

From Pilot to Scale: A Process-Oriented Explanation of Artificial Intelligence Scaling in Tunisian Telecommunications Firms

Manel OUESLATI¹, Wadie NASRI²

¹PhD Candidate in Management FSEGS, Tunisia

²Associate Professor of Marketing ISG Gabès, Tunisia

ORCID: <https://orcid.org/0009-0008-2329-8053>

ORCID: <https://orcid.org/0009-0002-6824-1831>

DOI: <https://doi.org/10.51583/IJLTEMAS.2026.150900164>

Received: 01 October 2026; Accepted: 06 October 2026; Published: 26 October 2026

ABSTRACT

Artificial intelligence (AI) initiatives may demonstrate technical feasibility during pilot experimentation without progressing toward sustained organizational deployment. Although existing research identifies AI implementation phases and organizational readiness factors, further understanding is needed of how implementation conditions become differently consequential when organizations attempt to move beyond bounded experimentation. This study examines the pilot-to-scaling transition in Tunisian telecommunications firms through a process-oriented and context-sensitive perspective. Drawing on 11 semi-structured interviews across three telecommunications operators, the study adopts a cross-sectional qualitative design and reconstructs participants' experiences retrospectively. Data were analyzed through an abductive approach informed by Gioia's data-structuring principles, with NVivo matrix coding used as a descriptive analytical aid. Five interconnected dimensions were identified: bounded experimentation and value proving; production exposure and technological interdependence; organizational capability mobilization; local institutional and resource embeddedness; and scaling legitimation and organizational sensemaking. Participants' accounts suggest that movement toward operational deployment makes existing technological and organizational interdependencies more visible and managerially consequential, while requiring sustained capability mobilization and continued organizational justification. The study interprets this transition as an innovation management threshold, understood as a sensitizing interpretive concept rather than a new implementation stage or an established causal mechanism. It further offers a phase-contingent interpretation of implementation conditions and examines how locally embedded institutional and resource conditions enter organizational scaling attempts. The findings highlight the importance of distinguishing pilot readiness from scaling readiness.

Keywords: Artificial intelligence scaling; AI implementation; pilot-to-scale transition; innovation management; telecommunications

INTRODUCTION

Artificial intelligence (AI) is increasingly embedded in organizational innovation and digital transformation initiatives. Beyond its technical capabilities, AI raises distinctive managerial challenges because implementation requires organizations to coordinate data, infrastructures, business processes, managerial decisions, and user practices. Berente et al. (2021) characterize the management of AI as involving communication, leadership, coordination, and control around technologies marked by autonomy, learning, and inscrutability. More broadly, digital innovation research shows that digitalization challenges conventional assumptions about innovation processes, organizational actors, and firm boundaries (Nambisan et al., 2017).

A growing body of research has therefore moved beyond treating AI adoption as a simple binary decision. Jöhnk et al. (2021) show that organizational AI readiness depends on assets, capabilities, and commitment adapted to the intended adoption purpose. Research on AI project management similarly demonstrates that AI projects require the simultaneous management of project-management, agile, and AI-workflow logics, which can generate organizational tensions and coordination challenges (Vial et al., 2023). More directly, Haefner et al. (2023) conceptualize AI implementation and scaling as a multi-phase process involving proving the concept, productionizing, and platformizing, with different socio-technical requirements across implementation phases.

These studies establish that AI implementation evolves across stages and that different resources and capabilities become relevant beyond initial experimentation. However, an important issue remains insufficiently explained: what changes organizationally when an AI initiative moves from a bounded pilot toward sustained and wider deployment. Existing studies identify readiness factors, project-management challenges, and implementation phases, but provide more limited explanation of how technological dependencies, organizational capabilities, institutional requirements, and organizational interpretations become simultaneously consequential during the pilot-to-scaling transition. A technically successful pilot does not necessarily mean that an organization is able to integrate, maintain, govern, resource, legitimize, and sustain the same AI solution in operational use.

The issue is particularly relevant because the conditions surrounding experimentation and wider deployment are not necessarily identical. During a pilot, organizations can evaluate technical feasibility and initial business value within relatively bounded conditions. Wider deployment, by contrast, can require integration with legacy systems and organizational processes, sustained resource commitments, operational ownership, monitoring and maintenance arrangements, governance mechanisms, and continued managerial and user support. The analytical problem is therefore not simply to identify additional barriers to AI adoption, but to understand how the nature and relevance of implementation conditions change when organizations attempt to move beyond experimentation.

Context also matters in explaining this transition. Information-systems research in developing countries has emphasized that local contexts should not be treated merely as geographical settings in which established theories are replicated. Ramadani and Almaarif (2022) argue for greater attention to context-specific phenomena and to the theoretical relevance of local institutional, social, economic, and organizational conditions. This perspective is particularly relevant to AI scaling because organizational deployment may interact with locally embedded conditions such as institutional arrangements, human-capital availability, linguistic requirements, technological dependencies, and access to external organizational resources.

Against this background, the present study investigates AI implementation in Tunisian telecommunications firms, focusing specifically on the transition from pilot experimentation toward wider organizational deployment. Telecommunications provides a relevant setting because AI applications interact with data-intensive infrastructures, legacy systems, customer and network processes, organizational coordination, and regulatory requirements. Tunisia also provides a context in which personal-data protection, specialized human-capital availability, multilingual usage requirements, and access to external technological resources may become relevant to AI implementation.

The study adopts a process-oriented and context-sensitive perspective and uses the Technology-Organization-Environment (TOE) framework, institutional theory, and Diffusion of Innovation (DOI) theory as complementary sensitizing lenses rather than as a predetermined causal model. Accordingly, the study asks:

How and why does the transition from AI pilot projects to large-scale deployment become a distinct innovation management challenge in Tunisian telecommunications firms?

Drawing on 11 semi-structured interviews across three Tunisian telecommunications operators, the study develops three complementary contributions. First, it provides an interpretive explanation of the pilot-to-

scaling transition as an innovation management threshold, integrating production exposure, sustained capability mobilization, and organizational legitimization. Rather than introducing an additional implementation stage, this perspective complements research on AI implementation phases (Haefner et al., 2023) and organizational technology assimilation (Fichman & Kemerer, 1999) by examining why established implementation requirements become more visible and managerially consequential beyond bounded experimentation. Second, it offers a phase-contingent interpretation of implementation conditions and innovation-related perceptions, distinguishing pilot readiness from scaling readiness. Third, it contributes to context-sensitive information-systems research by examining how locally embedded regulatory, talent-related, linguistic, and external-resource conditions enter organizational attempts to scale AI. These contributions are grounded in participants' retrospective accounts and are presented as interpretive insights rather than longitudinally demonstrated causal mechanisms.

LITERATURE REVIEW

Artificial Intelligence Implementation and Scaling: From Experimentation to Large-Scale Deployment

Artificial intelligence implementation should not be understood as a single organizational adoption event. Increasingly, research conceptualizes AI implementation as a multi-stage socio-technical process in which organizations move from experimentation toward production and broader organizational use. Haefner et al. (2023) distinguish three phases of AI implementation and scaling: proving the concept, productionizing, and platformizing. These phases involve different technical and organizational requirements and indicate that successful experimentation does not automatically lead to sustained deployment.

During early experimentation, organizations typically seek to establish technical feasibility and initial business value. Moving toward production requires more systematic integration with organizational data, infrastructures, processes, and responsibilities. Platformization extends these requirements further by creating reusable technical and organizational capabilities capable of supporting multiple AI applications (Haefner et al., 2023).

This phase-based perspective is consistent with broader research on digital innovation. Nambisan et al. (2017) argue that digitalization changes the boundaries, actors, and processes through which innovation is organized. Haefner et al. (2021) similarly show that AI can reshape innovation management and require firms to reconsider how innovation processes are structured. More generally, information-technology innovation research has called for moving beyond a simple binary adoption paradigm toward concepts capable of capturing implementation and assimilation more fully (Fichman, 2004).

Research on AI project management further demonstrates that implementation involves organizational challenges beyond model development. Vial et al. (2023) show that AI projects combine project-management, agile, and AI-workflow logics, creating tensions that require coordination among technical and business actors.

Taken together, this literature establishes that AI implementation unfolds through different phases and requires both technical and organizational transformation. Phase models describe the principal implementation situations, while research on assimilation gaps draws attention to the distance between initial uptake and extensive use (Haefner et al., 2023; Fichman & Kemerer, 1999). Neither distinction, by itself, fully specifies how a technically feasible pilot can prompt a different managerial assessment once previously bounded technological dependencies, cross-functional commitments, institutional requirements, and legitimacy concerns must be addressed together. The present study examines this interpretive and managerial

reorientation without claiming that existing phase or assimilation concepts are incorrect or insufficient in every setting.

Technological and Organizational Conditions of Artificial Intelligence Scaling

The Technology-Organization-Environment (TOE) framework provides a useful basis for examining the conditions surrounding organizational technology implementation. It distinguishes technological, organizational, and environmental dimensions that influence how firms adopt and implement innovations (Tornatzky et al., 1990).

In AI implementation, technological conditions include data quality, technological infrastructure, interoperability, system integration, and the ability to maintain AI applications in operational environments. Organizational conditions include financial resources, specialized expertise, managerial support, coordination mechanisms, and organizational capabilities.

Research on AI readiness reinforces this multidimensional perspective. Jöhnk et al. (2021) identify multiple categories of organizational AI readiness and argue that organizations must possess assets, capabilities, and commitment appropriate to the specific purpose of AI adoption. Readiness therefore cannot be reduced to technical infrastructure alone.

Mikalef and Gupta (2021) similarly conceptualize AI capability as the coordinated deployment of complementary organizational resources. Their perspective shifts attention from possessing AI technology toward the ability to mobilize technical, human, and organizational resources around AI initiatives.

Managerial capabilities are also important. Berente et al. (2021) characterize AI management as involving communication, leadership, coordination, and control around technologies marked by autonomy, learning, and inscrutability. These requirements become particularly relevant when AI initiatives extend beyond isolated experimentation and interact more extensively with organizational systems and routines.

The literature therefore identifies a broad range of technological and organizational conditions relevant to AI implementation. Yet these conditions are often conceptualized as general readiness factors or capabilities. Less attention has been devoted to how their relevance changes when firms move specifically from a bounded pilot toward wider organizational deployment.

From Technical Feasibility to Organizational Integration

An important distinction in AI implementation concerns the difference between demonstrating that an AI application can work and establishing that it can operate sustainably within an organization.

A pilot or proof of concept primarily allows organizations to test feasibility, model performance, and initial business value. Wider deployment creates a different requirement: the AI application must interact continuously with existing data sources, information systems, operational routines, organizational actors, and governance arrangements.

Consequently, technical performance alone is insufficient to demonstrate scaling readiness. An AI model that performs successfully during experimentation may still face difficulties when integrated with legacy systems, organizational workflows, security requirements, maintenance arrangements, or operational responsibilities.

This distinction is consistent with Haefner et al.'s (2023) separation between proving the concept and productionizing AI. It also corresponds to the broader distinction between adoption and extensive organizational assimilation. Fichman and Kemerer (1999), for example, show that organizational acquisition of an information technology does not necessarily result in extensive organizational deployment.

AI project management research reinforces this argument. Vial et al. (2023) demonstrate that AI projects require continuous coordination among technical, managerial, and business logics. Consequently, the move toward production is not simply an extension of pilot activities but involves integrating technical development with business priorities and organizational practices.

The relevant question is therefore not only whether an AI application is technically successful, but whether the organization can integrate, operate, maintain, govern, and sustain it beyond experimental conditions.

Institutional and Locally Embedded Conditions of Artificial Intelligence Scaling

AI implementation also occurs within institutional environments that influence organizational decisions and implementation requirements. Institutional theory distinguishes coercive, normative, and mimetic pressures through which organizations respond to regulation, professional expectations, and practices within their organizational fields (DiMaggio & Powell, 1983).

Such pressures can become particularly relevant during broader deployment because production-level AI applications may interact more extensively with regulation, data protection, security requirements, professional norms, and legitimacy expectations.

Context is particularly important in developing-country information-systems research. Ramadani and Almaarif (2022) argue that developing-country settings should not simply be treated as geographical locations for reproducing theories developed elsewhere. Instead, local institutional, organizational, economic, technological, and social conditions can themselves contribute to theoretical explanation.

For AI scaling, this means examining which characteristics of the local environment become relevant when firms attempt wider deployment. These conditions may include access to specialized expertise, institutional arrangements, technological providers, linguistic requirements, availability of organizational resources, and links with external or multinational structures.

Importantly, such conditions should not be assumed to characterize all developing countries. Their analytical importance must be established through the empirical material. A context-sensitive approach therefore asks how locally embedded conditions become involved in the scaling process, rather than treating national context as a generic explanatory variable.

Diffusion of Innovation Perceptions as Phase-Dependent Interpretations

Diffusion of Innovation (DOI) theory provides a complementary perspective for understanding how organizational actors interpret innovation characteristics. Rogers (2003) identifies five perceived attributes associated with diffusion: relative advantage, compatibility, complexity, trialability, and observability. These attributes are relevant to AI because organizational actors must evaluate not only whether an application functions technically but also whether it fits existing systems and practices, whether its benefits are visible, and whether its implementation appears manageable.

However, DOI is not used in the present study as a predetermined causal model. Nor does the study assume that these perceptions mediate relationships between organizational conditions and deployment outcomes. Instead, DOI is used as an interpretive lens for understanding how different implementation conditions are perceived by organizational actors. This distinction is important because perceptions may become salient in different ways across implementation situations. Trialability may be particularly relevant during pilot experimentation, when organizations test a bounded use case. Compatibility and complexity may become more salient when applications must interact with legacy systems, processes, and infrastructures. Relative advantage and observability may become particularly relevant when managers must justify continued investment and wider deployment.

This phase-sensitive interpretation is consistent with research distinguishing initial adoption from organizational assimilation. Greenhalgh et al. (2004) emphasize implementation and sustainability in

addition to diffusion, while Fichman and Kemerer (1999) demonstrate that organizational adoption does not necessarily result in extensive use.

Accordingly, DOI provides a vocabulary for examining how organizational actors interpret implementation conditions across different reported situations rather than a fixed set of predictors of AI adoption.

Research Gap and Theoretical Positioning

Existing research has substantially advanced understanding of organizational AI readiness, AI project management, and the socio-technical requirements associated with implementation and scaling (Haefner et al., 2023; Jöhnk et al., 2021; Vial et al., 2023). However, three related gaps remain.

First, although implementation-stage models and assimilation research already recognize movement beyond initial adoption (Haefner et al., 2023; Fichman & Kemerer, 1999), a more specific issue is how actors describe a change in the managerial question at the pilot-to-scaling boundary: from whether an AI use case works to whether it can be organizationally integrated, sustained, governed, and justified. Our study seeks to explain this reorientation, not to propose another universal sequence of implementation stages.

Second, technological conditions, organizational capabilities, managerial coordination, institutional influences, and innovation perceptions are often examined through separate theoretical perspectives. This separation provides less insight into how these dimensions become simultaneously relevant when organizations attempt to move beyond pilot experimentation.

Third, although developing-country IS research emphasizes context-sensitive theorizing, AI-scaling research provides more limited explanation of how locally embedded institutional and resource conditions become involved specifically in the transition toward wider deployment. The present study addresses these gaps through a process-oriented and context-sensitive perspective. TOE is used to structure technological, organizational, and environmental conditions surrounding implementation. Institutional theory directs attention to regulatory, normative, competitive, and legitimacy-related influences. DOI provides an interpretive vocabulary for examining compatibility, complexity, relative advantage, trialability, and observability.

These three perspectives are used as complementary sensitizing lenses rather than as components of a predetermined causal model. The analysis therefore does not assume that one theoretical dimension causes or mediates another. Instead, the theoretical lenses guide attention toward different aspects of participants' accounts of the pilot-to-scaling transition.

The proposed conceptual vocabulary has deliberately limited scope. 'Production exposure' does not rename productionization; it labels how participants described previously bounded dependencies becoming visible and consequential around attempts at deployment. 'Innovation management threshold' is an interpretive synthesis of the change in managerial evaluation across these situations, not a discrete stage, a validated latent variable, or a claim that constraints arise only after the pilot. These concepts are refined inductively from the reported material and compared with prior phase models, assimilation gaps, and socio-technical research in the discussion (Haefner et al., 2023; Fichman & Kemerer, 1999; Berente et al., 2021). This positioning leads to the following research question: How and why does the transition from AI pilot projects to large-scale deployment become a distinct innovation management challenge in Tunisian telecommunications firms?

CONCEPTUAL FRAMEWORK

This study adopts a process-oriented and context-sensitive conceptual framework to examine how organizational actors describe the transition from AI pilot experimentation toward wider deployment. The framework does not treat AI implementation as a single adoption decision. Instead, it distinguishes between bounded experimentation and broader organizational deployment as two analytically different

implementation situations. During bounded experimentation, organizations can test technical feasibility, evaluate initial business value, and explore specific use cases within relatively controlled conditions. Wider deployment, by contrast, requires AI applications to interact more extensively with organizational data infrastructures, legacy systems, business processes, governance arrangements, operational responsibilities, resource commitments, and institutional requirements. The framework therefore directs attention to how implementation conditions become differently salient as organizations move beyond the pilot.

Three complementary theoretical lenses guide the analysis. The Technology-Organization-Environment (TOE) framework structures attention toward technological, organizational, and environmental conditions surrounding implementation. Institutional theory sensitizes the analysis to regulatory, normative, competitive, and legitimacy-related influences. Diffusion of Innovation (DOI) theory provides an interpretive vocabulary for examining how actors discuss compatibility, complexity, relative advantage, trialability, and observability. These perspectives are not combined into a predetermined causal model. Nor does the framework assume that one theoretical dimension mediates another. Instead, they are used as complementary sensitizing lenses for interpreting participants' accounts of the pilot-to-scaling transition.

In this framework, the pilot-to-scaling boundary is an analytical comparison rather than an empirically verified point in time. Accordingly, the emerging concepts of production exposure and innovation management threshold are treated as interpretive summaries of participants' reported implementation concerns. Their usefulness depends on their capacity to clarify how several familiar conditions become jointly salient; they are not assumed to be distinct causal drivers or independently measured constructs. The analytical focus is therefore placed on three related questions: which implementation conditions become salient when AI moves beyond bounded experimentation; how organizational actors interpret these conditions; and how local institutional and resource conditions enter attempts to achieve wider deployment.

Figure 1 summarizes this sensitizing framework. The connections shown in the figure represent analytical relationships to be explored in the interview material rather than hypothesized causal effects.

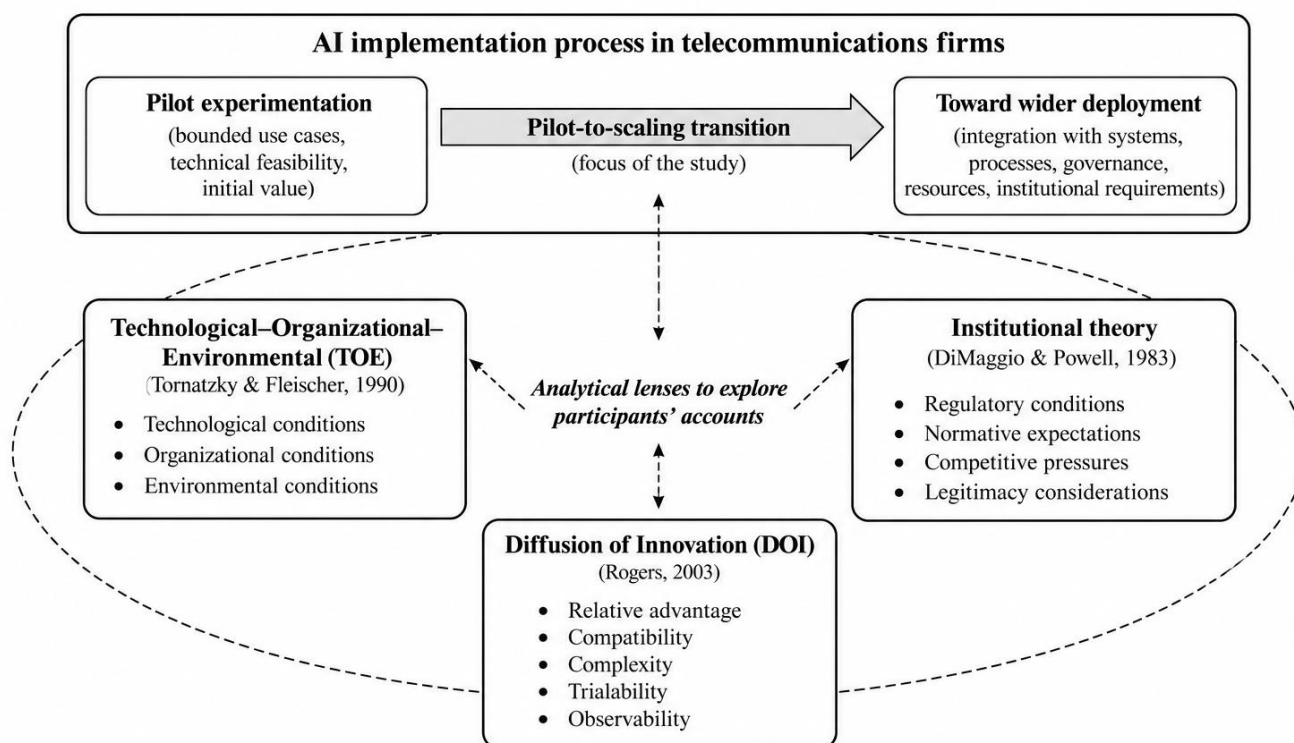


Figure 1. Sensitizing framework for exploring participants' accounts of the transition from AI pilots toward wider deployment. Links indicate analytical connections rather than predetermined causal relationships.

METHODOLOGY

Research Design and Epistemological Stance

This study adopts a cross-sectional, qualitative, exploratory, and theory-informed research design. Epistemologically, it takes an interpretivist stance: organizational actors' accounts are treated as situated interpretations of AI implementation experiences rather than as direct measurements of objective organizational processes. The study reconstructs the transition from AI pilot experimentation toward wider deployment through participants' retrospective accounts rather than through longitudinal observation of the same projects over time.

This design is appropriate because the research question concerns how organizational actors experience and interpret changing technological, organizational, and institutional conditions as AI initiatives move beyond bounded experimentation (Langley & Abdallah, 2011; Myers, 2013).

Semi-structured interviews were selected as the primary data source because they provide thematic consistency while allowing participants to elaborate unexpected experiences and organizational issues (DiCicco-Bloom & Crabtree, 2006; Kallio et al., 2016). TOE, DOI, and institutional theory informed the inquiry as sensitizing perspectives rather than as a predetermined causal model.

Research Context

The empirical setting consists of three telecommunications operators in Tunisia, anonymized as Operators A, B, and C. Telecommunications provides a relevant setting for examining AI scaling because firms operate data-intensive customer, marketing, fraud, and network processes requiring interaction between AI applications and existing information infrastructures. The sector is formally regulated by the Instance Nationale des Télécommunications, and the three major operators are subject to regulatory decisions concerning market organization, interconnection, infrastructure, and service conditions (Instance Nationale des Télécommunications, 2026). Tunisia also has a national personal-data protection framework based on Organic Law No. 2004-63, administered through the Instance Nationale de Protection des Données Personnelles (Instance Nationale de Protection des Données Personnelles, n.d.).

Rather than treating Tunisia as a generic developing-economy variable, the study adopts a context-sensitive approach. Contextual characteristics are considered analytically relevant when participants themselves associate them with the pilot-to-scaling transition. This approach follows calls in developing-country information-systems research to theorize local institutional, technological, social, and organizational conditions rather than treating national context merely as a geographical setting (Ramadani & Almaarif, 2022).

Sampling and Participants

A purposive sampling strategy was used to select organizational actors with direct knowledge of AI initiatives or responsibility for strategic, managerial, technical, or operational decisions related to AI implementation. Purposive sampling was appropriate because the study required information-rich participants able to describe concrete experiences relevant to the transition from AI experimentation toward wider deployment (Palinkas et al., 2015).

The final sample comprised 11 participants from three anonymized Tunisian telecommunications operators. The participants included senior executives, a chief information officer, digital-transformation and innovation managers, a customer-service manager, data and AI managers, AI project managers, and data/machine-learning engineers. This functional variation provided perspectives from strategic, managerial, operational, and technical levels. Sample adequacy was assessed in relation to the focused research question and the recurrence of analytically relevant concepts in the interview material. Thematic saturation was considered to have been reached when later interviews no longer generated substantively new first-order

concepts or second-order themes relevant to the research question. Subsequent interviews primarily reinforced or refined recurring patterns related to data and infrastructure dependencies, organizational coordination, capability requirements, resource commitment, and institutional conditions (Guest et al., 2006).

Table 1. Participant profiles

Participant	Role / Position	Operator
P1	AI / Digital Transformation Manager	A
P2	Chief Executive Officer	A
P3	Chief Information Officer	B
P4	Customer Service Manager	B
P5	Digital Transformation & Innovation Director	C
P6	Chief Executive Officer	C
P7	Chief Executive Officer	B
P8	Data Engineer / Machine Learning Engineer	B
P9	Data Engineer / Machine Learning Engineer	C
P10	Data & Analytics Manager / AI Project Manager	B
P11	Data & AI Manager / AI Project Manager	C

Note. Organizations are anonymized as Operators A, B, and C to preserve confidentiality.

Data Collection and Interview Protocol

Data were collected through 11 semi-structured interviews conducted between October 2025 and February 2026. Interviews lasted approximately 45-60 minutes and were conducted either face-to-face or remotely according to participant availability. All interviews were conducted in French, audio-recorded with participants' consent, and transcribed verbatim. Participants were assigned identifiers P1-P11, and the three organizations were anonymized as Operators A, B, and C. The English excerpts reported in the manuscript were translated from the French transcripts for reporting purposes while preserving their original meaning.

The interview guide was informed by the conceptual framework and covered the status of AI initiatives, data quality, infrastructure and system integration, internal expertise, managerial support, financial and organizational resources, external partners, competition, regulation, perceived benefits and risks, and the transition from experimentation toward wider deployment. Questions remained open-ended, and follow-up prompts were used to clarify differences between conditions encountered during controlled experimentation and those associated with broader implementation.

Data Analysis

The interview material was analyzed through an abductive and theory-informed qualitative coding process drawing on the data-structuring principles proposed by Gioia et al. (2013). The analysis moved iteratively between participants' accounts, emerging empirical patterns, and the sensitizing theoretical concepts provided by TOE, DOI, and institutional theory.

In the first stage, coding remained close to participants' language and experiences in order to identify first-order concepts concerning AI experimentation and deployment. In the second stage, related first-order

concepts were compared and grouped into more abstract second-order themes. Particular attention was directed toward differences between conditions described in relation to bounded experimentation and those associated with production or wider organizational deployment. In the third stage, related second-order themes were consolidated into aggregate dimensions capturing the principal patterns identified in participants' accounts of the pilot-to-scaling transition.

All interview material was organized and coded using NVivo. Matrix coding queries were subsequently employed as a complementary analytical aid to inspect recurring co-occurrences among contextual conditions, DOI-related interpretations, and implementation situations within the same interview corpus. Because these matrices were generated from the same qualitative material used for coding, they were not treated as independent validation, prevalence measures, statistical associations, or evidence of causal relationships. Their function was limited to supporting qualitative pattern inspection.

Research Quality and Trustworthiness

Research quality was addressed through credibility, dependability, confirmability, and transferability (Lincoln & Guba, 1985; Shenton, 2004), together with the principle of meaningful coherence in qualitative research (Tracy, 2010). Credibility was supported by incorporating participants occupying different organizational and hierarchical positions, thereby providing strategic, managerial, operational, and technical perspectives. Dependability was supported through a structured coding process, iterative comparison between empirical material and emerging categories, and systematic data management using NVivo. Confirmability was strengthened by maintaining explicit connections between analytical interpretations and participants' accounts, including representative quotations in the findings. Transferability was supported through transparent reporting of the empirical setting, participant profiles, and data-collection procedures.

Particular caution was exercised when interpreting retrospective accounts. Because the study did not observe projects longitudinally, participants' descriptions of differences between pilot and wider deployment were treated as reconstructed organizational experiences rather than as directly observed temporal or causal sequences. The analysis therefore distinguishes interpretive patterns reported by participants from claims of longitudinal causality. NVivo co-occurrences were likewise treated as descriptive analytical aids rather than as causal evidence.

Ethical Considerations and Generative Artificial Intelligence Disclosure

Participation was voluntary, and informed consent was obtained before the interviews. Participants were anonymized using identifiers P1-P11, and the organizations were referred to as Operators A, B, and C. Interview recordings and transcripts were treated confidentially and used exclusively for research purposes.

Generative artificial intelligence disclosure. OpenAI's ChatGPT was used during manuscript preparation to support language editing, structural reorganization, literature-search assistance, and articulation of higher-order themes from the authors' pre-existing coding and NVivo outputs. It was not used to collect data, conduct interviews, independently code the raw transcripts, or generate empirical observations. All citations, interpretations, tables, and final wording were reviewed and validated by the authors, who retain full responsibility for the work.

FINDINGS

Analytical Overview

The analysis of participants' retrospective accounts identified five interconnected dimensions associated with the transition from AI pilot experimentation toward wider organizational deployment: (1) bounded experimentation and value proving, (2) production exposure and technological interdependence, (3) organizational capability mobilization, (4) local institutional and resource embeddedness, and (5) scaling legitimation and organizational sensemaking.

These dimensions are not interpreted as a fixed sequence of implementation stages. Rather, they represent recurring and interconnected patterns in participants' accounts of what became relevant as AI initiatives moved, or were considered for movement, beyond controlled experimentation. The analysis therefore focuses on differences in reported implementation conditions rather than claiming a longitudinal causal sequence.

Table 2. Illustrative coding structure of the pilot-to-scaling transition

Representative interview excerpts and summaries	Second-order themes	Aggregate dimensions
"We identify a problem, propose an AI solution, and then test it in a pilot. If the results are good, we discuss a broader deployment." (P4)	Staged experimentation	Bounded experimentation and value proving
"We do a quick POC to prove the value, then a pilot with KPIs, and if the results are good, we deploy." (P10)	Performance validation	Bounded experimentation and value proving
"We are still mostly in the pilot phase... the transition to scale is our main challenge." (P2)	Persistence of pilot-stage initiatives	Bounded experimentation and value proving
"The real challenge started when we wanted to move to actual deployment... limitations of the infrastructure and data quality." (P3)	Exposure of infrastructure and data dependencies	Production exposure and technological interdependence
"Often, the data team builds the model, but after that there is a gap for production." (P8)	Model-to-production gap	Production exposure and technological interdependence
"A model may work in testing, but in production it degrades." (P9)	Model maintenance, monitoring, and drift	Production exposure and technological interdependence
"There is a lack of coordination between IT and business units; business teams want rapid results." (P3)	Cross-functional coordination	Organizational capability mobilization
"Sometimes we complete a POC, but we do not have the budget to industrialize it." (P8)	Post-POC resource commitment	Organizational capability mobilization
"The management is supportive as long as the project is clear and profitable." (P2)	Conditional managerial commitment	Organizational capability mobilization
Shortage of specialized AI profiles and difficulty retaining talent in Tunisia (P8/P9)	Local talent scarcity and international mobility	Local institutional and resource embeddedness
Uncertainty surrounding local regulation and strong customer-data protection requirements (P2/P5)	Regulatory uncertainty and data protection	Local institutional and resource embeddedness
Customer-facing AI must handle Tunisian dialect, Arabic, and French (P4)	Linguistic and local-use adaptation	Local institutional and resource embeddedness
Group-level standards, tools, and experience can support local initiatives (P7)	External technological and organizational scaffolding	Local institutional and resource embeddedness

“The decision depends greatly on the ability to demonstrate a measurable impact.” (P10)	Demonstration of observable business value	Scaling legitimization and organizational sensemaking
Scaling decisions depend on measurable ROI, time-to-value, system integration, and user acceptance (P11)	Business-case legitimization	Scaling legitimization and organizational sensemaking
“There is a risk of blind trust or, on the contrary, complete rejection of the model.” (P8)	User trust and interpretive appropriation	Scaling legitimization and organizational sensemaking

Note. Entries in quotation marks are representative interview excerpts; entries without quotation marks are author summaries of participants’ accounts. Quotations were translated from French into English while preserving their original meaning. Participant identifiers correspond to Table 1. The table presents illustrative examples rather than the complete coding scheme.

Bounded Experimentation and Value Proving

Participants described pilot projects as relatively bounded environments in which organizations could test technical feasibility, evaluate initial performance, and establish preliminary evidence of business value before committing resources to wider deployment. Their accounts commonly associated early experimentation with the identification of a business problem, assessment of technical feasibility, evaluation of costs and expected value, and managerial validation.

P10 described this progression as “a quick POC to prove the value, then a pilot with KPIs, and if the results are good, we deploy.” This account illustrates how experimentation was used to generate evidence supporting subsequent organizational consideration rather than implying automatic progression toward scale.

Other participants described initiatives that remained largely at the pilot stage. P2 stated that the organization was still “mostly in pilot” and that “the transition to scale is our main challenge.” Taken together, these accounts suggest that bounded experimentation served both as a means of testing AI applications and as a decision point at which organizations assessed whether broader commitment was warranted.

Production Exposure and Technological Interdependence

Participants described a noticeable change in the technological conditions surrounding AI applications when discussing movement beyond bounded experimentation. Their accounts indicated that limitations that could be partly contained during pilots became more visible or consequential when organizations attempted operational deployment.

P3 described this shift explicitly: “The real challenge started when we wanted to move to actual deployment: that is when we realized the limitations of the infrastructure and data quality.” The same participant referred to data silos across CRM, billing, and network systems, legacy architectures, limited cloud environments, and insufficient MLOps capabilities.

Technical participants provided related accounts. P8 stated that “often, the data team builds the model, but after that there is a gap for production.” Wider deployment was associated with integration into existing systems, automated model updating, monitoring, and management of model drift. P9 similarly observed that “a model may work in testing, but in production it degrades.” These accounts support production exposure as an interpretive label for the reported increase in visibility and practical consequences of technological and organizational dependencies when participants considered or attempted operational deployment. In this empirical material, the label covers data and legacy-system integration, model monitoring and maintenance,

and responsibility for keeping an application operational. It does not imply that those dependencies were created by scaling or that a new chronological phase was observed.

Organizational Capability Mobilization

Participants also described wider deployment as requiring organizational capabilities that extended beyond those needed to conduct a bounded pilot. Their accounts referred to coordination among IT, data teams, business functions, senior management, compliance units, and external providers.

P3 reported “a lack of coordination between IT and business units” and indicated that business teams often expected rapid results. Participants also associated movement beyond experimentation with sustained resource commitment. P8 explained: “Sometimes we complete a POC, but we do not have the budget to industrialize it.” P10 similarly identified changing priorities, limited post-POC budgets, integration requirements, and coordination difficulties as conditions associated with stalled progression after promising experimentation.

Managerial support was also described as conditional. Senior participants associated continued support with demonstrable business value and profitability, whereas initiatives characterized by uncertain or delayed returns were described as more difficult to sustain. These accounts suggest a distinction between the availability of organizational capabilities and their continued mobilization for wider deployment. Scaling was therefore described not only as requiring resources, but also as requiring their sustained coordination and commitment across organizational functions.

Local Institutional and Resource Embeddedness

Participants’ accounts identified several conditions rooted in the local institutional and resource environment. Four issues were particularly recurrent: regulatory uncertainty, customer-data protection requirements, availability and retention of specialized AI talent, and linguistic adaptation. Participants referred to uncertainty surrounding aspects of local rules applicable to personal data and AI-supported decision making and emphasized compliance, cybersecurity, and customer-data protection requirements. Technical respondents also described a limited local supply of specialized machine-learning and data-engineering profiles and difficulties retaining such employees in the context of international employment opportunities.

Linguistic adaptation emerged particularly in customer-facing applications. Participants reported that chatbots needed to accommodate Tunisian dialect as well as Arabic and French, and that inadequate linguistic performance could affect user trust. Local embeddedness was not described exclusively as a source of constraint. One senior participant reported that international group structures could provide technological standards, tools, expertise, and previous implementation experience. The empirical material therefore suggests that locally situated conditions can constrain scaling attempts while external organizational connections can also provide resources that support them.

Scaling Legitimation and Organizational Sense Making

Participants further described wider deployment as requiring continued organizational justification. During experimentation, technical feasibility and initial performance were prominent concerns. When discussing broader deployment, participants referred more strongly to measurable business value, costs, managerial approval, and acceptance by organizational users.

P10 explained that “the decision depends greatly on the ability to demonstrate a measurable impact.” Participants referred to KPIs and business outcomes when considering whether successful experimentation should lead to broader deployment. P11 similarly associated industrialization decisions with measurable ROI, time-to-value, system integration, data quality, security, and business-user acceptance.

User acceptance represented another aspect of this process. P8 cautioned that insufficient understanding of AI could lead either to “blind trust” or to complete rejection of the model. These accounts indicate that technical performance alone was not treated as sufficient for sustained organizational use.

We therefore interpret scaling as involving a process of organizational legitimation and sensemaking, in which actors assess whether AI produces sufficient observable value, can be trusted, and can be incorporated into organizational routines.

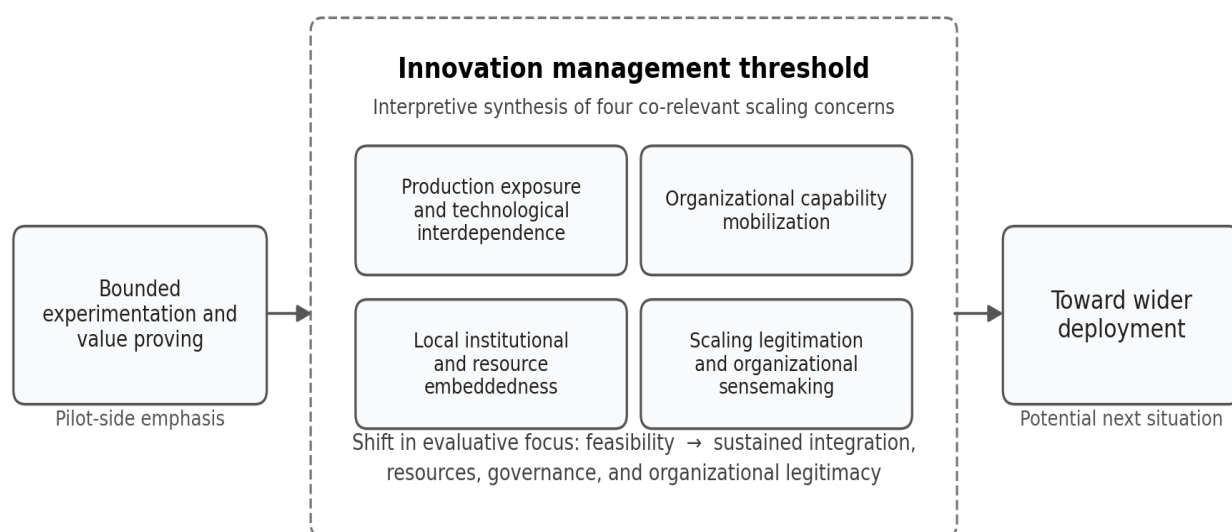
An Emergent Interpretive Account of the Transition From Pilot To Scaling

Taken together, participants’ accounts support an interpretive reconstruction in which the nature of the AI implementation challenge differs as initiatives move beyond bounded experimentation. During pilots, participants primarily emphasized feasibility, initial value, and managerial validation. When discussing movement toward production and wider deployment, they emphasized data and infrastructure dependencies, legacy-system integration, MLOps and maintenance requirements, broader organizational coordination, resource commitment, governance, and continued managerial support. These technological and organizational requirements were discussed alongside locally embedded regulatory, talent, linguistic, and external-resource conditions, while broader deployment also required continued justification through measurable value and organizational acceptance.

We interpret these patterns as indicating that movement from pilot experimentation toward wider deployment can expose technological, organizational, and institutional interdependencies that are less visible under bounded experimental conditions. This interpretation does not imply a uniform sequence, nor does it establish a causal mechanism observed longitudinally. Rather, it integrates the recurring dimensions reconstructed from participants’ retrospective accounts.

Figure 2 synthesizes the five aggregate dimensions identified in the interview material. It places bounded experimentation alongside four co-relevant concerns reported in connection with wider deployment: production exposure, capability mobilization, local institutional and resource embeddedness, and organizational legitimation. The innovation management threshold names this interpretive synthesis; no causal links among these concerns are inferred. The positioning of the dimensions does not imply a fixed sequence, successful scaling, or longitudinally demonstrated relationships.

Figure 2. Interpretive account of the pilot-to-scaling transition



The diagram organizes retrospective accounts; it does not posit ordered stages, causal arrows between dimensions, or achieved scaling.

DISCUSSION

From Bounded Experimentation to Production Exposure

The findings suggest that the transition from bounded AI experimentation toward wider organizational deployment can be understood through the interpretive concept of production exposure. We define production exposure as the increased visibility and managerial significance of technological and organizational interdependencies when an AI initiative is considered for sustained operational use beyond a controlled pilot environment.

Production exposure must be distinguished from established notions in AI implementation research. First, it is not equivalent to productionizing. Haefner et al. (2023) identify productionizing as a phase of AI implementation involving operational integration; production exposure instead concerns how existing implementation dependencies become more salient and consequential as organizations approach operational deployment.

Second, production exposure differs from deployment complexity. Deployment complexity refers to technical and organizational difficulties associated with implementation, whereas production exposure emphasizes when and why such difficulties become visible and relevant to managerial decision-making in the transition beyond experimentation.

Third, production exposure should not be confused with technical debt. Sculley et al. (2015) discuss long-term maintenance liabilities arising from design compromises and dependencies in machine-learning systems.

Production exposure does not denote the accumulation of these liabilities; rather, it captures how existing dependencies and limitations may become more consequential as organizations attempt sustained operational deployment.

Finally, production exposure is analytically distinct from socio-technical interdependence. The latter concerns relationships among technologies, organizational actors, processes, and structures. Production exposure focuses specifically on the increased visibility and managerial consequences of those relationships during the reported pilot-to-scaling transition (Berente et al., 2021; Haefner et al., 2023).

The empirical accounts support this bounded interpretation. P3 reported infrastructure and data-quality limitations when the organization attempted actual deployment. P8 described a model-to-production gap, while P9 noted that models may degrade in production. These participants' statements indicate that establishing technical feasibility under controlled experimental conditions need not demonstrate the ability to integrate, monitor, maintain, and govern an application in operational use.

The concept therefore does not identify a new implementation stage or an entirely new class of obstacles. Its explanatory value lies in clarifying why familiar technological and organizational interdependencies can become more consequential when an initiative moves beyond bounded experimentation. Whereas Fichman and Kemerer (1999) examine the gap between technology acquisition and extensive organizational assimilation, the present study focuses more narrowly on the managerial significance of dependencies reported at the pilot-to-scaling boundary. Because the study is cross-sectional and retrospective, production exposure is an interpretation of participants' accounts, not an independently observed temporal or causal mechanism.

Scaling as Capability Mobilization and Organizational Legitimation

A second interpretation concerns the distinction between possessing organizational capabilities and mobilizing them for wider deployment. AI-readiness research has established that successful AI implementation depends on multiple complementary resources and capabilities (Jöhnk et al., 2021). Berente

et al. (2021) likewise emphasize communication, leadership, coordination, and control in the management of AI.

The present findings suggest that these capabilities become particularly consequential when organizations attempt to move beyond a pilot that has already demonstrated technical feasibility. Participants described completed POCs that were not immediately industrialized because of post-POC funding limitations, changing priorities, coordination difficulties, integration requirements, or the need to retain specialized expertise.

This distinction suggests that scaling readiness is not equivalent to pilot readiness. An organization may possess sufficient capabilities to experiment with AI without being able or willing to mobilize the broader resources required for sustained operational deployment.

The findings also extend this argument beyond resource availability. Participants associated wider deployment with continued organizational justification through measurable value, managerial commitment, user acceptance, and operational use. Scaling therefore involved both capability mobilization and organizational legitimization.

This interpretation connects with Vial et al. (2023), who show that AI project management requires coordination among different organizing logics. The present findings add a phase-sensitive perspective by suggesting that such coordination becomes particularly visible when an AI initiative must become embedded in ordinary organizational operations rather than remain a bounded experiment.

DOI Perceptions as Phase-Contingent Interpretations

The findings also provide a phase-contingent interpretation of Diffusion of Innovation attributes. Rogers' (2003) concepts of relative advantage, compatibility, complexity, trialability, and observability remain

analytically useful, but the present design does not establish that these perceptions change over time within the same projects or participants.

Instead, the interview accounts indicate that different innovation attributes were discussed in relation to different implementation concerns. Trialability was closely associated with bounded experimentation, where organizations could test AI applications before making broader commitments. Compatibility and complexity became prominent in participants' descriptions of interaction with legacy systems, APIs, CRM, billing systems, production infrastructures, maintenance, and monitoring.

Relative advantage and observability were discussed more strongly in relation to decisions about continued investment and broader deployment, particularly where participants referred to measurable ROI, KPIs, and demonstrated organizational value.

DOI is therefore interpreted here as a phase-contingent sensemaking lens rather than as a fixed causal model. The contribution is not to demonstrate that innovation perceptions objectively change across phases, but to show that different attributes become salient in participants' accounts of different implementation situations.

Locally Embedded Conditions in the Scaling Transition

A fourth interpretation concerns the way local context enters the scaling process. The findings do not support treating Tunisia as a homogeneous proxy for "developing countries." Instead, participants identified specific locally embedded conditions associated with wider AI deployment.

These included uncertainty surrounding aspects of data regulation, customer-data protection requirements, shortages and international mobility of specialized AI talent, multilingual and Tunisian-dialect requirements

for customer-facing applications, and access to technological resources through multinational groups or external providers.

This interpretation is consistent with the broader case for considering context in information-systems research (Ramadani & Almaarif, 2022). Their work concerns the conditions of information-systems scholarship in developing countries rather than AI scaling itself. In the present study, the contribution lies in showing how specific institutional and resource conditions appear in participants' accounts of attempted deployment. Some were described as constraining implementation through regulatory uncertainty, limited specialized expertise, or localization requirements; others, including international group relationships, could facilitate access to standards, technologies, and implementation experience.

The relevance of the Tunisian setting therefore lies not in suggesting that these conditions characterize developing economies generally, but in showing how specific institutional and resource conditions became embedded in participants' accounts of the transition toward wider deployment.

The pilot-to-Scaling Transition as an Innovation Management Threshold

Taken together, the findings suggest that the transition from AI pilot experimentation toward wider organizational deployment can be interpreted as an innovation management threshold. We conceptualize this threshold as a sensitizing interpretive concept rather than as a newly validated construct, a discrete temporal event, or an additional universal stage of AI implementation.

Existing studies distinguish implementation phases, including proving the concept, productionizing, and platformizing (Haefner et al., 2023), and show that initial technology adoption need not lead to extensive organizational assimilation (Fichman & Kemerer, 1999). These perspectives establish phase differences and assimilation gaps. Our interpretation addresses a narrower but complementary question: what becomes managerially consequential when organizational actors describe moving, or considering moving, from bounded AI experimentation toward sustained operational deployment?

The proposed threshold captures a shift in the scope of the reported managerial problem, from demonstrating technical feasibility and preliminary business value toward establishing conditions for integration, maintenance, governance, sustained resource commitment, coordination, and organizational acceptance. This is not merely an increased count of adoption barriers. Rather, the accounts suggest that existing requirements become more jointly consequential when an AI initiative must be incorporated into routine organizational operations.

The analytical contribution is an interpretation bringing together three closely related concerns: production exposure, whereby technological and organizational dependencies become more visible; sustained capability mobilization, whereby resources and responsibilities must be coordinated beyond a pilot team; and organizational legitimation, whereby continued investment and use require managerial justification and acceptance. Locally embedded institutional and resource conditions cut across these concerns. The five empirical dimensions remain distinct; the threshold is their synthesis, not an additional aggregate dimension.

This formulation complements rather than replaces established implementation-stage and assimilation perspectives, as well as research on changing actors and organizational boundaries in digital innovation (Nambisan et al., 2017). Its incremental explanatory value lies in articulating why technical pilot success does not by itself demonstrate organizational readiness for broader operational deployment.

An alternative interpretation remains plausible. Some difficulties described as emerging around scaling may already have existed during project selection, early architecture decisions, data preparation, or resource planning but remained insufficiently visible during bounded experimentation. The cross-sectional retrospective design does not establish a common temporal sequence or demonstrate that scaling creates the difficulties observed. Longitudinal research is needed to examine these interpretations further.

Contributions and Implications

Theoretical contributions

This study offers three complementary theoretical contributions to research on artificial intelligence implementation and scaling. Rather than proposing an alternative implementation-stage model, it develops an interpretive account of how established technological, organizational, and institutional conditions become differently consequential beyond bounded experimentation.

First, the study contributes to AI implementation and innovation management research by refining the interpretation of the pilot-to-scaling transition. Haefner et al. (2023) identify proving the concept, productionizing, and platformizing as different implementation phases; Fichman and Kemerer (1999) show that initial adoption does not ensure organizational assimilation. Building on these perspectives, this study interprets an innovation management threshold as a reported reconfiguration of managerial requirements, not as an extra phase or a new causal mechanism.

Its theoretical value lies in bringing together production exposure, sustained capability mobilization, and organizational legitimation to explain why pilot feasibility does not by itself demonstrate readiness for wider deployment. The threshold names an interpretive synthesis of these requirements, while retaining the distinct empirical dimension of local institutional and resource embeddedness.

Second, the study contributes to organizational AI readiness and innovation-diffusion research through a phase-contingent interpretation of implementation conditions and perceived innovation attributes. Existing work identifies relevant organizational assets, capabilities, and commitments (Jöhnk et al., 2021), while Diffusion of Innovation theory distinguishes trialability, compatibility, complexity, relative advantage, and observability (Rogers, 2003).

In participants' retrospective accounts, bounded experimentation was more closely associated with technical feasibility, testing, and initial value, whereas wider deployment raised integration, operational complexity, continued resource commitment, and observable organizational value. This interpretation distinguishes pilot readiness from scaling readiness and treats DOI attributes as sensitizing categories rather than as fixed predictors or statistically tested mediators. It does not claim to measure change within the same projects over time.

Third, the study contributes to context-sensitive information-systems research by examining how locally embedded conditions enter attempts to scale AI. Consistent with the broader argument for considering context in IS research (Ramadani & Almaarif, 2022), the findings show how participants in Tunisian telecommunications firms connected deployment concerns with data-protection requirements, regulatory uncertainty, specialized AI expertise, linguistic adaptation, and external organizational resources.

The contextual contribution is not to assert that these conditions are unique to Tunisia or typical of developing economies. Instead, it is to show how they are implicated in participants' interpretations of technological integration, capability mobilization, and organizational legitimation. Taken together, the three contributions provide a process-oriented and context-sensitive explanation grounded in reconstructed organizational experiences rather than verified longitudinal sequences or causal effects.

Managerial Implications

The findings suggest that managers should distinguish explicitly between pilot readiness and scaling readiness. A technically successful proof of concept should not automatically be interpreted as evidence that an organization is ready for wider deployment. Before industrialization, managers should assess data stability, system-integration requirements, monitoring and maintenance arrangements, security, operational ownership, governance, and cross-functional responsibilities.

The findings also suggest that resources for industrialization should be considered before the pilot has been completed. Scaling budgets may need to extend beyond model development to include data engineering, MLOps infrastructure, system integration, computing or cloud resources, maintenance, retraining, cybersecurity, and long-term operational support. Clear ownership across IT, data teams, business units, management, and compliance can help reduce the gap between technically successful models and applications that become embedded in organizational processes.

Observable business value and user appropriation should also form part of scaling readiness. Pilots may therefore be assessed not only through technical performance measures but also through business KPIs that remain relevant after deployment. Attention to user understanding, model limitations, human oversight, and change-management practices may further support sustained organizational use.

Based on these findings, the study proposes a pilot-to-scale decision gate as a practical managerial device. Such a gate can prompt managers to assess whether an AI initiative is ready not only technically, but also in terms of integration, maintenance, funding, governance, organizational ownership, user acceptance, and continued legitimacy. The effectiveness of this proposed tool was not evaluated in the present study and should therefore be examined in future research.

LIMITATIONS AND FUTURE RESEARCH

This study has several limitations that should be considered when interpreting its findings.

First, the empirical setting is restricted to 11 participants across three telecommunications operators in Tunisia. Although the sample incorporates strategic, managerial, operational, and technical perspectives and thematic saturation was judged to have been reached for the focused research question, the study does not claim statistical representativeness. The findings are therefore intended to support analytical interpretation within the organizational and institutional context examined. Transferability to other sectors, countries, and organizational settings should be assessed empirically.

Second, the study adopts a cross-sectional qualitative design. Participants retrospectively described AI initiatives at different stages, including experimentation, pilot deployment, and wider implementation. The study therefore reconstructs the pilot-to-scaling transition from participants' accounts rather than observing the same projects longitudinally. Temporal ordering cannot be independently verified, and the concepts of production exposure and innovation management threshold should consequently be interpreted as reconstructed patterns rather than directly observed process mechanisms. Future longitudinal research could follow specific AI initiatives from proof of concept through production, industrialization, and wider organizational deployment.

Third, the findings rely primarily on self-reported interview data. Participants' accounts may be affected by selective recall, retrospective rationalization, or organizational positioning. Several precautions were used to reduce interpretive overreach: the study includes participants from different organizational and hierarchical positions, maintains explicit links between interpretations and interview excerpts, treats theoretical frameworks as sensitizing rather than deterministic, and avoids interpreting NVivo co-occurrences as causal or statistical evidence. Nevertheless, these procedures cannot eliminate the limitations inherent in retrospective accounts. Future studies could combine interviews with project documentation, implementation logs, governance records, performance indicators, or direct observation of AI project teams.

Fourth, the qualitative design does not allow the relationships identified among technological, organizational, institutional, and interpretive conditions to be treated as statistically tested causal effects. The NVivo matrix queries were generated from the same interview corpus and were used only as descriptive analytical aids. Future quantitative or mixed-method research could examine whether the relationships identified qualitatively are also observed across larger organizational samples.

The findings should also be interpreted within specific boundary conditions. The empirical context involves

a regulated, data-intensive sector characterized by legacy infrastructures, customer-data protection requirements, specialized technical capabilities, and organizational interdependence across multiple functions. The relevance of the findings may therefore differ in less regulated sectors, organizations with simpler technological infrastructures, smaller firms, or settings with different institutional and labor-market conditions. Comparative studies across banking, healthcare, energy, public services, and other organizational contexts could help identify where the proposed pilot-to-scaling dynamics remain applicable and where they require modification.

Finally, future research could examine the pilot-to-scaling transition across different organizational levels and stakeholder groups. Multi-level studies could investigate how executive, managerial, technical, operational, and user perspectives interact during scaling decisions and whether different actors interpret scaling readiness, organizational value, and implementation risk differently.

CONCLUSION

This study examined how and why the transition from AI pilot experimentation toward wider organizational deployment becomes a distinct innovation management challenge in Tunisian telecommunications firms. Based on 11 semi-structured interviews across three telecommunications operators, the analysis identified five interconnected dimensions in participants' retrospective accounts of this transition.

The findings suggest that successful pilot experimentation does not necessarily establish organizational readiness for sustained AI deployment. Whereas bounded experimentation emphasizes technical feasibility and preliminary business value, accounts of movement toward operational deployment highlight system integration, monitoring and maintenance, governance, cross-functional coordination, continued resource commitment, and organizational acceptance. The study interprets this distinction through two complementary concepts. Production exposure refers to the increased visibility and managerial significance of existing technological and organizational interdependencies around attempted deployment. The innovation management threshold is a broader sensitizing synthesis of the changing managerial requirements, integrating production exposure, capability mobilization, and continued organizational legitimation.

Neither concept is proposed as an additional implementation stage, an independently validated construct, or a universal causal mechanism. Instead, both complement established work on AI implementation phases and technology assimilation by articulating how known requirements become differently consequential in reported implementation situations. The findings also indicate that innovation-related perceptions can be interpreted in relation to implementation situations and that locally embedded regulatory, linguistic, talent-related, and external-resource conditions feature in participants' accounts of scaling attempts. For managers, the practical implication is to distinguish pilot readiness from scaling readiness by assessing operational integration, governance, maintenance, resourcing, ownership, and legitimacy alongside technical performance.

Because the research relies on cross-sectional retrospective interviews, it does not establish longitudinal transitions or causal ordering within the same projects. Future longitudinal and comparative studies could examine whether the proposed interpretive concepts remain useful across AI initiatives, sectors, and institutional environments.

ACKNOWLEDGEMENTS

The authors thank the organizational participants who contributed their time and experience to the study.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this article.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Data Availability

The raw interview transcripts are not publicly available because the confidentiality assurances given to participants and the potentially identifiable nature of the qualitative data preclude open sharing. De-identified excerpts supporting the findings are included in the article. Further information may be available from the corresponding author subject to ethical and confidentiality constraints.

REFERENCES

1. Berente, N., Gu, B., Recker, J., & Santhanam, R. (2021). Managing artificial intelligence. *MIS Quarterly*, 45(3), 1433-1450. <https://doi.org/10.25300/MISQ/2021/16274>
2. DiCicco-Bloom, B., & Crabtree, B. F. (2006). The qualitative research interview. *Medical Education*, 40(4), 314-321. <https://doi.org/10.1111/j.1365-2929.2006.02418.x>
3. DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review*, 48(2), 147-160. <https://doi.org/10.2307/2095101>
4. Fichman, R. G. (2004). Going beyond the dominant paradigm for information technology innovation research: Emerging concepts and methods. *Journal of the Association for Information Systems*, 5(8), 314-355. <https://doi.org/10.17705/1jais.00054>
5. Fichman, R. G., & Kemerer, C. F. (1999). The illusory diffusion of innovation: An examination of assimilation gaps. *Information Systems Research*, 10(3), 255-275. <https://doi.org/10.1287/isre.10.3.255>
6. Gioia, D. A., Corley, K. G., & Hamilton, A. L. (2013). Seeking qualitative rigor in inductive research: Notes on the Gioia methodology. *Organizational Research Methods*, 16(1), 15-31. <https://doi.org/10.1177/1094428112452151>
7. Greenhalgh, T., Robert, G., Macfarlane, F., Bate, P., & Kyriakidou, O. (2004). Diffusion of innovations in service organizations: Systematic review and recommendations. *The Milbank Quarterly*, 82(4), 581-629. <https://doi.org/10.1111/j.0887-378X.2004.00325.x>
8. Guest, G., Bunce, A., & Johnson, L. (2006). How many interviews are enough? An experiment with data saturation and variability. *Field Methods*, 18(1), 59-82. <https://doi.org/10.1177/1525822X05279903>
9. Haefner, N., Parida, V., Gassmann, O., & Wincent, J. (2023). Implementing and scaling artificial intelligence: A review, framework, and research agenda. *Technological Forecasting and Social Change*, 197, 122878. <https://doi.org/10.1016/j.techfore.2023.122878>
10. Haefner, N., Wincent, J., Parida, V., & Gassmann, O. (2021). Artificial intelligence and innovation management: A review, framework, and research agenda. *Technological Forecasting and Social Change*, 162, 120392. <https://doi.org/10.1016/j.techfore.2020.120392>
11. Instance Nationale de Protection des Données Personnelles. (n.d.). Textes: Protection des données personnelles en Tunisie. Retrieved October 1, 2026, from <https://www.inpdp.tn/Texte.html>
12. Instance Nationale des Télécommunications. (2026). Décisions de l'Instance Nationale des Télécommunications. Retrieved October 1, 2026, from <https://www.intt.tn/>
13. Jöhnk, J., Weißert, M., & Wyrski, K. (2021). Ready or not, AI comes—An interview study of organizational AI readiness factors. *Business & Information Systems Engineering*, 63(1), 5-20. <https://doi.org/10.1007/s12599-020-00676-7>
14. Kallio, H., Pietilä, A.-M., Johnson, M., & Kangasniemi, M. (2016). Systematic methodological review: Developing a framework for a qualitative semi-structured interview guide. *Journal of Advanced Nursing*, 72(12), 2954-2965. <https://doi.org/10.1111/jan.13031>
15. Langley, A., & Abdallah, C. (2011). Templates and turns in qualitative studies of strategy and management. In D. D. Bergh & D. J. Ketchen, Jr. (Eds.), *Building methodological bridges (Research*

- Methodology in Strategy and Management, Vol. 6, pp. 201-235). Bingley, England: Emerald Group Publishing. [https://doi.org/10.1108/S1479-8387\(2011\)0000006007](https://doi.org/10.1108/S1479-8387(2011)0000006007)
16. Lincoln, Y. S., & Guba, E. G. (1985). *Naturalistic inquiry*. Beverly Hills, CA: Sage.
17. Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, 58(3), 103434. <https://doi.org/10.1016/j.im.2021.103434>
18. Myers, M. D. (2013). *Qualitative research in business and management* (2nd ed.). London, England: Sage.
19. Nambisan, S., Lyytinen, K., Majchrzak, A., & Song, M. (2017). Digital innovation management: Reinventing innovation management research in a digital world. *MIS Quarterly*, 41(1), 223-238. <https://doi.org/10.25300/MISQ/2017/41:1.03>
20. Palinkas, L. A., Horwitz, S. M., Green, C. A., Wisdom, J. P., Duan, N., & Hoagwood, K. (2015). Purposeful sampling for qualitative data collection and analysis in mixed method implementation research. *Administration and Policy in Mental Health and Mental Health Services Research*, 42(5), 533-544. <https://doi.org/10.1007/s10488-013-0528-y>
21. Ramadani, L., & Almaarif, A. (2022). Considering context in information systems research: Understanding the conditions of developing country scholarship. *The Electronic Journal of Information Systems in Developing Countries*, 88(1), e12200. <https://doi.org/10.1002/isd2.12200>
22. Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). New York, NY: Free Press.
23. Sculley, D., Holt, G., Golovin, D., Davydov, E., Phillips, T., Ebner, D., Chaudhary, V., Young, M., Crespo, J.-F., & Dennison, D. (2015). Hidden technical debt in machine learning systems. *Advances in Neural Information Processing Systems*, 28, 2503-2511. <https://mlanthology.org/neurips/2015/sculley2015neurips-hidden/>
24. Shenton, A. K. (2004). Strategies for ensuring trustworthiness in qualitative research projects. *Education for Information*, 22(2), 63-75. <https://doi.org/10.3233/EFI-2004-22201>
25. Tornatzky, L. G., Fleischer, M., & Chakrabarti, A. K. (1990). *The processes of technological innovation*. Lexington, MA: Lexington Books.
26. Tracy, S. J. (2010). Qualitative quality: Eight “big-tent” criteria for excellent qualitative research. *Qualitative Inquiry*, 16(10), 837-851. <https://doi.org/10.1177/1077800410383121>
27. Vial, G., Cameron, A.-F., Giannelia, T., & Jiang, J. (2023). Managing artificial intelligence projects: Key insights from an AI consulting firm. *Information Systems Journal*, 33(3), 669-691. <https://doi.org/10.1111/isj.12420>