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The Impact of Artificial Intelligence on SaaS Business Models: Strategic Transformation of Traditional SaaS ISVs Toward AI-as-a-Service

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Abstract—**Artificial intelligence is reshaping the economics, architecture, and strategic logic of Software-as-a-Service (SaaS), moving enterprise software from standardized subscription access toward intelligent, adaptive, and outcome-oriented service delivery. This paper examines how AI transforms SaaS business models, focusing on the strategic transition of traditional independent software vendors (ISVs) toward AI-as-a-Service (AIaaS). Using a mixed-method conceptual approach that triangulates academic literature, industry evidence, and comparative transformation patterns, the study develops an integrated framework linking AI capability maturity, business model redesign, responsible AI governance, and organizational capability. Findings indicate that AI creates differentiation through automation, prediction, generative assistance, and decision support, but also introduces risks tied to inference cost, data readiness, explainability, privacy, and accountability. The paper argues that successful AIaaS transformation requires strategic alignment among customer outcomes, data architecture, model operations, revenue design, and governance maturity rather than the simple addition of AI features to an unchanged commercial model. The study contributes a diagnostic framework and a comparative typology of transformation pathways for ISVs seeking to evolve toward responsible, scalable, and economically viable AI-enabled service models.**

Keywords — **Artificial Intelligence, SaaS, AI-as-a-Service, Business Model Transformation, Independent Software Vendors, Dynamic Capabilities, Responsible AI Governance, Platform Ecosystems.**

I. INTRODUCTION

Artificial intelligence is changing SaaS from a standardized application-delivery model into an adaptive service system capable of sensing context, recommending action, and learning from usage patterns [1]. This shift is strategically significant because customer adoption increasingly depends not only on product functionality but on the quality of data pipelines, model governance, and a vendor's capacity to translate intelligence into measurable outcomes. For traditional independent software vendors (ISVs), the change requires moving from feature roadmaps toward capability roadmaps in which analytics, prediction, automation, and human oversight function as connected components of the offering, consistent with the dynamic-capabilities view that competitive advantage stems from a firm's capacity to reconfigure resources rather than from possessing any single resource [2].

The transformation is uneven across sectors: regulated industries, small-business markets, and global enterprise platforms carry different expectations for transparency, auditability, and contractual responsibility. Effectiveness therefore depends on the alignment between technical maturity and business model design — how vendors define value, price usage, manage risk, and demonstrate performance. Traditional ISVs stand to gain strategic advantage by combining domain expertise with responsible AI capability, but risk losing competitiveness if AI is treated as a superficial add-on rather than a redesign of the underlying business model. These dimensions — value-proposition redesign, revenue-model change, technological capability, and governance maturity — recur throughout the analysis that follows and form the basis of the conceptual model developed in Section III.

This gap between adoption and realized value, illustrated in Fig. 1, is the central practical motivation for the study: it is not evidence that AI lacks value for SaaS vendors, but evidence that value realization depends on organizational and business model factors beyond the technology itself — precisely the factors this paper investigates.

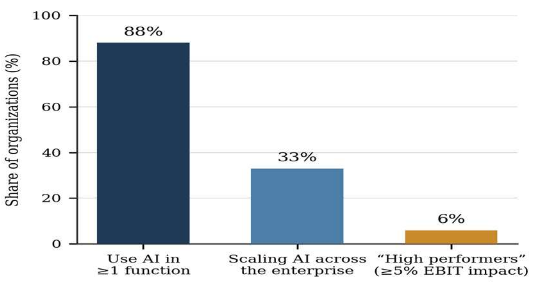

Fig. 1. Enterprise AI adoption narrows sharply at each stage from initial use to scaled, value-generating deployment. Source: McKinsey State of AI, 2025 [18].

A. *Research Aim and Objectives*

The aim of this research is to examine how artificial intelligence transforms SaaS business models and to develop a strategic framework explaining how traditional ISVs can move toward AI-as-a-Service while improving value creation, revenue design, governance, and organizational capability. Five objectives guide the study: (i) to evaluate how AI changes the SaaS value proposition from access to software toward intelligent decision support and outcome enablement; (ii) to analyze how AI affects subscription, usage-based, consumption-based, and outcome-based revenue models; (iii) to examine the technological capabilities required for AI-as-a-Service, including data architecture, model operations, and security controls; (iv) to identify governance, compliance, and trust requirements that shape enterprise adoption; and (v) to propose a strategic transformation framework for traditional ISVs.

B. Research Questions

The central research question is: how can traditional ISVs redesign their SaaS business models to capture value from artificial intelligence while maintaining trust, scalability, economic viability, and responsible governance? Four sub-questions guide the inquiry: how AI capability maturity and data readiness shape a vendor's ability to redesign its value proposition; how responsible AI governance shapes enterprise trust and adoption; how outcome-aligned pricing affects perceived value relative to conventional subscription pricing; and what organizational capabilities allow ISVs to sustain transformation beyond isolated pilots.

C. Significance of the Study

The study is significant across several dimensions. Strategically, it offers traditional ISVs a framework for competing against AI-native entrants without abandoning the domain expertise that remains a source of advantage [3]. Economically, it examines how AI capability translates into monetizable value through pricing, retention, and productivity mechanisms that remain poorly measured in both academic and industry literature [4]. Technologically, it connects data architecture, model operations, and workflow design to business model outcomes rather than treating them as purely engineering concerns [5]. For policy and governance, it examines how emerging frameworks such as the NIST AI Risk Management Framework [6], the OECD AI Principles [7], and UNESCO's ethics recommendation [8] are being operationalized inside commercial SaaS vendors. Societally, it contributes to understanding how AI-enabled SaaS reshapes the division of labor between people and systems [9], [10]. Academically, the study extends dynamic capabilities, business model innovation, and platform strategy theory into the empirical context of AI-as-a-Service, responding to calls for more integrated research connecting AI adoption to firm-level strategic outcomes [11]–[13].

In practice, these dimensions matter most in combination: a vendor with strong technical capability but weak governance evidence may struggle to close enterprise deals, while a vendor with strong governance documentation but limited AI capability may fail to differentiate on outcomes, illustrating why the study treats these dimensions as interacting rather than independent.

The remainder of this paper is organized as follows. Section II reviews the theoretical and empirical literature relevant to AI-enabled SaaS transformation. Section III presents the research methodology, conceptual model, and hypotheses. Section IV reports results and discusses their implications for the study's hypotheses. Section V concludes with a summary of findings, recommendations, and directions for future research.

II. LITERATURE REVIEW

A. Theoretical Foundations

The study draws on four complementary theoretical traditions. SaaS and digital business model theory frames value creation, delivery, and capture as an integrated architecture rather than a technology stack alone [14], [15]. AI is treated as a general-purpose technology whose value depends on complementary organizational investment rather than on the algorithm itself [4]. Dynamic capabilities theory explains how firms sense opportunities, seize them through resource reconfiguration, and transform routines to sustain advantage under changing conditions [2]. Platform ecosystem theory and network-effects literature explain how data and usage feedback loops compound advantage for vendors that successfully aggregate demand and supply across a platform [16], [17]. Together, these traditions support treating AI-as-a-Service as a strategic configuration in which software, data, models, governance, and commercial terms are integrated into a repeatable service proposition, rather than as an isolated technology upgrade.

A resource-based perspective further clarifies why data functions as a strategic asset in this context: proprietary usage data, domain-specific training signal, and customer feedback loops are difficult for competitors to replicate quickly, and their value compounds as products learn from accumulated interaction. This resource-based logic complements the dynamic-capabilities view by explaining not only how firms reconfigure resources, but why data-intensive resources in particular generate a widening rather than a static advantage as AI-enabled products scale.

B. Global Market Perspectives

AI-enabled SaaS adoption follows distinct regional patterns [18], [19]. North American markets lead in enterprise AI platform investment and cloud-native delivery; European markets emphasize regulatory compliance and trust-centered adoption; Asia-Pacific markets combine scale, mobile-first ecosystems, and industrial AI use cases; and the Middle East, Africa, and Latin America show accelerating digital-economy investment alongside localized platform development. These differences shape how vendors sequence AI capability investment relative to governance and localization requirements, reinforcing the need for a framework that is sensitive to context rather than assuming a single global adoption path.

In North America, hyperscale cloud providers and enterprise software incumbents have driven early, capital-intensive investment in foundation-model access and AI platform tooling, giving vendors in this market a head start on technical capability but also exposing them to intense price and feature competition. European adoption has been shaped more strongly by data-protection and AI-specific regulatory requirements, which has slowed feature rollout in some segments but produced more mature governance and documentation practices among vendors that adapted early. Asia-Pacific markets show a distinctive pattern of AI adoption embedded in mobile-first ecosystems, alongside significant industrial and manufacturing AI use cases that differ from the productivity-software focus common elsewhere. Markets across the Middle East, Africa, and Latin America are notable for the pace of digital-economy investment and government-led AI strategy, creating openings for vendors able to combine global AI capability with strong local compliance and language support.

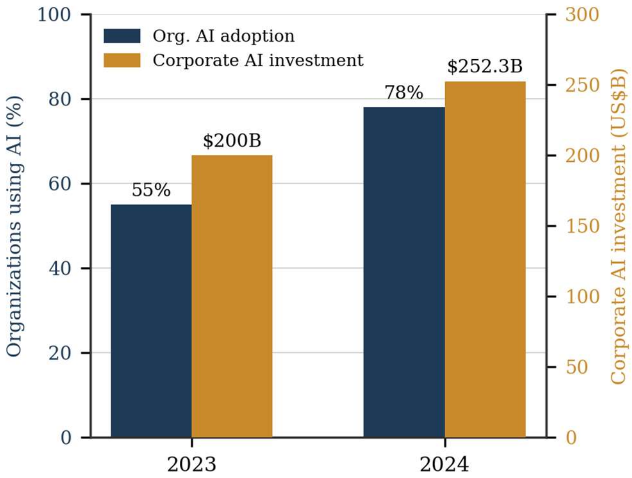

Fig. 2. Organizational AI adoption and global corporate AI investment both accelerated sharply between 2023 and 2024. Source: Stanford HAI AI Index, 2025 [19].

C. Technological Pathways to AI-as-a-Service

Traditional ISVs pursue AI-as-a-Service through several overlapping technological pathways: modernizing data architecture and enterprise integration; establishing machine learning operations (MLOps) and model lifecycle management; embedding generative AI, autonomous agents, and workflow automation directly into products; and extending value through APIs, marketplaces, and embedded AI delivery models [5], [20]. Each pathway carries different capital intensity, time-to-value, and organizational skill requirements, and vendors frequently combine pathways rather than choosing a single technological route.

Vendors modernizing data architecture typically prioritize unifying fragmented operational data into governed, queryable pipelines before layering machine-learning features on top, since model quality is bounded by the quality and completeness of the underlying data. MLOps investment extends this foundation by adding versioning, monitoring, and retraining discipline so that model performance does not silently degrade as usage patterns shift. Generative AI and agentic automation represent a further pathway in which the product itself initiates multi-step actions on a user's behalf rather than only producing recommendations for a human to act on, which raises the stakes for reliability and oversight design.

D. Economic Impacts on SaaS Business Models

AI reshapes SaaS economics along several dimensions. Subscription pricing is giving way to usage-based, consumption-based, and outcome-based structures that more directly reflect the value of intelligent automation [21]. Unit economics become more complex as inference cost, model monitoring, and compute overhead must be incorporated into gross-margin management [4]. Customer lifetime value and retention increasingly depend on demonstrable decision-quality and productivity improvement rather than feature breadth alone, and ecosystem monetization through partner and marketplace channels creates new revenue-sharing considerations [16]. These pricing shifts also change how vendors forecast revenue: usage- and outcome-based models can improve alignment between price and value but introduce greater revenue variability than fixed-seat subscriptions, requiring more sophisticated forecasting and customer-communication practices to maintain predictability for both vendor and buyer. A 2026 survey of software and AI company executives found investors now favor hybrid, outcome-based, and usage-based structures over flat-fee or seat-based pricing by a wide margin, shown in Fig. 3 [32].

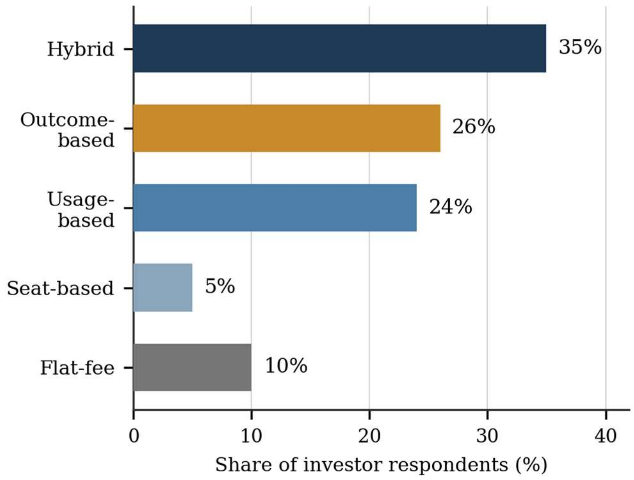

Fig. 3. Investors increasingly prefer hybrid and outcome-aligned pricing over flat-fee or seat-based models. Source: Growth Unhinged / K. Poyar, State of B2B SaaS and AI Monetization, 2026 [32].

E. Governance, Trust, and Risk

Enterprise adoption of AI-enabled SaaS is gated by governance maturity. Model risk, bias, and explainability directly affect procurement decisions in regulated and risk-sensitive sectors [22]. Data privacy, security, and compliance requirements intersect with AI-specific concerns such as training-data provenance and model drift. Responsible AI practice functions increasingly as a trust-building capability rather than a compliance cost, consistent with the direction of established frameworks including the NIST AI Risk Management Framework, the OECD AI Principles, and UNESCO's ethics recommendation [6]–[8].

Vendors that treat governance as a design requirement from the outset — defining who is accountable for a model's output, how that output can be audited, and how customers are notified of material model changes — appear better positioned to clear enterprise procurement review than vendors that add governance documentation only in response to a specific customer request.

F. Organizational Transformation of Traditional ISVs

Sustained AI-as-a-Service transformation requires organizational change beyond technology adoption: cross-functional teams spanning product, engineering, sales, and customer success; product management practices oriented toward continuous customer discovery rather than fixed release cycles; sales and customer-success models built around demonstrated value realization; and culture and change-management capability able to sustain experimentation while protecting reliability and trust [23]. These organizational shifts are frequently the slowest element of transformation to implement, because they require redefining incentive structures, hiring profiles, and internal metrics that were built around a stable, feature-based release cadence rather than a continuously learning product.

G. Research Gap and Conceptual Direction

Existing business model literature treats digital transformation, platform strategy, and responsible AI governance largely as separate streams, with limited integration into a single applied framework for the specific transition from conventional SaaS to AI-as-a-Service [24]. The literature on ISV transformation similarly lacks a comparative typology of transformation pathways that connects strategic intent to operating capability and governance maturity. This study addresses that gap by integrating strategy, technology, and governance constructs into a single conceptual model, developed in Section III.

In particular, existing typologies of digital transformation rarely distinguish between vendors that achieve technical AI maturity without corresponding governance maturity and vendors that achieve both together, even though the evidence in Section IV suggests this distinction is decisive for whether transformation produces durable commercial advantage.

III. RESEARCH METHODOLOGY

A. Research Design

The study adopts a mixed-method conceptual design combining structured literature synthesis, comparative case logic, and interpretation of industry evidence. This approach is appropriate because AI-as-a-Service transformation involves both observable business outcomes and less visible managerial judgment about architecture, governance, and customer value, for which theory-building approaches are more suitable than confirmatory hypothesis testing on a large probability sample [25], [26]. Primary evidence is treated as insight into vendor decision processes, while secondary evidence provides broader context on market shifts, regulatory expectations, and technology patterns. Analysis emphasizes triangulation, comparing strategic coherence, operating capability, and governance maturity rather than relying on a single indicator such as revenue growth or model accuracy.

This triangulated approach also allows the study to distinguish between AI initiatives that generate durable, measurable improvement and those that generate short-term interest without a corresponding change to underlying cost structure, customer retention, or governance maturity — a distinction the findings in Section IV return to repeatedly.

B. Data Collection and Analysis

Data collection combines primary insight from practitioner-facing sources with secondary evidence from academic literature and industry reporting, using purposive rather than probability sampling appropriate to an emerging and unevenly documented phenomenon [27]. Quantitative patterns in adoption, pricing, and productivity indicators are read alongside qualitative evidence of practitioner reasoning, following a convergent mixed-method logic in which findings from different data types are integrated around shared constructs rather than treated as sequential or subordinate strands [28]. Reliability is supported through consistent coding categories linked explicitly to research questions and conceptual constructs; validity is supported by connecting findings to established theory in digital transformation, platform strategy, and dynamic capabilities.

Where primary and secondary evidence diverged, greater weight was given to corroborated patterns appearing across multiple independent sources rather than to any single practitioner account, reducing the risk that isolated anecdote would be mistaken for a general pattern.

C. Conceptual Model

The study's conceptual model integrates four constructs, summarized in Table I and diagrammed in Fig. 4: AI capability maturity, business model redesign, responsible AI governance, and organizational capability. The AI capability maturity construct draws on foundational definitions of intelligent systems [29] and on classic accounts of network effects in platform markets [16], while business model redesign and governance draw on dynamic capabilities theory [2] and responsible AI governance frameworks [6], [22]. The model is structured around interaction rather than addition — AI capability alone does not generate strategic advantage; value emerges only when technical maturity is paired with business model redesign, credible governance, and organizational capability able to sustain change beyond isolated pilots [2].

TABLE 1

Construct	Operational Meaning	Expected Role in Transformation
AI Capability Maturity	Readiness of models, data, MLOps, security, and workflow integration	Improves product intelligence and scalability
Business Model Redesign	Changes in value proposition, pricing, revenue logic, and customer success	Converts AI capability into commercial value
Responsible AI Governance	Controls for explainability, privacy, bias, security, and accountability	Builds enterprise trust and adoption
Organizational Capability	Cross-functional skills across product, engineering, sales, and support	Enables sustained transformation rather than isolated pilots

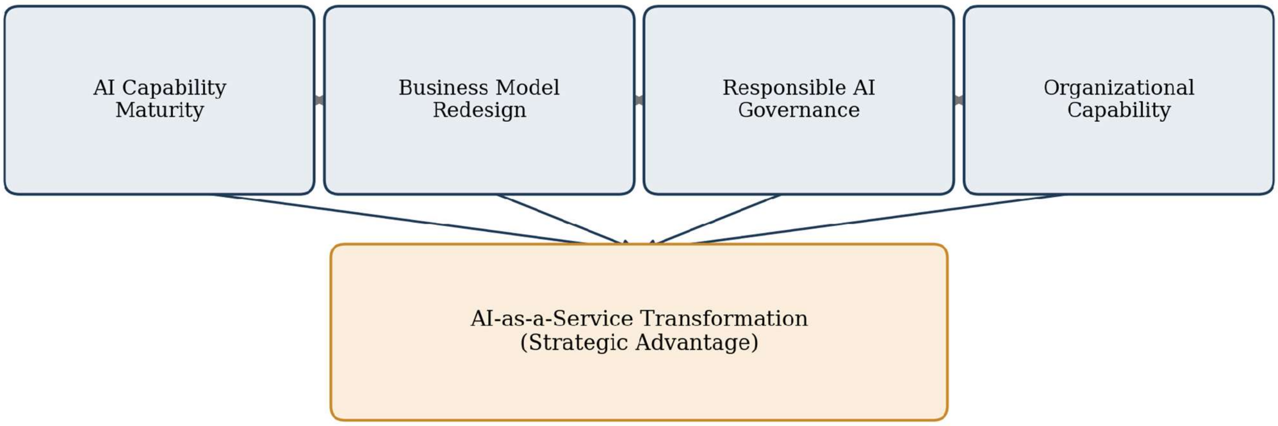

Fig. 4. The four constructs interact rather than add: transformation success requires all four to reinforce one another.

D. Hypothesis Development

Five hypotheses translate the conceptual model into testable propositions, illustrated in Fig. 5: H1, AI capability maturity is positively related to SaaS value-proposition differentiation; H2, data readiness strengthens the relationship between AI capability maturity and customer value realization; H3, responsible AI governance positively moderates enterprise trust in AI-enabled SaaS offerings; H4, outcome-aligned pricing improves perceived value when AI capabilities deliver measurable workflow improvement; and H5, cross-functional operating maturity improves the success of ISV transformation toward AI-as-a-Service. Support for each hypothesis is assessed through convergence of evidence across primary and secondary sources rather than inferential statistical testing, consistent with pattern-matching logic in theory-testing case and mixed-method research [30], [26].

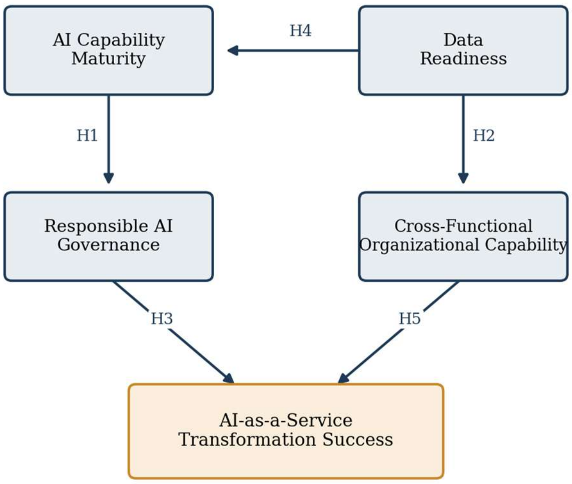

Fig. 5. Hypothesized relationships among the four conceptual-model constructs and transformation success.

E. Ethical Considerations

The study follows standard ethical practice for research involving practitioner insight, including informed consent, confidentiality, and careful, non-attributable use of secondary industry data. Because much of the evidence draws on publicly available industry reporting and non-attributable practitioner insight, particular care was taken to avoid presenting proprietary vendor information in a way that could be traced back to a specific organization or individual.

IV. RESULTS AND DISCUSSION

A. Overview of Findings

Across the evidence examined, AI-as-a-Service functions best as a strategic operating model rather than as an isolated software feature. Vendors that integrate AI into the core value proposition are better positioned than those that attach isolated automation features without changing revenue logic, delivery processes, or customer-success metrics. AI increases the strategic importance of proprietary data, domain expertise, and feedback loops, but these resources generate advantage only when governed, refreshed, and connected to product-learning cycles. Pricing becomes more complex as vendors move from seat-based subscription toward usage, consumption, outcome, or hybrid models, and these models introduce new margin-management challenges tied to inference cost, monitoring, and explainability requirements. For customers, AI-enabled SaaS reduces friction and automates repetitive tasks, but adoption slows when outputs cannot be explained, audited, or aligned with existing business processes.

These patterns held consistently across the vendor evidence examined, regardless of company size or sector, suggesting that the underlying dynamics are structural to AI-enabled SaaS transformation rather than specific to a single market segment.

B. Strategic Transformation Analysis

Strategically, transformation centers on redesigning the value proposition around intelligent decision support rather than static functionality, sharpening competitive differentiation through data network effects, and repositioning the vendor within a broader ecosystem of models, data partners, and workflow platforms. The principal limitation observed is that vendors pursuing AI-native competitive differentiation without corresponding investment in data governance and operating discipline struggle to convert technical capability into durable advantage [3].

Vendors that succeeded in this repositioning typically treated ecosystem participation as a deliberate strategic choice — selecting which models, data partners, and workflow integrations to build around — rather than accumulating integrations opportunistically in response to individual customer requests.

This dynamic is particularly visible in market segments where AI-native entrants compete directly against incumbent ISVs: incumbents that can combine established customer relationships and domain data with credible AI capability tend to defend share more effectively than those competing on AI novelty alone.

C. AI-as-a-Service Capability Analysis

Capability-level findings center on four requirements: data readiness and enterprise integration; model operations and lifecycle control, including monitoring for drift and performance degradation; human-in-the-loop design that preserves oversight for high-stakes decisions; and scalability, reliability, and cost control as usage grows. Vendors lacking data readiness and MLOps maturity remain constrained to isolated pilots regardless of strategic intent, confirming the resource- and capability-based logic underlying the conceptual model [2], [31].

Notably, the vendors furthest along in AI-as-a-Service maturity tended to treat model operations as a permanent operating discipline comparable to security or reliability engineering, with dedicated ownership, rather than as a one-time technical project completed alongside a product launch.

For many traditional ISVs, this requirement is complicated by legacy architecture: monolithic codebases and siloed operational data stores were not designed for the continuous data flow that AI features require, making architecture modernization a prerequisite rather than a parallel workstream.

D. Business Model Performance Analysis

Business-model-level findings show that revenue-model evolution toward usage- and outcome-based pricing improves alignment between price and realized value, but requires new capability in metering, forecasting, and customer communication [21]. Customer value and retention increasingly depend on demonstrated productivity or decision-quality improvement rather than feature novelty. Cost structure and gross margin require active management of inference and compute cost, and sales and customer-success functions must shift toward evidence-based value demonstration rather than feature-led selling.

Vendors that paired new pricing models with clear, quantified before-and-after evidence of customer impact were able to sustain premium pricing more effectively than vendors relying on the novelty of AI features alone.

Sales cycles for AI-enabled capabilities also lengthened in several cases, as enterprise buyers introduced additional technical and governance review steps not previously required for conventional feature releases, a pattern with implications for how vendors forecast bookings and structure sales compensation.

E. Governance and Risk Analysis

Governance-level findings indicate that responsible AI governance functions as a trust-building capability that supports enterprise adoption rather than as a compliance constraint that slows it [6], [22]. Security, privacy, and compliance controls intersect directly with AI-specific risks such as model drift and training-data provenance. Explainability and customer trust are closely linked: enterprise buyers increasingly require auditable reasoning for AI-driven recommendations before scaling deployment, and vendor accountability in procurement processes is becoming an explicit evaluation criterion alongside functional capability.

This pattern was especially pronounced in regulated sectors such as financial services and healthcare, where procurement teams increasingly request documented evidence of model testing, monitoring, and escalation procedures as a condition of purchase rather than as an optional addition.

F. *Comparative Analysis of ISV Transformation Models*

Evidence across vendors suggests four recurring transformation pathways, compared in Table II and positioned in Fig. 6: a feature-embedded model in which AI capabilities are added to existing products without changing pricing or delivery; a platform-extension model in which AI is offered as an extensible layer across an existing product suite; an AI-native reinvention model in which the core product is redesigned around AI-driven workflows; and an outcome-based service model in which pricing and delivery are restructured around measurable customer outcomes. These pathways differ in capital intensity, time-to-value, governance burden, and revenue-model implications, and vendors often progress through more than one pathway as capability matures.

TABLE 2

Model	Value Proposition	Revenue Logic	Governance Burden	Typical Adoption Stage
Feature-Embedded AI	AI added as incremental features to an existing product	Unchanged subscription pricing	Low	Early / pilot
AI Platform Extension	AI offered as an extensible layer across the product suite	Add-on subscription or tiered pricing	Moderate	Scaling
AI-Native Product Reinvention	Core workflows redesigned around AI-driven intelligence	Usage- or hybrid-based pricing	High	Advanced
Outcome-Based AI Service	Delivery and pricing restructured around measurable outcomes	Outcome- or consumption-based pricing	Highest	Mature / differentiated

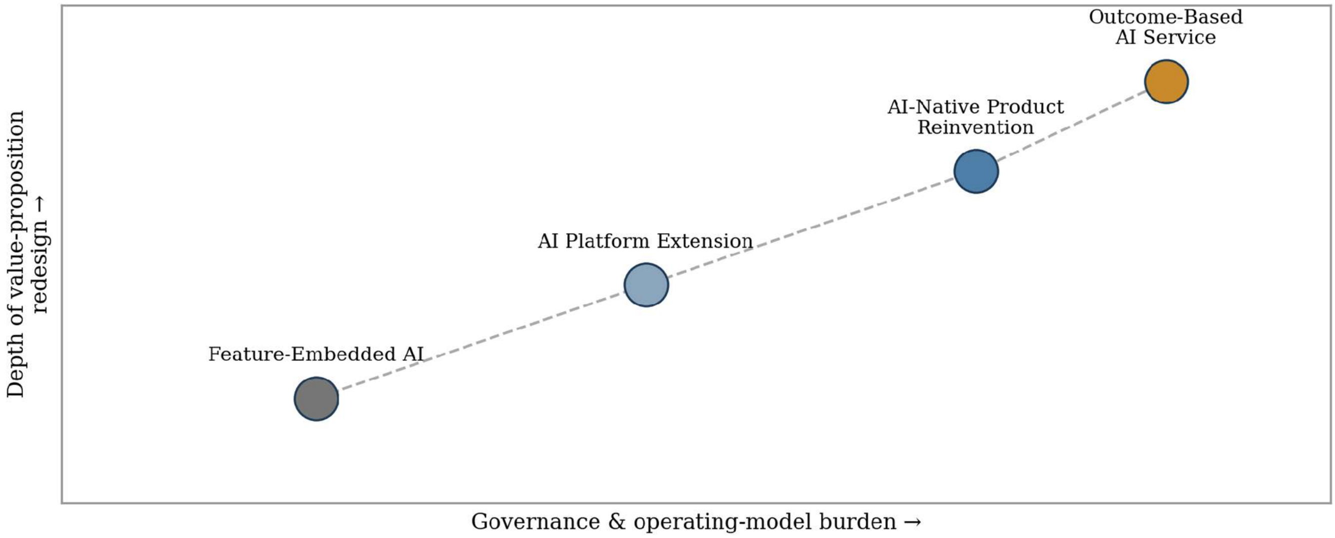

Fig. 6. The four transformation models form a rough progression from incremental, low-governance-burden feature addition toward transformative, high-governance-burden outcome-based delivery.

G. *Discussion of Hypotheses and Implications*

The evidence broadly supports H1 and H2: AI capability maturity is associated with stronger value-proposition differentiation, and this relationship strengthens where data readiness is higher. Support for H3 is strong — responsible AI governance emerges consistently as a precondition for enterprise trust rather than a downstream compliance activity. H4 receives qualified support: outcome-aligned pricing improves perceived value primarily where vendors can demonstrate measurable workflow improvement, but is harder to sustain without mature metering and forecasting capability. H5 is also strongly supported, with cross-functional organizational capability repeatedly identified as the binding constraint separating durable transformation from isolated pilots [1], [2]. Taken together, the findings indicate that successful AI-as-a-Service transformation depends on the interaction of capability, business model redesign, governance, and organizational maturity rather than on any single dimension in isolation.

Where support was weaker, it concerned the pace at which organizational capability could be built relative to the pace of technical experimentation: several vendors reported that pilot-stage AI capability outpaced the cross-functional readiness needed to operationalize it, temporarily widening the gap between demonstrated technical potential and realized commercial value.

H. Managerial Implications

For practitioners, the findings suggest a practical sequencing: establish data readiness and governance baseline capability before scaling customer-facing AI features; instrument every AI capability with a measurable outcome metric before pricing around it; and treat organizational readiness, rather than model performance alone, as the most common constraint on scaling a promising pilot into a durable product line. Vendors that skipped this sequencing by scaling AI features ahead of governance and organizational readiness were, in the evidence reviewed, the most likely to encounter stalled deals, customer trust setbacks, or unsustainable cost structures.

V. CONCLUSION

The findings support the central argument that AI creates sustainable SaaS advantage only when it is embedded in a coherent business model linking data assets, model performance, customer outcomes, and responsible oversight, rather than treated as a marketing layer applied to an unchanged commercial model [2], [3]. Strategically, advantage accrues to vendors that redesign their value proposition around AI rather than those that add AI features to an unchanged model, reinforcing that business model innovation — not technology adoption alone — is the decisive variable in this transition [24]. Economically, AI value must be demonstrated and measured before it can be monetized at premium levels [4], [9]. Technologically, data readiness and MLOps maturity function as gating capabilities that constrain AI initiatives to pilots when absent [2], [31]. On governance, responsible AI practice operates as a trust-building capability rather than an external compliance cost [6]–[8].

This interaction effect is the paper's central contribution: it reframes AI-as-a-Service not as a technology adoption question but as a business model design question, in which capability, commercial architecture, and governance must be sequenced deliberately rather than pursued independently.

Five recommendations follow from these conclusions: traditional ISVs should begin transformation with customer-outcome mapping before selecting AI features or model providers; product leaders should link every AI capability to measurable value, explicit risk controls, and defined human oversight; engineering teams should modernize data architecture and model operations ahead of, rather than alongside, customer-facing AI launches; revenue teams should pilot usage- or outcome-based pricing in bounded segments before broad rollout, paired with clear performance evidence; and boards and executives should establish responsible AI governance as a standing strategic function rather than a compliance afterthought [6], [7].

Taken as a set, these recommendations function as a sequencing guide rather than a checklist to be completed simultaneously, since attempting all five dimensions at once without a clear starting point is itself a common cause of stalled AI initiatives.

The study's principal limitation is its reliance on a purposive rather than probability sample, which limits statistical generalization and is mitigated through triangulation rather than claims of representativeness. Because AI-enabled SaaS transformation is fast-moving, future research should evaluate how AI changes customer lifetime value, revenue predictability, and vendor accountability using longitudinal and comparative designs, and should work toward shared metrics for AI value realization that allow vendor claims to be independently verified [5], [19]. Overall, the study contributes a structured, interaction-based framework for understanding AI-as-a-Service as a managerial, technological, and economic transformation of the global SaaS industry, relevant to software executives, product leaders, investors, regulators, and researchers.

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