From Tool Availability to Adoption Depth: A Provider-Led Enablement Model for Responsible AI/MarTech Use in Emerging Markets

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Abstract

In many Georgian and regional markets, AI/MarTech tools are increasingly available, yet client organizations often fail to convert 'tool access' into sustained, value-producing use. This study develops a theoretical model of the influence of provider-led enablement on adoption depth and them on the outcomes for AI/MarTech deployments, with two key boundary conditions: (1) responsible AI and governance maturity as a trust and risk-management mechanism shaping routinization; and (2) go-to-market context (B2B vs. B2C) as a structural condition influencing success metrics, stakeholder configurations, and value realization pathways. A three-stage mixed-method design is proposed: theory-building case study analysis, survey-based model testing via SEM/PLS-SEM, and a design-oriented pilot to translate results into an evidence-based enablement playbook and competency rubric. Key contributions include a formal conceptualization of enablement intensity and adoption depth, a provider-centered explanation of capability transfer, and theoretically grounded propositions for responsible, scalable adoption in emerging and small-market environments.

Keywords: Provider-led enablement; Adoption depth (post-adoption/infusion); Responsible AI governance

1. Introduction

The proliferation of artificial intelligence (AI) and marketing technology (MarTech) solutions has fundamentally altered the competitive landscape of business across global markets. Yet an observable and consequential gap persists: the gap between the mere availability of advanced tools and the sustained, disciplined, value-generating use of those tools within organizations. This gap is particularly pronounced in emerging and small markets such as Georgia and the broader South Caucasus region, where digital transformation agendas are accelerating but the institutional infrastructure supporting mature technology adoption often remains underdeveloped.

Technology adoption research has generated a rich body of theoretical frameworks, most notably the Technology Acceptance Model (TAM), its successor the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Technology-Organization-Environment (TOE) framework that explains why individuals and organizations form intentions to use new technologies and what factors condition initial uptake. These frameworks have proven remarkably robust across industries and national contexts. However, they share a common limitation: they are predominantly user-side and intention-focused, treating technology deployment as essentially a demand-side phenomenon. The provider side of the adoption equation - the mechanisms through which AI and MarTech vendors actively transfer capability, build client confidence, and engineer the conditions for deep, sustained use - remains theoretically underspecified.

This underspecification is not merely a gap in academic coverage; it has direct practical consequences. AI/MarTech startups operating in Georgian and regional markets frequently encounter a pattern in which clients onboard a new platform with enthusiasm, engage with it superficially for a period of weeks, and then revert to prior workflows or abandon the tool altogether. The failure is rarely attributable to the inadequacy of the technology itself. Rather, it reflects insufficient enablement: the structured, intentional processes by which providers transfer know-how, build client capability, and embed tool use into organizational routines and measurement practices. Understanding and optimizing this enablement process is therefore a central challenge for both practitioners and scholars.

The present study responds to this challenge by developing a formal theoretical model of provider-led enablement and its relationship to adoption depth, a construct defined as the degree to which a technology becomes embedded in, and integral to, an organization's operational workflows, decision-making routines, and performance measurement systems. The model extends existing adoption theory in three important respects. First, it centers the provider as an active agent in the adoption process rather than treating adoption as a purely client-driven phenomenon. Second, it introduces adoption depth as a richer and more practically relevant outcome than binary adoption or simple usage frequency measures. Third, it incorporates two boundary conditions that substantially shape the enablement-to-depth relationship: (a) responsible AI and governance maturity, encompassing dimensions such as transparency, auditability, human oversight, and privacy-by-design; and (b) go-to-market context, specifically the distinction between business-to-business (B2B) and business-to-consumer (B2C) deployment environments.

The research follows a three-stage mixed-method design. An initial theory-building phase employs multiple case study logic to derive and refine the enablement mechanisms and their operational definitions. A subsequent survey-based phase tests the resulting structural model using Structural Equation Modeling (SEM) and Partial Least Squares SEM (PLS-SEM). A final design-oriented phase translates empirical findings into an actionable enablement playbook and competency rubric for AI/MarTech providers.

The paper proceeds as follows. Section 2 reviews the relevant theoretical literature and articulates the gaps this study addresses. Section 3 presents the conceptual model and the propositions derived from it. Section 4 describes the methodology in detail. Section 5 presents the expected results and their interpretation. Section 6 offers conclusions, practical recommendations, and directions for future research.

2. Theoretical Background and Research Methodology

2.1 Technology Adoption Frameworks: Achievements and Limitations

The Technology Acceptance Model (Davis, 1989) established perceived usefulness and perceived ease of use as the twin determinants of technology adoption intention, initiating a research tradition that has dominated the field for over three decades. UTAUT (Venkatesh et al., 2003) extended this model by incorporating social influence, facilitating conditions, and individual-level moderators. TOE (Tornatzky and Fleischer, 1990) shifted the level of analysis to the organization, identifying technological, organizational, and environmental contexts as co-determining factors in adoption decisions.

These frameworks have accumulated substantial empirical support and continue to inform both academic inquiry and consulting practice. However, they share a structural bias toward the demand side of the adoption relationship.

The provider is essentially absent from their theoretical logic: technology is modeled as a given stimulus, and adoption is modeled as an organizational or individual response. The processes through which providers shape perceptions, build capabilities, reduce friction, and create the conditions for sustained use are not theorized. This limitation becomes particularly acute in AI/MarTech markets, where the technology is complex, rapidly evolving, and deeply intertwined with client workflows, making the quality of provider enablement a critical determinant of whether adoption survives beyond the initial trial phase.

Diffusion of innovations theory (Rogers, 2003) offers some relevant conceptual resources. Rogers' attributes of innovations (relative advantage, compatibility, complexity, trialability, and observability) have direct implications for enablement design: providers who engineer high trialability (e.g., through sandboxed environments and pilot programs), reduce perceived complexity (e.g., through templates and playbooks), and enhance observability (e.g., through dashboard-based performance reporting) should, ceteris paribus, accelerate and deepen adoption. However, Rogers' framework remains at the level of innovation attributes rather than specifying the provider behaviors that actualize these attributes in practice.

2.2 Adoption Depth as a Theoretical Construct

Binary adoption measures (used/not used) are increasingly recognized as inadequate for capturing the value that organizations realize from technology investments. Post-adoption research (Bhattacherjee, 2001; Jasperson et al., 2005) has demonstrated that continued use is not a stable equilibrium but an ongoing achievement, susceptible to erosion when the conditions that initially supported adoption are not sustained. Infusion theory (Cooper and Zmud, 1990) extends this insight by distinguishing between routine use (the incorporation of technology into standard workflows) and infusion (the exploitative and expansive use of technology capabilities beyond initial adoption). This study builds on these contributions by operationalizing adoption depth as a multidimensional construct encompassing: (a) workflow integration, the degree to which the tool is embedded in standard operating procedures; (b) measurement routinization, the degree to which tool-generated data is incorporated into performance reporting and decision-making; and (c) capability expansion, the degree to which users actively explore and adopt advanced tool features over time.

2.3 Responsible AI Governance as a Boundary Condition

The governance of AI systems has emerged as a central concern for regulators, scholars, and practitioners across the globe (Jobin et al., 2019; European Commission, 2021). For the purposes of this study, responsible AI governance is understood as an organizational-level capability encompassing transparency (the ability to explain AI-generated outputs), auditability (the capacity to trace and review AI decision processes), human oversight (the maintenance of meaningful human control over AI-influenced decisions), and privacy-by-design (the integration of data protection principles into system architecture). The theoretical claim advanced here is that governance maturity functions as a trust mechanism: organizations with higher governance maturity are better positioned to routinize AI/MarTech tool use because they can manage the associated risks, satisfy regulatory requirements, and maintain stakeholder confidence. Governance immaturity, conversely, creates uncertainty and risk aversion that inhibits routinization even when tool performance is technically satisfactory.

2.4 Go-to-Market Context: B2B versus B2C

The distinction between B2B and B2C deployment contexts is theoretically significant for several reasons. B2B adoption typically involves multiple organizational stakeholders with heterogeneous interests, longer sales and implementation cycles, and success metrics oriented toward operational efficiency, pipeline generation, and revenue attribution. B2C adoption, by contrast, is often characterized by higher user volume, shorter decision cycles, and success metrics centered on customer acquisition cost, lifetime value, and engagement rates. These structural differences imply distinct enablement designs: B2B enablement may prioritize organizational change management, executive alignment, and integration with CRM and ERP systems, while B2C enablement may emphasize user-facing training, A/B testing infrastructure, and real-time analytics.

2.5 Research Methodology

The study adopts a three-stage sequential mixed-method design.

Stage 1: Theory-Building Case Studies. Following Eisenhardt (1989) and Yin (2018), the first stage employs multiple case study logic to build and refine the theoretical model. Cases are selected purposively to maximize theoretical variation across: (a) provider type (native AI startup vs. established MarTech vendor); (b) go-to-market context (B2B vs. B2C); and (c) governance maturity (nascent vs. developing vs. established). Data collection combines semi-structured interviews with provider and client informants, document analysis of enablement materials and contractual artifacts, and direct observation of onboarding and training sessions. Case analysis follows a replication logic: theoretical propositions are refined iteratively as evidence from successive cases is incorporated. A minimum of eight cases are planned, consistent with the requirements of theory-building case research.

Stage 2: Survey-Based Model Testing. The second stage tests the structural model derived in Stage 1 using a survey administered to marketing and technology professionals in Georgian and regional organizations that have deployed AI/MarTech solutions within the past three years. Constructs are operationalized using reflective multi-item scales adapted from validated instruments in the adoption and governance literature. The primary analytical method is PLS-SEM, selected for its appropriateness for theory-testing with complex models and its robustness with moderate sample sizes (Hair et al., 2019). A target sample of 150–200 complete responses is planned. Measurement model assessment follows established criteria for convergent and discriminant validity (AVE > 0.5; HTMT < 0.85). The structural model is assessed using bootstrapping procedures to evaluate the significance and magnitude of path coefficients.

Stage 3: Design-Oriented Translation. The third stage translates the empirical findings into a practical enablement playbook and competency rubric for AI/MarTech providers operating in Georgian and similar markets. This phase draws on design science research principles (Hevner et al., 2004) and involves iterative co-design with practitioners, followed by a structured pilot evaluation using pre/post assessment of enablement capability and adoption depth indicators.

3. Research Results and Conceptual Model

3.1 The Provider-Led Enablement Model

Based on the theoretical synthesis described above, this study proposes a model in which provider-led enablement intensity directly determines the development of client learning capacity, which in turn drives adoption depth. Responsible AI governance maturity and go-to-market context function as moderating boundary conditions on the enablement-to-depth pathway.

Enablement intensity is operationalized across five key dimensions, each grounded in the literature on technology transfer, organizational learning, and customer success management:

(1) Onboarding quality: the completeness, clarity, and contextual adaptation of initial setup and orientation processes. High-quality onboarding reduces early-stage friction and prevents the abandonment that commonly occurs in the first weeks after tool deployment.

(2) Training depth: the extent to which training activities build genuine capability (conceptual understanding of how the tool works, practical skill in configuring and using it, and metacognitive awareness of when and why to apply it) rather than surface-level familiarity.

(3) Templates and playbooks: the provision of structured, contextually relevant use-case templates, workflow blueprints, and decision heuristics that reduce the cognitive load associated with adapting a generic tool to specific organizational contexts.

(4) Integration support: technical and process assistance in connecting the AI/MarTech tool to existing organizational systems (CRM, ERP, data warehouses, reporting infrastructure), which is a critical prerequisite for workflow integration.

(5) Customer success routines: ongoing, structured engagements between provider and client designed to monitor adoption health, identify and resolve barriers, celebrate wins, and expand use over time.

3.2 Client Learning Capacity as a Mediating Mechanism

The model posits that enablement intensity drives adoption depth primarily through the development of client learning capacity (the organizational capability to acquire, process, and apply knowledge about the AI/MarTech tool and its applications). This construct draws on absorptive capacity theory (Cohen and Levinthal, 1990) and is operationalized along three dimensions: prior related knowledge (existing digital and analytical literacy within the client organization), knowledge integration mechanisms (structures and processes for sharing tool-related learning across teams), and learning motivation (the degree to which tool use is actively incentivized and celebrated within the organization).

The learning capacity mediation hypothesis holds that enablement practices are only as effective as the client's capacity to absorb and institutionalize the knowledge they convey. This implies that providers operating with clients of low initial learning capacity should front-load their enablement efforts on capacity-building activities (digital literacy development, establishment of internal champion networks, creation of communities of practice) rather than on feature-rich but cognitively demanding training content.

3.3 Key Propositions

The following theoretical propositions summarize the expected empirical relationships:

P1: Provider-led enablement intensity is positively associated with client learning capacity, such that higher enablement intensity produces higher levels of knowledge acquisition, integration, and motivation.

P2: Client learning capacity is positively associated with adoption depth, such that organizations with higher learning capacity achieve greater workflow integration, measurement routinization, and capability expansion.

P3: Client learning capacity partially mediates the relationship between enablement intensity and adoption depth, with a significant direct effect of enablement intensity on adoption depth remaining after controlling for learning capacity.

P4: Responsible AI governance maturity positively moderates the impacto of learning capacity on adoption depth relationship, such that the effect of learning capacity on adoption depth is stronger when governance maturity is higher.

P5: Go-to-market context (B2B vs. B2C) moderates the enablement intensity and learning capacity relationship, with different enablement dimensions producing differential effects in B2B versus B2C contexts.

3.4 Expected Empirical Findings

While the full empirical validation of the model awaits the completion of the survey phase, the theory-building case studies conducted to date generate several preliminary findings that both support the model's structure and enrich its specification.

First, across cases, onboarding quality and customer success routines emerge as the enablement dimensions most strongly associated with client reports of sustained use and confidence. Templates and playbooks, while perceived as valuable, appear to produce adoption depth only when accompanied by sufficient training to enable adaptation rather than mechanical application.

Second, governance maturity emerges as a salient concern particularly in B2B contexts, where procurement processes and executive sponsors increasingly demand evidence of responsible AI practices as a precondition for deployment. In B2C contexts, governance concerns are present but mediated more through regulatory compliance requirements than through internal organizational norms.

Third, the B2B/B2C distinction is found to shape not only the structure of enablement but also the definition of adoption depth itself. B2B clients tend to define adoption depth in terms of pipeline and revenue attribution, while B2C clients foreground engagement metrics and customer lifetime value. This finding implies that adoption depth measurement instruments must be context-sensitive rather than universal.

Fourth, preliminary evidence suggests a threshold effect in enablement intensity: below a certain minimum threshold (encompassing at least adequate onboarding and some form of recurring customer success engagement) adoption depth fails to develop regardless of tool quality. Above this threshold, incremental enablement investments produce diminishing but positive returns on adoption depth.

4. Conclusion: Recommendations and Future Perspectives

This study addresses a consequential gap at the intersection of technology adoption theory and AI/MarTech practice in emerging markets. By theorizing provider-led enablement as a central mechanism through which tool availability is converted into adoption depth, and by specifying the moderating roles of responsible AI governance maturity and go-to-market context, the model advances understanding of post-adoption dynamics in ways that existing frameworks do not accommodate.

The practical implications of the model are substantial. For AI/MarTech providers operating in Georgian and regional markets, the central lesson is that commercial success depends not only on product quality but on the intentional design and execution of enablement systems. Providers who invest in structured onboarding, deep training, contextually relevant playbooks, robust integration support, and disciplined customer success routines will, according to the model, generate higher adoption depth in their client base; and adoption depth, in turn, is expected to be the primary driver of client retention, expansion revenue, and positive referral behavior.

The incorporation of responsible AI governance into the enablement model carries a specific implication: providers should not treat governance compliance as a regulatory burden to be minimized but as an enablement investment to be leveraged. Clients who are guided through the development of transparency, auditability, and oversight practices in the context of AI/MarTech deployment are, according to the model, more likely to achieve the deep routinization that generates sustained value. Governance capacity-building should therefore be integrated into enablement playbooks rather than treated as a separate compliance track.

Several important limitations of the present work must be acknowledged. The model is developed primarily in the context of Georgian and regional markets, and its generalizability to other emerging market environments with different institutional configurations, regulatory frameworks, and digital maturity levels remains an empirical question. The survey-based validation phase will be conducted with a sample of organizations operating in these markets, and cross-national replication studies will be necessary to establish broader external validity. Future research should extend the model in several directions. First, longitudinal designs are needed to trace the dynamics of adoption depth over time, capturing not only the initial development of deep use but also potential erosion, reinvigoration, and evolution as tools are updated and organizational contexts change. Second, the role of individual-level factors (particularly the characteristics of internal champions and the influence of organizational culture on learning capacity) merits more systematic theoretical and empirical attention. Third, the model's propositions regarding the threshold effect in enablement intensity should be subjected to formal testing using methods capable of detecting nonlinear relationships, such as fuzzy-set qualitative comparative analysis (fsQCA) or response surface analysis.

The design-oriented translation of this research into an evidence-based enablement playbook represents a distinctive contribution to the applied AI/MarTech literature. By grounding practitioner-facing tools in a formally specified and empirically validated theoretical model, this study aspires to bridge the persistent divide between academic knowledge production and practitioner knowledge use in the technology adoption domain. The playbook and competency rubric developed in Stage 3 are intended to be directly applicable by AI/MarTech startups in Georgia and comparable markets, providing them with a structured, evidence-based approach to designing and executing enablement programs that generate adoption depth and the value that flows from it.

In conclusion, the transition from tool availability to adoption depth is neither automatic nor inevitable. It is the product of deliberate, theory-informed enablement work on the part of providers, work that this study aims to both explain and improve.

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