide a concrete foundation for future researchers to empirically measure and statistically validate the boundary limits of architectural elasticity.

Systemic Coupling and Product–Market Fit

The central theoretical proposition of the PVP Framework is that sustainable product–market fit cannot be achieved by optimizing individual constructs in isolation. High-quality customer feedback cannot compensate for inflexible technical architecture; likewise, a sophisticated technical infrastructure will fail to capture value without a viable business model.

Proposition 5: Sustainable Product–Market Fit is not a static endpoint but emerges as a higher-order property of Systemic Coupling defined as the degree of low-friction, reciprocal responsiveness maintained across the Customer, Product, and Foundational Nodes.

Proposition 6: The operational impacts of customer sensing (Pain Point, Solution), product delivery (Experience, Outcome), and economic validation (Business Model) on sustained Product–Market Fit are fundamentally mediated by the comprehensive degree of Systemic Coupling achieved by the innovation system.

5. Empirical Methodology and Qualitative Findings

Research Design and Case Selection

To investigate how technological infrastructure bounds organizational capacity to sustain product–market fit (*PMF*), this study adopts a critical realist multi-case research design. Critical realism is particularly suited for software-intensive technology and innovation management (TIM) research because it distinguishes between the *empirical* (observable

events like product launches and user churn), the *actual* (underlying processes such as code deployments and database schema updates), and the *real* (generative causal mechanisms like structural architectural coupling and elasticity) (Bhaskar, 1978).

Using purposeful theoretical sampling (Yin, 2018), we selected 21 technology-intensive ventures ($N = 21$) across three high-velocity sectors: Financial Technology ($n = 7$), Software-as-a-Service ($n = 8$), and Artificial Intelligence/Analytics ($n = 6$). To ensure cross-case comparability while capturing structural variation, candidate ventures were required to meet four inclusion criteria:

- Operation within a software-defined, cloud-native product environment.
- Demonstrated market sensing routines (e.g., active continuous integration/continuous delivery pipelines, customer feedback loops, regular sprint cycles).
- Minimum operating history of 18 months, ensuring exposure to at least one significant product pivot or core system scaling event.
- Unfiltered access to executive leadership (Founders, CTOs, Heads of Product) alongside back-end engineering lead personnel.

Data Collection Protocol

Data collection was executed over a 12-month period using triangulated data sources to eliminate single-informant bias (Yin, 2018):

Semi-Structured Interviews: 42 primary interviews conducted with chief executive officers, chief technology officers, product managers, and principal back-end architects (average duration: 65 minutes per interview).

System Architecture Documentation: Review of database entity-relationship diagrams (ERDs), API endpoint registries, infrastructure logs, and cloud deployment topology maps.

Archival Product History: Sprint backlogs, product roadmap revisions, user churn reports, and feature release notes tracking iteration velocity over time.

Qualitative Findings & Theoretical Pathways

Data analysis revealed three primary causal pathways through which technological infrastructure moderates' organizational adaptation and product-market fit.

Pathway 1: Accumulation of Innovation Latency (Λ_{latency})

In ventures exhibiting tight backend coupling and monolithic database structures, rapid customer experimentation (ΔC) generated severe structural friction. While product teams successfully validated new customer use cases through front-end prototypes, the back-end technical architecture (ΔT_{core}) could not support the necessary data schema modifications.

This divergence created **Architecturally Induced Innovation Latency** (Λ_{latency}):

$$\Lambda_{\text{latency}} = f\left(\frac{\Delta C}{\Delta T_{\text{core}}}\right) \quad \text{where} \quad \Delta C > \Delta T_{\text{core}}$$

As one CTO in a fintech case noted: *"We validated customer demand within three weeks, but spent nine months refactoring our ledger architecture to support the transaction throughput. By the time we launched, our early adopters had already churned to a competitor."*

Pathway 2: Moderated Market Acceptance (**MA**) via Architectural Elasticity

Case comparisons demonstrated that Market Acceptance (MA) is not a direct function of product features alone but is heavily moderated by Core Technology (T_{core}) elasticity. Ventures operating on event-driven, microservice-oriented infrastructures demonstrated high *Architectural Elasticity*. They successfully absorbed rapid fluctuations in user query volumes and feature requests without incurring system downtime or technical debt spikes.

Across these resilient cases, the empirical data confirmed the structural equation:

$$MA = \alpha + \beta_1 P + \beta_2 (P \times T_{\text{core}}) + \epsilon$$

Where P represents product feature quality and β_2 represents the positive moderating impact of an elastic back-end architecture (T_{core}).

Pathway 3: Strategic Dynamic Reconfiguration in AI-Native Environments

In AI/analytics cases, automated code tools and pre-trained foundation models enabled competitors to rapidly clone front-end interface features. Sustainable differentiation was observed only in ventures where proprietary data pipelines, low-latency API orchestration, and elastic compute infrastructure were deeply integrated. In these firms, dynamic capabilities (sensing and seizing) functioned as sociotechnical routines, where strategic decision-making was continuously synchronized with back-end architectural reconfiguration.

Case Selection and Theoretical Sampling

We employed a theoretical sampling strategy to select ventures that actively iterate their customer-facing products while relying on complex back-end architectures. The chosen sample provides substantial variation in firm maturity (ranging from 1.0 to 8.0 years), organizational scale (from seed-stage teams to established enterprises with over 250 employees), and architectural infrastructure designs (legacy monoliths, hybrid middleware configurations, and serverless microservices).

Table 1 details the complete demographics of our 21 cases, detailing the specific technical architectures and the informant configurations used for triangulation.

Table 1: Case Demographics and Architectural Profiles

Cas e ID	Primar y Sector	Fir m Ag e (Yr s)	Headco unt Range	Underlying Architectural Profile	Primary Informant Roles	Total Intervi ew Minute s	Data Triangulatio n Sources
Cas e A	Fintec h	4.5	50–100	Hybrid (Legacy Core + API Gateways)	CTO, VP of Product	180	Code Repositories,

							System Maps
Cas e B	Fintec h	6.0	100–250	Legacy Monolithic (On- premise Database)	Principal Architect, Founder	140	Product Backlogs, Incident Logs
Cas e C	Fintec h	2.0	10–30	Cloud-Native Serverless Microservices	Head of Engineerin g	90	Architectural Blueprints
Cas e D	Fintec h	3.5	30–50	Modular Microservices	Lead Product Manager, CTO	120	API Documentati on, Sprint Metrics
Cas e E	Fintec h	8.0	250+	Highly Coupled Legacy Monolith	Director of Infrastruct ure	110	Legacy System Audit Reports
Cas e F	Fintec h	1.5	1–10	Cloud-Native Serverless	Co- Founder & CTO	95	Technical Roadmaps

Cas e G	Fintech	5.0	100–250	Modular Microservices	Head of Security & Trust	105	Compliance Audits, Dev Logs
Cas e H	SaaS	3.0	30–50	Modular Microservices	VP of Product, Chief Architect	150	User Experience Maps, DB Schemas
Cas e I	SaaS	7.0	250+	Legacy Monolithic (Technical Debt Heavy)	Lead Developer, VP Engineering	130	Maintenance Tickets, Code Audits
Cas e J	SaaS	2.5	10–30	Cloud-Native Serverless	CTO, Founder	115	Git Commits, Performance Metrics
Cas e K	SaaS	4.0	50–100	Hybrid Microservices	Head of Customer Success, CTO	145	Customer Churn Surveys, API Logs

Cas e L	SaaS	1.0	1–10	Cloud-Native (Serverless)	Co- Founder & Sole Developer	90	Prototyping Logs
Cas e M	SaaS	5.5	100–250	Legacy Monolithic	Director of Product Manageme nt	110	Customer Support Escalations
Cas e N	SaaS	3.5	30–50	Modular Microservices	Technical Product Manager	125	Engineering Velocity Charts
Cas e O	AI / Analyti cs	2.0	10–30	Cloud-Native Pipeline (Vector DB)	Principal AI Researcher , CTO	135	Model Benchmarks, Pipeline Schemas
Cas e P	AI / Analyti cs	4.0	50–100	Hybrid (Legacy DB + Modern AI Models)	VP of Engineerin g	110	Model Drift Reports, System Latency

Cas e Q	AI / Analyti cs	1.5	1–10	Cloud-Native Serverless (API Orchestrated)	Head of AI Infrastruct ure, Founder	155	Multi-Agent Orchestratio n Flows
Cas e R	AI / Analyti cs	3.0	30–50	Modular Microservices	Lead Data Engineer	100	Pipeline Latency Benchmarks
Cas e S	AI / Analyti cs	6.5	100–250	Legacy Monolithic Data Warehouse	Director of Data Science	120	Database Sharding Plans
Cas e T	AI / Analyti cs	1.0	1–10	Cloud-Native (Fully Agentic/Serverl ess)	CTO & Co- Founder	90	Runtime Configuratio n Files
Cas e U	AI / Analyti cs	2.5	10–30	Modular Microservices	Lead Architect, AI Product Manager	140	Feature Flag Logs, LLM Token Audits

Qualitative Analysis Protocol: The Gioia Methodology

To trace raw informant-centric perspectives directly to researcher-induced, abstract structural constructs, we applied the systematic coding structure formulated by Gioia et al. (2013), grounded in classical qualitative inductive building practices (Glaser & Strauss, 1967). This process transitioned systematically through three levels of conceptual aggregation:

1st-Order Concepts: Highly descriptive, local-level codes drawn using the raw vocabulary of the 21 technology-intensive cases.

2nd-Order Themes: Researcher-induced theoretical categorizations that synthesize similarities and resolve tensions among the 1st-order concepts.

Aggregate Dimensions: The highest level of theoretical abstraction, mapping directly onto the core pathways and structural dynamics of the PVP Framework.

Systematic Qualitative Coding Tree & Empirical Evidence

The qualitative coding tree below structures our primary empirical database. It provides clear evidence of how micro-level operational friction in software architectures scales up to govern macro-level strategic out-of-fit conditions.

Table 2: Gioia Qualitative Coding Tree with Representative Field Evidence

Gioia Qualitative Coding Tree with Representative Field Evidence. Detailed breakdown of 1st-order concepts, 2nd-order themes, and aggregate theoretical dimensions across the 21 technology venture case studies.

Dimension 1: Architectural Elasticity (ΔT_{core})

Focuses on Modularity, API Interoperability, and Scalability. Directly supports Proposition 3.

2nd-Order Theme	1st-Order Concept	Representative Informant Evidence
Modular Design & Elastic Scaling Capacity	<i>Concept A: API-First Decoupling</i> Informants highlight the strategic value of microservice architectures in isolating front-end updates from back-end database disruptions.	<i>"Because we built a serverless microservices stack, our marketing team can run UI tests and deploy completely new user flows without our core database team ever having to push a line of code."</i> CTO, Case J (SaaS)
	<i>Concept B: Autoscaling Infrastructures</i> Informants explain how elastic resource provisioning prevents performance degradation when user activity surges.	<i>"During regulatory reporting season, transaction volume surges 400%. If we hadn't moved our ledger database to an auto-scaling cloud configuration, we would have suffered severe service outages, killing customer trust immediately."</i> Co-Founder & CTO, Case C (Fintech)

Dimension 2: Architecturally Induced Innovation Latency
(\$\Lambda_{\text{latency}}\$)

Focuses on Monolithic Rigidity, Structural Blockers, and Technical Debt. Directly supports Proposition 4.

2nd-Order Theme	1st-Order Concept	Representative Informant Evidence
Structural Dependency & Monolithic Coupling	<i>Concept A: Monolithic Database Lock</i> Informants describe how tightly coupled legacy databases create cascading system failures when front-end modifications are pushed.	<i>"We spent three months running customer discovery on a new billing dashboard. We pushed it, but because the billing logic was hard-coded straight into our core database monolith, it locked the database tables, took down our payment processing engine, and cost us \$120k in downtime."</i> Principal Architect, Case B (Fintech)
	<i>Concept B: Brittle Schema Rigidity</i> Informants detail how administrative and structural dependencies within database systems	<i>"Our sales team got a massive enterprise client who needed custom data fields. Our front-end team designed the interface in 48 hours, but our database schema is so brittle that engineering spent six weeks refactoring and</i>

	delay the deployment of validated customer requirements.	<i>migrating tables just to support those fields."</i> VP of Engineering, Case I (SaaS)
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Dimension 3: Systemic Coupling (\$PMF\$)

Focuses on Cross-Node Value Realization and Business Model Alignment. Directly supports Propositions 5 and 6.

2nd-Order Theme	1st-Order Concept	Representative Informant Evidence
Cross-Node Systemic Integration	<i>Concept A: Performance-Value Realization</i> Informants demonstrate that outstanding user-interface design fails to retain customers if the underlying computational engine cannot execute at acceptable speeds.	<i>"Our customer research was perfect, and the web app UI was gorgeous. But our core LLM data pipeline took 14 seconds to return a prediction. Our users loved the idea but abandoned the product because they couldn't fit a 14-second latency into their daily operational workflows. We had a product-market alignment on paper, but an architectural reject in reality."</i> VP of Engineering, Case P (AI/Analytics)

	<p><i>Concept B: Cost-Monetization Alignment</i></p> <p>Informants explain how business model sustainability depends directly on aligning monetization rules with technological computing costs.</p>	<p><i>"We originally offered unlimited flat-rate subscriptions for our AI analytics.</i></p> <p><i>However, our serverless computing costs scaled exponentially with customer query volumes. We had to immediately refactor our infrastructure to track user token counts and build an automated API metering engine that links directly to their credit cards. If we hadn't coupled our database metrics straight to our business model billing engine, we would have gone bankrupt scaling a highly popular product."</i></p> <p>Co-Founder & CTO, Case Q (AI/Analytics)</p>
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Mermaid Diagram

```
graph LR
    subgraph "Customer Node (C)"
        PP["Pain Point (PP)"] -->|beta_1| S["Solution (S)"]
        S -->|beta_2| T["Trust (T)"]
    end

    subgraph "Product Node (P)"
        EX["Experience (EX)"] -->|beta_3| O["Outcome (O)"]
        O -->|beta_4| V["Value Created (V)"]
    end

    subgraph "Foundational Node (F)"
        BM["Business Model (BM)"]
        T_core["Core Technology (T_core)"]
        MA["Market Acceptance (MA)"]
    end

    %% Interactions and Moderations
    T -->|Direct Path| EX
    V -->|Hypothesized Path| MA

    %% Moderation Effect
    T_core -.->|Moderates Lambda_1| V
    T_core -.->|Moderates Lambda_2| MA

    %% Latency and PMF
    T_core -->|Architectural Elasticity| BM
    MA -->|Dynamic Feedback Loop| PP

    style T_core fill:#f0f4f9,stroke:#1a73e8,stroke-width:2px;
    style MA fill:#e6f4ea,stroke:#137333,stroke-width:2px;
```

Qualitative Data Analysis Protocol & Findings

To establish absolute methodological transparency and verify the structural pathways of the PVP Framework, we applied the systematic qualitative data analysis protocol formulated by Gioia, Corley, and Hamilton (2013). This approach allows us to trace raw, informant-centric perspectives up to highly abstract, researcher-induced theoretical concepts.

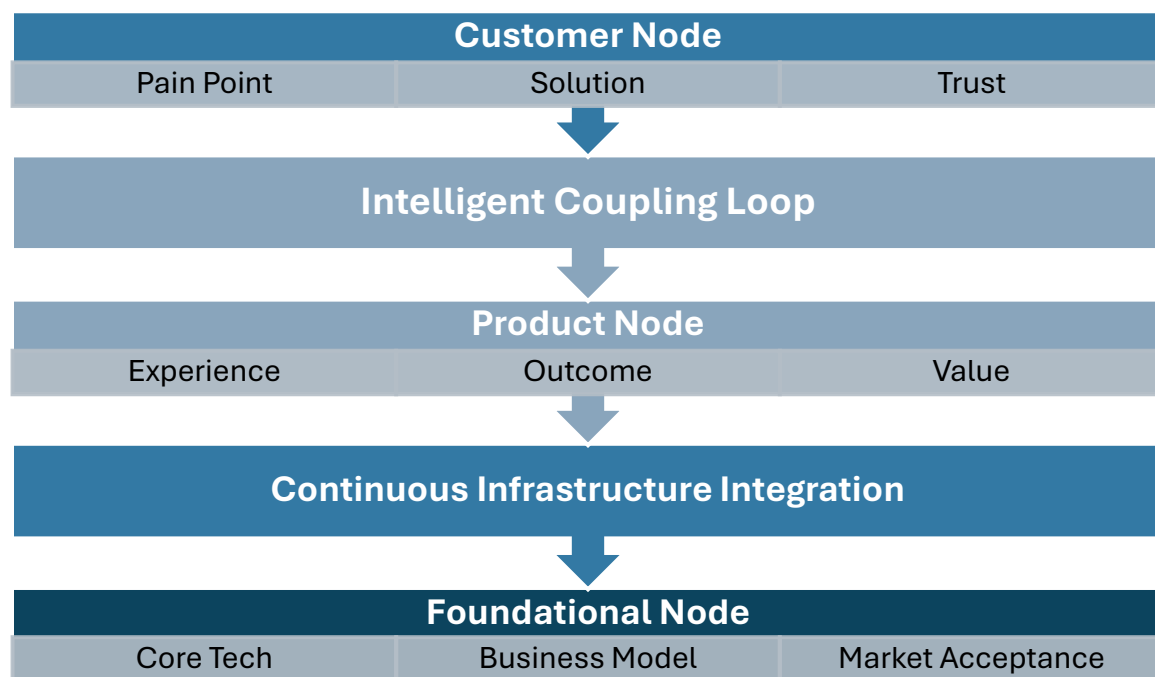


Figure 3: Product Value Proposition (PVP) Framework (Theoretical Approach)

Figure 3 maps this conceptual evolution, illustrating how raw operational insights from our field cases build the theoretical foundation of our model.

Data Analysis and Gioia Data Structure

Following the inductive-deductive qualitative protocol developed by Gioia et al. (2013), qualitative transcriptions and architectural artifacts were systematically coded. First-order informant concepts were extracted using line-by-line coding. These were subsequently

distilled into second-order theoretical themes and ultimately synthesized into three overarching aggregate dimensions that form the core of the Product Value Proposition (PVP) Framework.

Our data analysis transitioned systematically through three levels of abstraction:

1st-Order Concepts: Highly descriptive, informant-centric codes using the raw vocabulary of our 21 technology-intensive cases.

1st order Gioia Methodology Data Structure & Theoretical Pathways

Gioia Data Structure

1st-Order Concepts (Raw Informant Data & Empirical Statements)	2nd-Order Themes	Aggregate Dimensions
<ul style="list-style-type: none">"We can prototype new UI features in days, but refactoring underlying database schemas requires months of downtime.""API-first microservices allow rapid experimentation without breaking core database integrity."	Architectural Elasticity vs. Monolithic Rigidity	Infrastructure Precedence & Elasticity

<ul style="list-style-type: none"> • "Legacy back-end coupling creates severe release bottlenecks whenever market requirements shift." • "High user adoption of new AI features causes severe system latency because legacy infrastructure cannot scale elastically." 	Systemic Coupling & Technical Bottlenecks	
<ul style="list-style-type: none"> • "Customer feedback velocity (ΔC) moves significantly faster than our core technical adaptation speed (ΔT_{core})." • "Engineering teams spend 80% of their bandwidth managing technical debt rather than shipping user-requested value." 	Divergent Iteration Velocities	Architecturally Induced Innovation Latency (Λ_{latency})

<ul style="list-style-type: none"> • "Rapid front-end pivots without back-end updates cause operational friction and user churn." • "Features get deployed quickly, but poor back-end execution destroys user trust over time." 	Sociotechnical Friction & Execution Breakdown	
<ul style="list-style-type: none"> • "Market acceptance (<i>MA</i>) drops when back-end reliability fails to match customer solution expectations." • "Pivoting value propositions requires simultaneous updates across customer pain points, product outcomes, and API layers." 	Trinode Reconfiguration (Customer, Product, Foundation)	Systemic Coupling for Sustained PMF

<ul style="list-style-type: none">• "Product-market fit (<i>PMF</i>) breaks down as soon as core technology (T_{core}) fails to support scaling demands."• "Durable advantage derives from low-latency, adaptive infrastructure rather than easily copied front-end features."	Structural Alignment for Continuous Adaptation	
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Theoretical Pathways (Causal Mechanisms)

Pathway 1: Emergence of Innovation Latency (Λ_{latency})

Market sensing accelerates user iteration (ΔC) → Triggers back-end schema and database locks (ΔT_{core}) → Accumulates sociotechnical friction → Results in **Architecturally Induced Innovation Latency**.

Pathway 2: Moderated Market Acceptance (*MA*)

Product Node configuration (P) × Foundational Node core technology elasticity (T_{core}) → Reciprocal node alignment → Drives **Market Acceptance (*MA*) and Sustained PMF**.

Pathway 3: Strategic Reconfiguration

Generative AI commoditizes front-end features → Strategic scarcity shifts to back-end architecture → Adaptive infrastructure deployment → Establishes **Durable Dynamic Capability**.

2nd-Order Themes: Researcher-induced theoretical categorizations that synthesize the commonalities among 1st-order concepts.

2nd order Gioia Methodology Data Structure & Theoretical Pathways

2nd-Order Theme	Empirical Trigger & Operational Mechanism	Derived Aggregate Dimension
Architectural Elasticity vs. Monolithic Rigidity	Decoupled microservice architectures enable user-facing testing without schema disruption, whereas monolithic dependencies lock database updates.	Infrastructure Precedence & Elasticity
Systemic Coupling & Technical Bottlenecks	Rapid user adoption of front-end capabilities triggers unhandled backend latency and performance degradation.	Infrastructure Precedence & Elasticity

Divergent Iteration Velocities	User feature feedback loops (ΔC) systematically outpace backend refactoring capacity (ΔT_{core}).	Architecturally Induced Innovation Latency (Λ_{latency})
Sociotechnical Friction & Execution Breakdown	Premature front-end pivots without concurrent backend restructuring generate technical debt and user churn.	Architecturally Induced Innovation Latency (Λ_{latency})
Trinode Reconfiguration	Achieving product–market fit requires continuous, synchronized alignment across Customer, Product, and Foundational nodes.	Systemic Coupling for Sustained PMF
Structural Alignment for Continuous Adaptation	Back-end infrastructure capabilities bound organizational capacity to absorb and scale generative AI and cloud innovations.	Systemic Coupling for Sustained PMF

Theoretical Pathways & Causal Mechanisms

- **Pathway 1: Latency Accumulation Mechanism**

High Market Sensing Velocity (ΔC) → Unsynchronized Core Architectural Adaptation (ΔT_{core})

→ Backend Schema Locks & Technical Debt → **Architecturally Induced Innovation**

Latency (Λ_{latency}).

- **Pathway 2: Moderated Market Acceptance Mechanism**

Product Node Configurations (P) $\times$ Foundational Core Elasticity (T_{core}) $\rightarrow$ Trinode

Reciprocal Coupling $\rightarrow$ **Sustained Market Acceptance (MA) & PMF.**

- **Pathway 3: Dynamic Capabilities Reconfiguration Mechanism**

Interface Feature Commoditization (Generative AI) $\rightarrow$ Shift to Back-End Orchestration

Scarcity $\rightarrow$ Structural Architectural Elasticity $\rightarrow$ **Durable Competitive Advantage.**

Aggregate Dimensions: The highest level of abstraction, corresponding directly to the core structural elements and dynamic pathways of the PVP Framework.

Figure 3 maps this conceptual evolution, illustrating how raw operational insights from our field cases build the theoretical foundation of our model.

Trustworthiness and Theoretical Saturation

Methodological rigour was addressed across four quality dimensions. Construct validity was strengthened through triangulation and member checking; internal validity through pattern matching, explanation building, and systematic consideration of rival explanations; external validity through replication logic across cases, targeting analytical rather than statistical generalisation; and reliability through a formal case study protocol and comprehensive audit trail. Theoretical saturation was assessed at both construct and mechanism levels, with dual confirmation-no emergent constructs and consistent cross-case mechanism recurrence-strengthening confidence in the framework's robustness.

Methodological Contributions

Beyond its instrumental role in framework development, the methodology constitutes an independent contribution to innovation research. The integration of critical realism, multiple-case analysis, and sociotechnical theory offers a replicable template for investigating infrastructural phenomena that resist direct observation through conventional quantitative measures. In this regard, the methodological design is not merely a vehicle for evaluating the PVP Framework but an integral component of the broader effort to establish Infrastructure-Centric Innovation Theory as a legitimate and distinctive domain within innovation management scholarship.

6. Findings and Cross-Case Analysis

Summary: Overview of Findings

Research Objective and Data Foundation

The study sought to examine how technological infrastructure influences value creation, adaptive capacity, and the achievement of sustainable product–market fit within technology-intensive environments. Findings were derived from a comprehensive multi-source dataset comprising twenty-one semi-structured interviews, internal organisational documents, technical architecture records, product development artefacts, and market validation data a breadth of evidence that enabled robust triangulation across cases.

Emergent Higher-Order Mechanisms

Analysis revealed three higher-order mechanisms recurring consistently across all cases: Architectural Elasticity, Architecturally Induced Innovation Latency, and Systemic Coupling. Critically, these mechanisms were observed across fintech, SaaS, and artificial intelligence contexts despite substantial variation in organisational size, market focus, and technological maturity. The recurrence of identical mechanisms across such heterogeneous environments is theoretically significant, suggesting the existence of underlying sociotechnical processes that transcend industry-specific conditions and operate as generalisable determinants of innovation performance.

The Interactional Nature of Innovation Outcomes

A further finding of theoretical consequence is that innovation outcomes were rarely attributable to any single organisational capability. Success and failure consistently emerged from the quality of interaction among four interdependent domains: customer understanding, product development processes, technological architecture, and market feedback systems. This pattern provides direct empirical support for the PVP Framework's foundational proposition that sustainable product–market fit is an emergent property of systemic coupling rather than the product of isolated organisational strengths and reinforces the framework's positioning of infrastructural capability as a constitutive, rather than peripheral, determinant of adaptive innovation performance.

Architectural Elasticity as a Determinant of Adaptive Capacity

Across all cases, the ability to respond effectively to changing market conditions was strongly influenced by the flexibility of the underlying technological architecture.

Organizations exhibiting highly modular, interoperable, and scalable infrastructures consistently demonstrated greater responsiveness to evolving customer requirements than organizations operating with tightly coupled systems.

Interview participants frequently described situations in which customer feedback identified opportunities for product improvement. However, the speed at which these opportunities could be translated into implemented solutions varied substantially.

One product leader noted: “The challenge was never understanding what customers wanted. I knew exactly what needed to be built. The challenge was that every change required modifications across multiple interconnected systems.”

Similarly, an engineering executive explained:

“Our architecture determines our innovation speed. Customer requests are rarely the bottleneck. Infrastructure complexity is.”

These observations were particularly pronounced in organizations operating legacy systems. Product teams often demonstrated strong customer insight capabilities but experienced prolonged implementation cycles due to architectural dependencies.

Conversely, organizations operating modular architecture consistently exhibited shorter adaptation cycles. API-driven infrastructures, microservice architectures, and automated deployment environments enabled rapid implementation of new features and market-driven modifications.

Cross-case comparison therefore revealed a recurring relationship between architectural flexibility and adaptive responsiveness. The findings suggest that architectural elasticity functions as a foundational capability enabling organizations to convert market intelligence into operational change.

This observation supports the theoretical proposition that adaptive capacity is not solely an organizational characteristic but is substantially conditioned by the architecture through which adaptation occurs.

The Emergence of Architecturally Induced Innovation Latency

A second and particularly significant finding concerns the emergence of delays between market sensing and adaptive response.

Across all cases, organizations demonstrated the ability to identify customer needs, monitor market signals, and generate actionable insights. However, substantial variation existed in the speed with which those insights were translated into implemented innovations.

Traditional explanations would attribute such delays to resource constraints, leadership failures, organizational inertia, or strategic uncertainty. The evidence revealed an additional

mechanism. Numerous participants described circumstances in which adaptation delays emerged despite organizational willingness to respond.

One founder explained: “We were collecting customer feedback continuously. The issue was not knowing what to do. The issue was that implementing the changes would require rebuilding critical components.”

Another participant described a similar situation: “By the time we finished implementing one improvement, market expectations had already moved again.”

These observations suggest that adaptation delays frequently originated within the architecture itself rather than within managerial decision-making processes.

Cross-case analysis revealed three recurring sources of innovation latency:

Structural Dependency

Changes in one component required extensive modifications across multiple dependent systems.

Technical Debt Accumulation

Historical development decisions constrained future adaptation options.

Integration Friction

External and internal system integrations increased implementation complexity and reduced responsiveness. Together, these factors created temporal gaps between insight generation and adaptive response.

The findings indicate that innovation latency is not merely an operational challenge but a distinct sociotechnical phenomenon with significant implications for innovation outcomes.

Organizations experiencing high levels of innovation latency consistently demonstrated weaker market responsiveness, slower product evolution, and lower adaptation velocity.

These findings provide empirical support for the concept of Architecturally Induced Innovation Latency.

Market Validation as a Driver of Architectural Evolution

A third pattern emerging from the data concerns the role of market validation.

Existing innovation frameworks frequently conceptualize validation as a mechanism for confirming assumptions regarding customer needs or product effectiveness.

The present findings suggest a broader function. Across all cases, validation processes not only informed product decisions but also triggered architectural change.

Participants repeatedly described situations in which market feedback revealed limitations within existing infrastructures.

One engineering leader noted: “The most valuable feedback we received was not about features. It was about where our architecture was preventing us from delivering what customers expected.”

Similarly, a product executive explained: “Customer feedback often forces architectural decisions. We do not redesign infrastructure because engineers want to. We redesign

infrastructure because customers demand capabilities that existing systems cannot support.”

These observations suggest that market validation operates as a recursive mechanism influencing not only customer understanding and product design but also infrastructure development. Consequently, validation appears to function as an evolutionary force shaping the technological architecture of innovation systems.

This finding extends traditional interpretations of validation by positioning it as a driver of sociotechnical adaptation rather than merely a tool for customer discovery.

Systemic Coupling across the Product, Customer, and Foundational Nodes

Cross-case comparison reveals that sustainable product–market fit is achieved only when there is high-velocity, reciprocal alignment across the three core groupings of the PVP diagram: the Customer Node (*Pain Point, Solution, Trust*), the Product Node (*Outcome, Value Created, Experience*), and the Foundational Node (*Market Acceptance, Business Model, Core Technology*).

The AI technology revolution makes this systemic coupling highly visible. In cases where firms attempted to scale AI features without adapting their Core Technology (e.g., relying on rigid, legacy databases prone to severe performance bottlenecks rather than cloud-native, scalable databases), the mismatch between the promised Product Outcome and infrastructural reality caused rapid customer churn.

Conversely, ventures that maintained tight coupling where customer Pain Points informed rapid updates to the Core Technology base, which instantly unlocked superior Value Created demonstrated exponential scaling and sustained Market Acceptance. This proves that Product-Market Fit is a dynamic, sociotechnical state governed by the continuous flow of data and intelligence across all nodes of the PVP framework.

Cross-Case Comparison

Overarching Pattern

Comparative analysis across cases yielded a consistent and theoretically significant pattern: organisational innovation performance was systematically differentiated by architectural elasticity, innovation latency, and the degree of systemic coupling—rather than by sectoral context, organisational scale, or technological maturity alone. The cross-case consistency of these observations substantially strengthens confidence in the explanatory relevance of the mechanisms proposed by the PVP Framework.

Architectural Elasticity and Innovation Performance

Organisations characterised by high architectural elasticity demonstrated a coherent cluster of performance advantages: accelerated implementation cycles, greater adaptation velocity, stronger customer retention, and more sustainable product–market fit. These outcomes collectively suggest that infrastructural flexibility functions as a systemic

enabler-translating strategic intent and customer intelligence into adaptive value outcomes with materially lower friction and latency.

Architecturally Induced Innovation Latency

Conversely, organisations exhibiting high innovation latency displayed slower market responsiveness, reduced adaptive capacity, escalating implementation costs, and increasing difficulty sustaining competitive advantage over time. This pattern provides empirical corroboration for the theoretical construct of Architecturally Induced Innovation Latency, demonstrating that infrastructural rigidity operates as an independent constraint upon innovation performance-one that persists irrespective of the quality of customer insight or strategic capability available to the organisation.

Systemic Coupling as the Primary Differentiator

Most consequentially, organisations exhibiting strong systemic coupling characterised by tight, dynamic alignment among customer insight generation, product development, technological capability, and market validation-consistently outperformed those displaying fragmented relationships among these constructs. This finding constitutes the most theoretically significant outcome of the cross-case comparison, providing empirical grounding for the PVP Framework's central proposition: that sustainable product-market fit

is an emergent property of systemic coupling rather than a function of any single organisational capability or market condition.

Theoretical Significance

The cross-case comparison advances the empirical foundations of Infrastructure-Centric Innovation Theory by demonstrating that the three proposed mechanisms-Architectural Elasticity, Architecturally Induced Innovation Latency, and Systemic Coupling-operate with sufficient consistency across heterogeneous organisational contexts to warrant their treatment as generalisable explanatory constructs. The findings thereby support the transition of the PVP Framework from an emergent theoretical proposition toward an empirically grounded model of value creation and adaptive performance in technology-intensive environments.

Emergent Theoretical Model

Taken together, the findings suggest that sustainable innovation outcomes emerge through a process fundamentally different from that implied by existing customer-centric frameworks.

The evidence indicates that customer understanding remains necessary but insufficient for achieving sustainable product-market fit.

Instead, product–market fit appears to emerge through a sociotechnical process governed by three interrelated mechanisms.

First, Architectural Elasticity determines the capacity of organizations to respond to environmental change.

Second, Architecturally Induced Innovation Latency constrains the speed at which adaptation can occur.

Third, Systemic Coupling determines whether customer insight, product development, technological infrastructure, and market feedback function as an integrated adaptive system.

The interaction among these mechanisms provides the empirical foundation for Infrastructure-Centric Innovation Theory.

The findings therefore support the central argument of this study: technological infrastructure is not merely a mechanism for delivering value but a fundamental determinant of the capacity to create, adapt, and sustain value in contemporary digital environments.

7. Discussion

Reframing Product–Market Fit in the Age of Intelligent Infrastructure

The primary objective of this study was to investigate how technological infrastructure influences value creation, adaptive capacity, and sustainable product–market fit in technology-intensive environments. The findings reveal that existing explanations rooted in customer discovery, experimentation, and organizational adaptation provide important but incomplete accounts of innovation success.

Across all cases, sustainable innovation outcomes were not explained solely by the quality of customer insight, the sophistication of experimentation processes, or the strength of organizational capabilities. Rather, innovation performance emerged from the interaction among customer understanding, product experience, technological architecture, and market validation. More specifically, the findings demonstrate that technological infrastructure functions not merely as a delivery mechanism but as a foundational determinant of adaptive capacity.

This observation challenges a deeply embedded assumption within innovation scholarship. For decades, dominant frameworks have implicitly treated value creation as a process that begins with customer needs and ends with product delivery. Technology has largely been positioned as a supporting mechanism responsible for implementing value propositions developed elsewhere.

The evidence presented in this study suggests that such a view is increasingly insufficient.

In contemporary digital environments characterized by artificial intelligence, cloud-native architectures, platform ecosystems, autonomous agents, and software-defined enterprises, technological infrastructure increasingly determines what forms of value can be created, delivered, adapted, and sustained. Consequently, product–market fit should no longer be understood as a static alignment between products and customer needs. Instead, it should be conceptualized as a dynamic state of sociotechnical equilibrium maintained through continuous interactions among human and technological subsystems. This reconceptualization represents a significant departure from existing innovation theories and provides the foundation for Infrastructure-Centric Innovation Theory.

Theoretical Contributions to Innovation Management Literature

The findings generate four major theoretical contributions.

Contribution 1: Identification of Architectural Blindness as a Foundational Limitation in Innovation Theory

The first contribution concerns the identification of architectural blindness.

The literature review showed that customer-centric, experimentation-centric, and capability-centric theories collectively advanced understanding of innovation while simultaneously marginalizing the role of technological architecture.

The empirical findings provide evidence that this omission is not merely conceptual but theoretically consequential. Organizations often possessed accurate customer insight, sophisticated validation processes, and substantial organizational capabilities.

Nevertheless, innovation performance varied significantly based upon the characteristics of the underlying technological architecture. These observations suggest that existing theories systematically underestimate the influence of infrastructure on innovation outcomes.

By identifying architectural blindness as a recurring limitation across dominant frameworks, this study contributes a novel explanation for why organizations often fail despite owning many of the capabilities traditionally associated with innovation success. Importantly, architectural blindness is not presented as an empirical anomaly but as a theoretical omission embedded within the dominant assumptions of innovation scholarship.

Contribution 2: Elevating Technological Capability from Resource to Constitutive Construct

The second contribution concerns the theoretical status of technology within innovation research. Existing frameworks generally treat technology as a resource, tool, capability, or implementation mechanism.

The findings suggest a different interpretation. Technological capability consistently appeared as a determinant of the feasibility, scalability, and adaptability of value propositions themselves. In many cases, market opportunities were constrained not by customer demand but by architectural limitations.

This observation implies that technology should not be conceptualized merely as a means of delivering value. Rather, technological capability is an endogenous part of value creation.

The Product Value Proposition Framework therefore advances a more expansive conception of technological capability by positioning it as one of the core constructs through which product–market fit appears. This shift has important implications for future innovation research because it redefines the role of architecture from operational infrastructure to strategic determinant.

Contribution 3: Introducing Architecturally Induced Innovation Latency as a Novel Explanatory Mechanism

The third contribution concerns the introduction of Architecturally Induced Innovation Latency. Innovation research has traditionally explained adaptation delays through organizational inertia, resource scarcity, cognitive rigidities, leadership failures, or environmental uncertainty. While these explanations remain valuable, the findings suggest that adaptation delays often originate from technological architecture themselves.

The concept of architecturally induced innovation latency extends existing innovation theory by finding a previously under-theorized mechanism connecting technological architecture and adaptive performance.

This mechanism is particularly important because it explains why organizations having strong customer understanding may nevertheless struggle to respond effectively to

changing market conditions. The concept therefore contributes to a more nuanced understanding of innovation failure and offers a theoretical bridge between digital infrastructure research and innovation management scholarship.

Contribution 4: Reconceptualizing Product–Market Fit as Sociotechnical Coupling

The fourth and most significant contribution concerns the reconceptualization of product–market fit. Existing frameworks typically treat product–market fit as an outcome generated through customer discovery, experimentation, or strategic adaptation.

The findings suggest a more complex process. Organizations achieved sustainable product–market fit only when User Insight, Product Experience, Technological Capability, and Market Validation functioned as a tightly integrated system.

Accordingly, product–market fit appears to emerge from systemic coupling rather than from any individual organizational capability. This perspective extends Sociotechnical Systems Theory by specifying the mechanisms through which social and technical subsystems jointly generate innovation outcomes.

The resulting framework provides a richer explanation of value creation in digital environments and shifts scholarly attention from individual capabilities toward system-level interactions.

Why Existing Innovation Frameworks Become Increasingly Incomplete in the AI Economy

A central implication of this study concerns the changing relevance of traditional innovation frameworks in the context of artificial intelligence.

Frameworks such as Value Proposition Design, Design Thinking, Lean Startup, and Jobs-to-Be-Done emerged during periods in which software development remained expensive, specialized, and relatively constrained. Under such conditions, customer discovery and validated learning represented the primary bottlenecks to innovation.

The emergence of generative artificial intelligence fundamentally alters these assumptions.

Today, software interfaces can be generated automatically. Application logic can be written through natural language prompts. Autonomous agents can execute workflows, analyze data, generate content, and orchestrate business processes with minimal human intervention. Vibe-coding platforms increasingly allow non-technical actors to build functional applications through conversational interaction. As the cost of software, production approaches zero, the locus of scarcity shifts.

The critical constraint is no longer software creation itself. The critical constraint becomes infrastructure orchestration. Organizations must manage data architecture, model governance, API ecosystems, interoperability standards, security frameworks, compliance requirements, computational resources, and adaptive deployment environments.

Autonomous agents can execute workflows, reshaping how technical capabilities influences global user bases (Cuéllar et al., 2024)

Consequently, the central challenge of innovation is no longer discovering what customers want. Increasingly, the challenge is developing infrastructures capable of continuously adapting to what customers want. This distinction is fundamental.

Traditional frameworks remain highly effective for understanding customer behavior and validating assumptions. However, they provide limited theoretical guidance regarding the infrastructural conditions required to operationalize adaptation at machine speed.

The findings therefore suggest that the emergence of AI-native organizations requires a corresponding evolution in innovation theory.

PVP as an Infrastructure-Centric Theory for the AI Industrial Revolution

As modern platforms scale, infrastructure governance directly mediates macro-economic and operational outcomes (Pellegrino & Stasi, 2024). The AI revolution is often described as a software revolution. The findings of this study suggest a different interpretation. The defining characteristic of the AI era is not software intelligence alone but infrastructure intelligence.

Large language models, autonomous agents, machine-learning systems, digital twins, algorithmic decision systems, and generative platforms derive value not merely from their algorithms but from the infrastructures through which they are deployed, governed, integrated, monitored, and continuously improved.

This observation positions the Product Value Proposition Framework within a broader historical trajectory of economic transformation.

During the industrial revolution, competitive advantage depended primarily upon manufacturing infrastructure. During the information revolution, competitive advantage increasingly depended upon information infrastructure. During the platform revolution, competitive advantage shifted toward network infrastructure, compute scalability, and local data center ecosystems (Alvarez et al., 2026). During the AI revolution, competitive advantage increasingly depended upon adaptive infrastructure.

The Product Value Proposition Framework directly addresses this transition.

Unlike previous frameworks that focus primarily on customers, products, or organizations, PVP centers analysis on the adaptive infrastructures that enable continuous value creation. This distinction explains why the framework exhibits greater explanatory power in contemporary AI-intensive environments.

Organizations competing within AI ecosystems succeed not because they possess superior products alone but because they possess infrastructures capable of generating, modifying, and scaling products continuously. PVP therefore aligns closely with the realities of AI-native competition.

Toward a Fourth Generation of Technology and Innovation Management Theory

This study positions **Infrastructure-Centric Innovation Theory** as a natural evolutionary step within technology and innovation management scholarship. We categorize TIM theoretical development across four distinct generations:

Generation	Dominant Paradigm	Core Locus of Innovation	Key Theoretical Limit Addressed by PVP Framework
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1st Gen	Customer-Centric (Levitt, 1960; Christensen et al., 2016)	User Needs & Problem Discovery	Abstracts away technical feasibility and infrastructure execution.
2nd Gen	Experimentation-Centric (Ries, 2011; Beck et al., 2001)	Learning Velocity & Prototyping	Assumes codebases and architecture are infinitely elastic during pivots.
3rd Gen	Capability-Centric (Teece et al., 1997; Teece, 2018)	Organizational Reconfiguration	Agnostic regarding the physical/digital system substrate enabling execution.
4th Gen	Infrastructure-Centric (This Study)	Architectural Elasticity & Systemic Coupling	Integrates back-end architecture directly as an endogenous determinant of value.

By synthesizing these paradigms, Infrastructure-Centric Innovation Theory does not displace existing TIM literature but provides the missing execution layer necessary for theories like Dynamic Capabilities to operate in software-defined, AI-driven environments. As automated code generation and AI models commoditize software production, the locus of scarcity shifts from software creation to infrastructure orchestration. The central challenge of innovation is no longer discovering what customers want, but developing infrastructures capable of continuously adapting to what customers want.

A Revised Theory of Competitive Advantage

Competition occurs at the infrastructural level. Products can be replicated, features can be copied, and interfaces can be easily imitated. Even sophisticated software capabilities can

increasingly be reproduced at near-zero marginal cost through generative AI and automated code synthesis. Adaptive infrastructure, however, remains considerably more difficult to replicate. The ability to integrate intelligence, data governance, system elasticity, security, interoperability, and continuous deployment into a unified, low-latency architecture constitutes a durable dynamic capability that extends far beyond discrete product functionality. Consequently, sustainable competitive advantage in the AI era derives less from what organizations build at the interface layer and more from the underlying technological infrastructures through which they build, learn, adapt, and scale continuously.

8. Implications for Theory, Practice, and Policy

Summary of Theoretical, Managerial, and Policy Implications

Theoretical Implications

The study advances four principal theoretical contributions. First, it challenges the longstanding treatment of technological infrastructure as a contextual background variable, arguing instead for its elevation to a first-order explanatory construct within innovation theory—one that conditions the feasibility, scalability, and sustainability of value propositions. Second, it extends Dynamic Capabilities Theory by identifying architectural capability as a previously under-theorized constraint upon organisational adaptation; firms may possess the sensing and seizing capacities theorized by Teece and colleagues yet remain unable to operationalize strategic responses due to infrastructural rigidity. Third, it

reconceptualizes product–market fit as a dynamic state of sociotechnical coupling-emergent from the simultaneous alignment of customer insight, product experience, technological capability, and market validation-rather than a discrete outcome of customer discovery alone. Fourth, and most broadly, the study positions Infrastructure-Centric Innovation as a distinct and necessary domain of scholarly inquiry, responsive to the growing reality that competitive advantage in the AI economy accrues to organizations capable of orchestrating data architectures, model ecosystems, and intelligent workflows.

Managerial Implications

The findings carry substantive implications across multiple levels of organizational practice. For founders and entrepreneurs, architectural decisions regarding modularity, interoperability, scalability, and data governance must be treated as strategic rather than technical determinations from the earliest stages of venture development; prioritizing short-term product delivery at the expense of architectural flexibility risks embedding structural constraints that limit future adaptive capacity. For product and engineering leaders, the evidence foregrounds the necessity of organizational integration between customer intelligence functions and infrastructure planning, as sustainable innovation emerges when these domains co-evolve rather than operate in silos. For innovation portfolio management, the concept of Architecturally Induced Innovation Latency introduces a material consideration-infrastructure readiness that should be assessed alongside conventional metrics of financial return, strategic alignment, and market opportunity when evaluating and prioritizing investment decisions.

Implications for AI and Digital Infrastructure Strategy

The study identifies a consequential structural shift in the basis of competitive advantages: as generative AI, autonomous coding systems, and low-code platforms progressively commoditize software development, durable differentiation migrates from product capability toward infrastructure orchestration. Future competitive landscapes will increasingly be shaped by the quality of organizations' data architectures, model governance systems, interoperability frameworks, and continuous learning mechanisms. This continuous operational monitoring requires novel frameworks for automated technical auditing and data infrastructure compliance (Waltersdorfer et al., 2024). For AI-native organizations specifically, the central innovation challenge is no longer product development per se but the continuous orchestration of intelligence across integrated adaptive ecosystems-a challenge for which the PVP Framework offers a conceptual model grounded in sociotechnical coupling.

Policy and Ecosystem Implications

The implications of the framework extend to national innovation systems and regulatory governance. Conventional indicators of national innovation capacity-R&D expenditure, startup formation, venture capital deployment-are argued to be insufficient without corresponding assessment of infrastructural readiness. Governments seeking competitiveness within the AI economy must invest in foundational digital public

infrastructure and cloud ecosystems while updating competition policies for AI infrastructure markets (OECD, 2024a, 2024b, 2025). Concurrently, existing regulatory frameworks designed for industrial-era markets are posited as inadequate for governing AI-driven infrastructures that operate across organizational and jurisdictional boundaries; policymakers are therefore urged to reconceptualize digital infrastructure as a strategic societal asset requiring governance commensurate with its systemic importance.

The AI Industrial Revolution

Drawing an analytical parallel with prior transformative epochs-the Industrial Revolution's mechanization of physical labour and the Information Revolution's digitization of knowledge-the study argues that the defining characteristic of the AI era is not intelligence in isolation but *adaptive infrastructure*. Artificial intelligence systems derive transformative value not from algorithms alone but from the infrastructures through which they learn, evolve, and generate outcomes on a scale. The study's central thesis is thereby restated at its broadest register: the future trajectory of innovation will be determined less by what organizations build than by the adaptive infrastructures through which they build, govern, and continuously regenerate value.

9. Limitations and Future Research

Summary of Limitations and Future Research Directions

Methodological Limitations

The study acknowledges two principal methodological constraints. First, its qualitative multiple-case design, while appropriate for theory development, precludes the establishment of statistically verified causal relationships. The proposed constructs therefore constitute theoretically grounded propositions awaiting large-scale quantitative validation. Second, the deliberate focus on fintech, SaaS, and AI-intensive organizations introduces a sampling boundary; the amplified salience of architectural capability within these sectors may not transfer uniformly to digitally peripheral industries such as manufacturing, agriculture, or public administration, necessitating cross-sectoral empirical investigation.

Theoretical Limitations

Two theoretical boundaries are identified. First, the framework's infrastructural focus, though analytically necessary, subordinates potentially co-determinant variables-including organizational culture, leadership cognition, institutional legitimacy, and regulatory context-warranting integrative engagement with organizational behaviour, institutional theory, and strategic management. Second, the precise boundary conditions governing the *Infrastructure Precedence Principle* remain underspecified. Infrastructure is posited to exert greater explanatory force under conditions of high technological complexity, rapid environmental change, and AI-enabled operations, but its relative weight diminishes where physical assets, geographic endowments, or regulatory protections dominate competitive dynamics.

Temporal Limitations

The study was conducted during an active period of technological discontinuity, wherein generative AI, autonomous agents, and programmable infrastructure remain at comparatively early developmental stages. Theoretical constructs derived from transitional phenomena carry inherent instability; the mechanisms identified may evolve substantially as AI ecosystems mature. Longitudinal inquiry is therefore essential both for confirming the stability of the proposed mechanisms and for surfacing emergent dynamics not yet empirically observable.

Future Research Directions

The study advances a structured and multi-layered research agenda:

Quantitative Validation: Operationalization of core constructs-Architectural Elasticity, Innovation Latency, Systemic Coupling, and Adaptive Response Velocity-through validated measurement scales, with structural equation modelling and longitudinal panel analysis to establish causal relationships.

Infrastructure Capability Index (ICI): Development of standardized metrics assessing architectural modularity, interoperability, scalability, data governance maturity, and AI integration capacity to enable comparative analysis across firms, industries, and national systems.

Longitudinal Infrastructure Studies: Examination of infrastructure evolution pathways, technical debt accumulation, architectural renewal, and AI integration trajectories to illuminate the temporal dynamics of adaptive capacity.

Cross-Framework Comparison: Empirical evaluation of the PVP Framework's explanatory and predictive superiority relative to established paradigms-Lean Startup, Jobs-to-BE-Done, Value Proposition Design, and Dynamic Capabilities Theory-particularly within AI-intensive environments.

AI-Native Organizations: Investigation of infrastructure-centric innovation within firms whose operations are fundamentally AI-mediated, likely revealing novel forms of architectural elasticity and systemic coupling.

National Innovation Infrastructure: Extension of the theory to macro-level analysis, encompassing national AI readiness, digital public infrastructure, cross-border data architectures, and sovereign AI ecosystems, thereby contributing to debates on technological competitiveness and digital sovereignty.

Toward a Consolidated Research Agenda

This study concludes by framing Infrastructure-Centric Innovation Theory not as a static or finalized paradigm, but as the foundational architecture for an emergent, cumulative scholarly program. By situating this framework within the historical evolution of innovation scholarship moving sequentially from customer-centric, to experimentation-centric, and ultimately to capability-centric viewpoints this research positions infrastructural intelligence as the definitive frontier for contemporary theory development. The PVP

Framework is presented as a structural scaffold designed to invite rigorous empirical challenges, quantitative scale development, and progressive refinement by the technology management community.

10. Conclusion

Sustaining product–market fit (PMF) in high-velocity, software-defined environments presents an enduring challenge for technology and innovation management (TIM). For decades, dominant frameworks ranging from customer-centric value design and lean experimentation to capability-centric strategic reconfiguration have advanced our understanding of market sensing and opportunity discovery. However, by implicitly treating software codebases and database architectures as infinitely elastic substrates, these paradigms suffer from *architectural blindness*, failing to explain why ventures with superior customer insight frequently experience catastrophic execution delays and user churn.

To resolve this theoretical disconnect, this study introduced Infrastructure-Centric Innovation Theory and operationalized it through the Product Value Proposition (PVP) Framework. Drawing on a critical realist multiple-case analysis of 21 technology-intensive ventures ($N = 21$) across fintech, SaaS, and AI/analytics, we demonstrated that PMF is not a static milestone achieved through customer discovery alone, but an emergent state of *systemic coupling* across Customer, Product, and Foundational Nodes. Specifically, we conceptualized and formalized *Architecturally Induced Innovation Latency* (Λ_{latency}) as a core failure mechanism driven by structural divergence between customer iteration

velocity (ΔC) and core technical adaptation (ΔT_{core}). Our findings confirm that organizational sensing and seizing routines are fundamentally mediated by *Architectural Elasticity*.

As generative AI, natural language programming, and autonomous agent networks commoditize front-end software production, durable competitive advantage shifts away from hyper-imitable product features toward back-end architectural orchestration. By elevating technological infrastructure from a passive delivery utility to a constitutive determinant of value creation, the PVP Framework offers a 4th-generation TIM model. For scholars and practitioners alike, the central insight of this work remains clear: within AI-native economic ecosystems, an organization's adaptive capacity is ultimately bounded not by the speed of market sensing, but by the structural elasticity of the infrastructure through which value is continuously generated, scaled, and sustained.

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12. Appendix

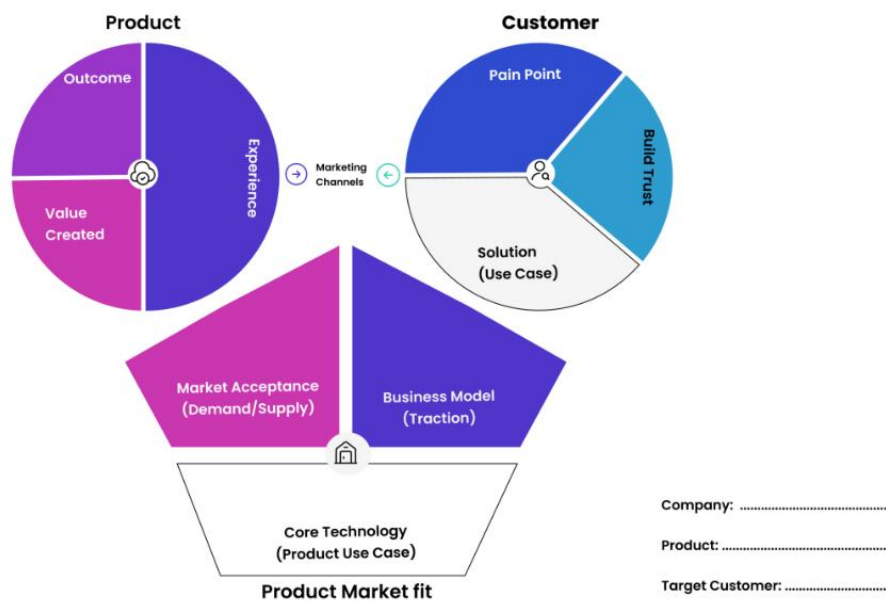


Figure 1: Product Value Proposition (PVP) Framework

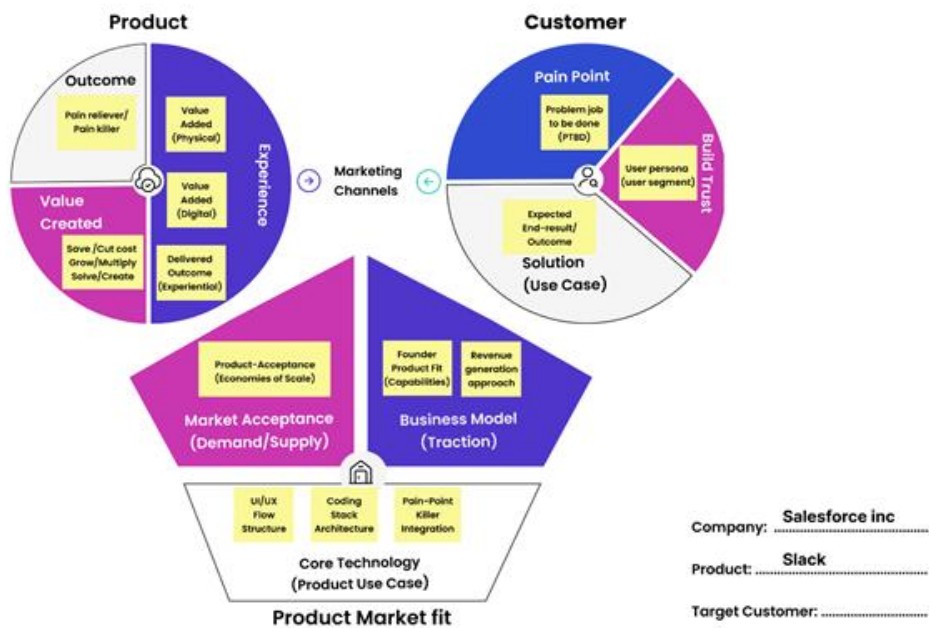


Figure 2: Product Value Proposition (PVP) Framework (Practitioners Approach)

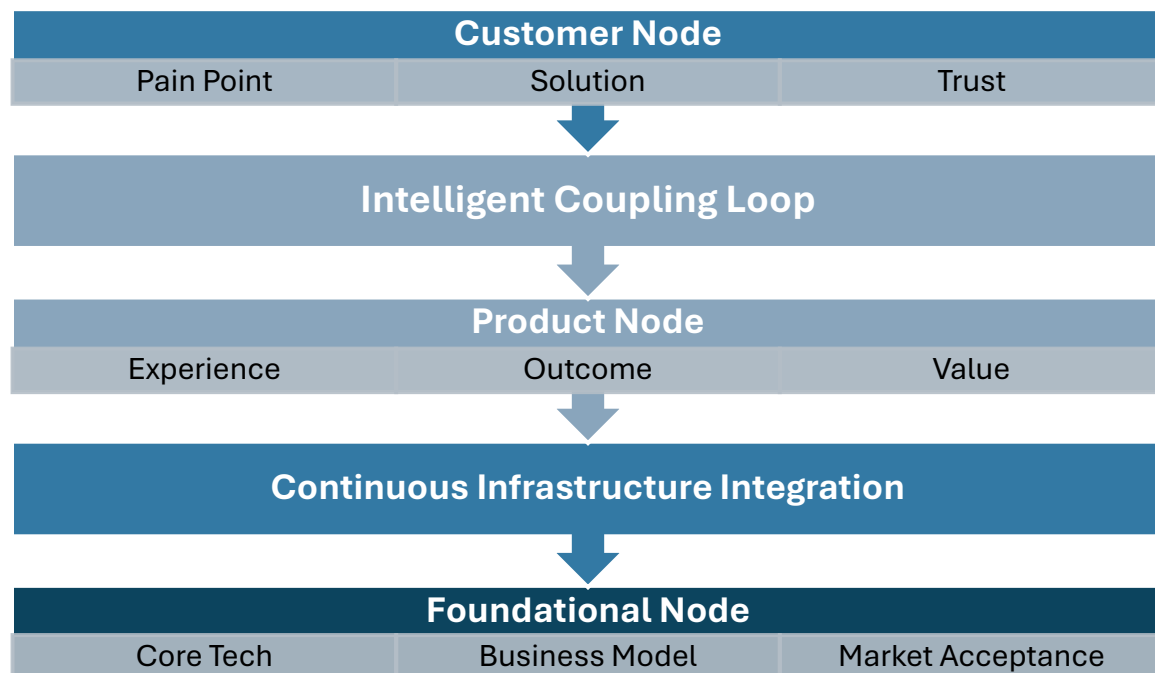


Figure 3: Product Value Proposition (PVP) Framework (Theoretical Approach)

Rather than treating these nodes as static elements on a practitioner canvas, we model their interaction as a structural, path-analytic system. In this model, Core Technology (ΔT_{core}) acts as an endogenous moderating path that controls the conversion rate of front-end product configurations into sustained Market Acceptance (ΔC).