

When AI Adoption Constraints Interact: Organizational Responses and Adoption Trajectories in Tunisian Telecommunications

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ABSTRACT

Purpose – This study examines how technological, organizational and environmental constraints may interact during organizational artificial intelligence (AI) adoption and how firms respond to these interdependencies in the telecommunications sector.

Design/methodology/approach – The study draws on 17 semi-structured interviews with managers and professionals directly involved in AI initiatives across three Tunisian telecommunications operators. An abductive thematic analysis combined open coding, the Technology–Organization–Environment (TOE) framework as a sensitizing device, relational coding, and within-case and cross-case comparison. Analytical matrices distinguished participant-stated linkages, process reconstruction and researcher inference.

Findings – The analysis identifies four recurrent but non-systematic mechanisms. First, some constraints may propagate across TOE domains, as capability shortages affect data preparation, model reliability and business trust. Second, some environmental pressures become consequential through their translation into internal technological and organizational requirements. Third, some organizational responses may mitigate an initial constraint while generating or intensifying secondary dependencies, costs or coordination burdens. Fourth, the projects examined followed differentiated adoption trajectories, including scaling, partial deployment, prolonged implementation and non-scaling.

Originality/value – The study develops a relational and conditional interpretation of TOE by shifting attention from isolated adoption factors to cross-domain propagation, the potential secondary effects of organizational responses and evolving adoption trajectories.

Practical implications – Managers should diagnose chains of constraints rather than isolated barriers and assess the possible secondary consequences of mitigation actions before scaling AI initiatives. Stage-specific assessments of data readiness, integration, governance, maintainability and business viability remain important in regulated, infrastructure-intensive organizations operating under resource constraints.

Keywords: Technology–Organization–Environment (TOE) framework, AI readiness, digital transformation, technology implementation, emerging economy

INTRODUCTION

Artificial intelligence (AI) has become an increasingly important component of organizational digital transformation. Firms deploy AI for customer management, operational optimization, forecasting, fraud detection, network management and decision support. Yet organizational AI adoption involves more than acquiring algorithms or computing infrastructure. Effective implementation depends on complementary resources, including reliable data, specialized skills, appropriate information infrastructures, managerial sponsorship and cross-functional coordination (Jöhnk et al., 2021; Mikalef and Gupta, 2021). AI adoption should therefore be understood as a socio-technical and organizational transformation rather than as a stand-alone technology implementation.

Research has consequently identified numerous technological, organizational and environmental conditions associated with organizational AI adoption. The Technology–Organization–Environment (TOE) framework has been widely used to organize these conditions by distinguishing technological characteristics and capabilities, organizational resources and structures, and environmental influences such as regulation, competition and vendor relationships (Tornatzky and Fleischer, 1990; Baker, 2012). Empirical studies have examined managerial support, technical capability, organizational readiness, government involvement, competitive pressure and vendor partnerships as important determinants of AI adoption (Chen et al., 2021; Chatterjee et al., 2021). More recent research confirms the relevance of these conditions across developing-country and sectoral contexts (Horani et al., 2025; Yang et al., 2024; Wong and Ngai, 2025).

Although this literature has substantially improved understanding of which conditions facilitate or constrain AI adoption, less is known about how these constraints become interconnected during implementation. A shortage of data-engineering skills, for example, may weaken data preparation; inadequate data preparation may reduce model reliability; reduced reliability may undermine business trust; and declining trust may subsequently slow adoption. In such sequences, technological and organizational constraints are not independent factors. Their effects depend partly on how one condition generates, amplifies or transforms another. This issue is consistent with calls to investigate how combinations of AI readiness conditions influence adoption outcomes (Jöhnk et al., 2021).

A related limitation concerns organizational responses to these constraints. Firms do not passively experience fragmented data, legacy systems, regulatory requirements, skill shortages or user resistance. They invest in data platforms, recruit specialists, establish governance arrangements, train users, redesign architectures and engage external providers. Although such responses can mitigate immediate constraints, they may simultaneously generate new dependencies, costs or coordination requirements. External expertise may compensate for an internal capability shortage while increasing vendor dependence; cloud infrastructure may improve scalability while increasing recurring costs; and formal governance may reduce uncertainty while adding validation and coordination requirements. Understanding AI adoption therefore requires examining not only constraints themselves but also how organizational responses reshape subsequent adoption conditions.

This issue becomes particularly important when AI adoption is viewed as an evolving trajectory rather than a binary decision. AI initiatives frequently progress through proofs of concept, pilots, partial operational use and subsequent scaling decisions, and the requirements for organizational readiness can change across these stages (Uren and Edwards, 2023). Telecommunications provides a particularly informative context for examining such processes because AI applications interact with extensive information infrastructures, legacy systems, high-volume customer and network data, multiple business functions and regulatory requirements. The Tunisian telecommunications sector further provides an emerging-economy setting characterized by resource constraints, a specialized labor market and a regulated competitive environment. The relevance of this setting therefore lies not simply in its geographical location, but in the organizational conditions under which interconnected AI adoption constraints can be observed.

Against this background, this study addresses the following research question: How do technological, organizational and environmental constraints interact in shaping AI adoption in Tunisian telecommunications firms, and how do firms respond to these interconnected constraints? Using TOE as a sensitizing analytical framework, the study examines relationships connecting initial constraints, their consequences, organizational responses and possible secondary constraints. It makes three contributions. First, it develops a relational use of TOE by examining situations in which the consequences of a constraint may propagate into another technological, organizational or environmental domain. Second, it shows that some organizational responses may reconfigure adoption conditions and, in certain situations, generate or intensify new dependencies, costs or organizational burdens. Third, it conceptualizes AI adoption as an evolving and conditional trajectory rather than a binary outcome, with projects progressing differently as configurations of constraints, responses and reassessment change over time.

LITERATURE REVIEW

Organizational AI adoption and Readiness

Organizational AI adoption depends on a configuration of complementary technological and organizational resources rather than on access to AI technologies alone. Mikalef and Gupta (2021) conceptualize AI capability as a combination of resources that enables organizations to generate value from AI, while Jöhnk et al. (2021) identify strategic alignment, resources, knowledge, culture and data as central dimensions of organizational AI readiness. These dimensions include financial resources, specialized personnel, IT infrastructure, AI awareness, upskilling, collaborative work, change management, data availability, data quality and data accessibility.

Data readiness is particularly important because AI development and operational use depend on the quality, accessibility and continuity of organizational data. Fragmented repositories, inadequate historical data and weak data flows can undermine model development and reliability. Yet data conditions are themselves shaped by organizational decisions concerning governance, staffing, architecture and process ownership. Technological and organizational readiness may therefore be mutually dependent rather than simply additive.

A similar interdependence characterizes people-related readiness. AI initiatives require technical expertise, domain knowledge and actors capable of translating between business requirements and technical development. They also require managers and users able to interpret algorithmic outputs, coordinate change and incorporate AI into organizational routines. Jöhnk et al. (2021) emphasize collaborative work and change management, while Uren and Edwards (2023) highlight the importance of connections between technical and business functions throughout the adoption journey. Raisch and Krakowski (2021) further show that automation and augmentation remain intertwined, reinforcing the continuing importance of human judgment and organizational coordination.

TOE and the Dominant Factor-Based View of AI Adoption

The Technology–Organization–Environment (TOE) framework conceptualizes organizational technology adoption through three contextual domains: technology, organization and environment (Tornatzky and Fleischer, 1990; Baker, 2012). The technological domain concerns the characteristics of the technology and the firm's technical context; the organizational domain encompasses resources, structures, managerial support and capabilities; and the environmental domain includes competitors, regulators, suppliers and other external actors.

TOE is particularly relevant to AI adoption because organizational implementation simultaneously depends on data, information infrastructure, technical expertise, managerial resources and environmental conditions. In telecommunications, Chen et al. (2021) examine AI adoption through innovation characteristics, managerial support, technical capability, government involvement, competitive pressure and vendor partnerships. Chatterjee et al. (2021) similarly integrate TOE into an organizational AI adoption model, while Yang et al. (2024) show through multiple cases that AI affordances, organizational readiness, competition and regulation can vary substantially across firms. Wong and Ngai (2025) extend this stream in telecommunications by linking TOE conditions to dynamic capabilities and operational performance.

Horani et al. (2025) provide a particularly relevant comparison for the present study. Drawing on survey data from 512 senior IT/IS managers in Jordan, they combine diffusion of innovation and TOE to examine organizational AI adoption intentions and identify technological and socio-environmental determinants. Their study confirms the usefulness of TOE for explaining organizational AI adoption in a developing-country context.

However, the dominant analytical logic remains largely factor-centered. Technological, organizational and environmental conditions are generally represented as antecedents whose independent or combined effects

explain adoption intentions or outcomes. This perspective identifies which conditions matter, but provides less explanation of how one constraint may generate, amplify or transform another during implementation. A firm may simultaneously face a shortage of specialized skills and poor data quality, for example, without the framework necessarily revealing whether the former contributed to the latter or how this sequence affected trust, governance and subsequent scaling decisions.

From Coexistence to Cross-Domain Constraint Propagation

Distinguishing barrier coexistence from barrier interaction is important for understanding organizational AI adoption. Coexistence refers to the simultaneous presence of several constraints, whereas interaction occurs when one constraint contributes to generating, amplifying or transforming another. Two organizations may therefore report similar lists of adoption constraints while experiencing different implementation consequences because the relationships among those constraints differ.

Consider, for example, insufficient data-engineering capability as an organizational constraint and fragmented or low-quality data as a technological constraint. If insufficient staffing weakens data preparation, which subsequently reduces model reliability and business trust, the analytically relevant phenomenon is not simply the presence of multiple barriers. It is a directional sequence connecting conditions located in different TOE domains. This study refers to this mechanism as cross-domain constraint propagation.

Such a relational use of TOE remains consistent with its contextual architecture while changing the unit of analytical attention. Rather than treating technological, organizational and environmental conditions exclusively as separate categories, it examines the mechanisms connecting them. This perspective responds to Jöhnk et al.'s (2021) call for greater attention to combinations of AI readiness factors. It does not reposition TOE as a process theory; instead, TOE domains are used as sensitizing categories within an analysis focused on relationships, sequences and consequences.

Organizational Responses and Secondary Constraints

Organizations respond to AI adoption constraints through capability development, governance mechanisms, infrastructure investment, external partnerships, training and process redesign. In conventional adoption and readiness perspectives, such interventions are generally conceptualized as facilitators because they increase the organization's capacity to implement AI. This interpretation is appropriate when the analytical question concerns whether a given capability facilitates adoption. It becomes less sufficient when an intervention alters the organizational configuration in ways that create additional requirements, dependencies or costs.

This study defines a secondary constraint as a new requirement, dependency or organizational burden that emerges from an action introduced to mitigate an initial AI adoption constraint. The concept does not imply that the organizational response is ineffective. For example, external expertise may successfully compensate for an internal skills shortage while simultaneously increasing vendor dependence. Cloud infrastructure may resolve scalability constraints while generating recurring costs, and governance mechanisms may improve accountability while increasing coordination or validation requirements.

Organizational responses can therefore become endogenous to the adoption process. Rather than following a linear sequence in which a constraint is identified and subsequently removed, mitigation can modify the configuration of conditions surrounding the project. An initial constraint prompts a response; the response reduces part of the original difficulty but may generate another constraint; and the organization subsequently reassesses the initiative within this modified configuration. The resulting process can therefore become recursive.

Complementary Theoretical Perspectives: Resource Dependence and Institutional Pressures

Although TOE remains the principal theoretical framework of this study, two complementary perspectives

help clarify mechanisms that may arise during organizational AI adoption. Resource dependence theory argues that organizations do not necessarily possess all resources required for their activities and may therefore depend on external actors that control critical resources. Organizations consequently seek to manage environmental interdependence and uncertainty (Pfeffer and Salancik, 1978; Hillman et al., 2009). This perspective is relevant to AI adoption when firms rely on technology vendors, cloud infrastructures or specialized external expertise to compensate for limited internal capabilities. Such responses may address an immediate constraint while simultaneously changing the organization's structure of dependence.

Institutional theory provides a complementary perspective on pressures originating in the organizational environment. DiMaggio and Powell (1983) distinguish coercive, mimetic and normative pressures that can shape organizational practices. In regulated environments, legal and regulatory requirements may exert coercive pressures that lead organizations to adapt structures, procedures or technical arrangements. Organizational responses are nevertheless not necessarily uniform. Oliver (1991) shows that organizations may respond differently to institutional pressures depending on the nature of those pressures and the conditions they face.

These perspectives do not replace TOE in the present study. They are used as complementary interpretive lenses to examine, respectively, dependencies that may emerge from organizational responses and the mechanisms through which environmental pressures are translated into internal technological or organizational requirements.

AI Adoption as an Evolving Trajectory

The distinction between proof of concept, pilot, partial operational use and enterprise-scale deployment is important for understanding organizational AI adoption. A technically successful proof of concept may not progress to broader implementation when integration, governance, maintenance, security, user acceptance or business-case requirements become more demanding. Uren and Edwards (2023) accordingly conceptualize AI adoption as an organizational journey in which different forms of readiness become salient at different stages.

This study therefore treats adoption as an evolving trajectory rather than a binary endpoint. Possible trajectories include scaling, partial deployment, prolonged implementation and non-scaling. These outcomes are not assumed to be predetermined at project inception. Instead, they can emerge from successive evaluations of technical feasibility, organizational capacity, environmental requirements and expected business value.

Combining this trajectory perspective with cross-domain constraint propagation and secondary constraints provides the conceptual basis for the empirical analysis. AI adoption can then be examined as a recursive sequence in which constraints interact, organizations respond, responses alter subsequent implementation conditions, and firms reassess whether and how an initiative should continue or scale.

METHODOLOGY

Research Design and Context

This study adopts a qualitative multi-firm design to investigate how AI adoption constraints become interconnected during implementation and how organizations respond to these interdependencies. A qualitative design is appropriate because the research question focuses on perceived sequences, organizational actions and evolving implementation consequences rather than on estimating the independent net effects of predefined variables. The study follows an abductive analytical logic, in which empirical observations were iteratively examined in relation to existing theoretical concepts to refine explanations when the data did not fit a purely factor-based account of AI adoption (Timmermans and Tavory, 2012).

The empirical setting comprises three telecommunications operators in Tunisia. Telecommunications provides an information-rich context for examining organizational AI adoption because AI initiatives depend on extensive information infrastructures, high-volume customer and network data, legacy systems, cross-functional processes and regulatory requirements. Tunisia additionally provides an emerging-economy setting characterized by resource constraints and a specialized labor market. The study does not seek statistical representativeness of the Tunisian telecommunications sector. Instead, comparison across three firms enables recurrent and contrasting mechanisms to be examined within a shared industrial and institutional context (Eisenhardt, 1989; Eisenhardt and Graebner, 2007).

Sampling and Participants

Participants were selected purposively based on their professional roles and direct involvement in AI-related initiatives. Eligibility required direct involvement in at least one AI-related project and a role providing first-hand knowledge of AI-related decision making, development, deployment, governance or organizational use. No formal criterion concerning professional seniority was imposed. Purposive sampling was appropriate because the study required information-rich participants able to reconstruct concrete implementation experiences and their organizational consequences (Palinkas et al., 2015).

Potential participants were initially identified on the basis of their functions within the three telecommunications operators and were contacted individually by email to request participation and arrange an interview. In total, 25 potential participants were contacted. Seventeen responded positively and agreed to participate, while eight did not respond; no explicit refusal was recorded among those who replied. Functional variation was sought across senior IT and digital leadership, data and AI, enterprise architecture, marketing and customer experience, and data protection and compliance in order to capture complementary technical, organizational, business and regulatory perspectives.

The final sample comprised 17 participants: six from Operator A, six from Operator B and five from Operator C. Sample adequacy was assessed primarily through the principle of information power rather than through a predetermined numerical threshold (Malterud et al., 2016). The assessment considered the focused nature of the research question, the participants' specialized expertise and direct involvement in AI initiatives, the diversity of functional perspectives represented, and the within-case and cross-case analytical strategy. As a supplementary assessment, the researcher reviewed the final three interviews and compared the themes and codes identified in these interviews with those already developed from the preceding interviews. The final three interviews did not introduce substantively new themes relevant to the research question, providing an additional indication of code saturation (Hennink et al., 2017). The sample was therefore considered adequate for the analytical aims of the study rather than statistically representative of the Tunisian telecommunications sector.

All 17 participants took part voluntarily after receiving information about the academic purpose of the study. Participant and organizational identifiers were anonymized throughout the analysis and reporting.

Table 1. Participant profile

Code	Organization	Functional perspective	AI-related involvement
A1	Operator A	Senior IT & digital transformation	Strategic arbitration, AI portfolio, budgets and vendors
A2	Operator A	Data & AI	Data/AI strategy, technical choices and implementation
A3	Operator A	Enterprise architecture	Integration, interoperability, cloud and security

Code	Organization	Functional perspective	AI-related involvement
A4	Operator A	Marketing & customer experience	Business requirements, POC validation and adoption
A5	Operator A	Data protection & compliance	Compliance, privacy, data governance and AI risk
A6	Operator A	Senior IT & digital transformation	AI portfolio, sponsorship and cross-functional coordination
B1	Operator B	Senior IT & digital transformation	Strategic direction, project arbitration and sponsorship
B2	Operator B	Data & AI	Data/AI strategy, industrialization and data quality
B3	Operator B	Enterprise architecture	Integration architecture, data flows, APIs and cloud
B4	Operator B	Marketing & customer experience	Business-side use, POC validation and user adoption
B5	Operator B	Data protection & compliance	Compliance validation, privacy, governance and risk
B6	Operator B	Senior IT & digital transformation	Project, budget, vendor and deployment decisions
C1	Operator C	Senior IT & digital transformation	Strategic arbitration, budgets, vendors and deployment
C2	Operator C	Data & AI	AI strategy, use-case prioritization and data quality
C3	Operator C	Enterprise architecture	Legacy integration, cloud architecture and security
C4	Operator C	Marketing & customer experience	Business requirements, use and employee adoption
C5	Operator C	Data protection & compliance	Privacy, regulation, governance and AI risk

Source: Authors' own elaboration. Operators and participants are anonymized.

Data Collection

Data were collected in March 2026 through online semi-structured interviews lasting approximately 30–45 minutes. Semi-structured interviewing was selected because it provided a common thematic structure while allowing participants to reconstruct concrete AI project experiences and explain relationships among implementation difficulties, organizational decisions and subsequent responses (Kallio et al., 2016).

The interview guide comprised 18 core questions. Interviews began by asking participants to describe their organizational role and a concrete AI initiative with which they had been directly involved. Subsequent

questions explored technological, organizational and environmental constraints, the consequences of those constraints, perceived interactions among them, organizational responses and the perceived effects of those responses.

Interviews were conducted in Tunisian Arabic and, with participants' agreement, were audio-recorded and fully transcribed in the original language by the researcher. All transcripts were subsequently translated from Tunisian Arabic into English by a bilingual professor of English proficient in both languages. As part of the original study, the co-author compared the English translations with the original Tunisian Arabic transcripts, with particular attention to technical terminology, contextual expressions and passages selected as illustrative quotations. When differences or ambiguities were identified, the original Tunisian Arabic transcript was used as the reference to clarify the intended meaning and adjust the English formulation where necessary. No formal independent back-translation procedure was conducted. Translation quality was therefore supported through bilingual human translation and systematic comparison with the source transcripts, consistent with a contextualized approach to cross-language research (Chidlow et al., 2014).

Data Analysis

Data analysis was conducted manually and followed an abductive thematic logic informed by Braun and Clarke's (2006) approach to thematic analysis and by abductive reasoning as described by Timmermans and Tavory (2012). The TOE framework was used as a sensitizing analytical framework rather than as a rigid a priori coding template. Technological, organizational and environmental domains therefore oriented analytical attention while allowing additional relationships and mechanisms to emerge from the interview material.

Analysis proceeded through several iterative stages. First, each transcript was read to identify concrete constraints, reported consequences, organizational actions and adoption outcomes. Second, open codes were assigned to recurrent issues, including data fragmentation, legacy systems, skills shortages, budget prioritization, regulatory requirements, user distrust, vendor dependence, training and governance. Third, relational coding was used to determine whether participants connected one condition to another. Particular attention was paid to sequences of the form: initial constraint → consequence → linked constraint → organizational response → perceived effect → secondary consequence.

Analytical matrices were then constructed to organize the relational evidence. For each candidate sequence, the analysis recorded the initial constraint, its reported consequence, any linked constraint, the organizational response, its perceived effect and any secondary consequence. The matrices distinguished direct participant-stated linkages from temporal or process reconstruction and from researcher inference. This distinction made the evidentiary path between interview material and the proposed cross-case mechanisms explicit.

Within-case analysis preceded cross-case comparison to reduce the risk of interpreting simple co-occurrence across interviews as evidence of interaction. Cross-case matrices were subsequently used to identify recurrent and contrasting mechanisms across Operators A, B and C and to compare resulting adoption trajectories. Negative or deviant evidence was retained, including a fraud-detection initiative whose operational use remained restricted and whose further scaling was uncertain because the cost-benefit relationship had become difficult to justify.

Standards for Relational Claims and Trustworthiness

Because the analysis focuses on relationships among constraints, particular attention was paid to avoiding unsupported causal interpretations. Relational evidence was evaluated at three levels. The strongest level consisted of an explicit participant statement that one condition generated, intensified or transformed another. The second consisted of a clear temporal or process sequence reconstructed within the same case and supported by multiple passages. The third consisted only of researcher inference. Such inferential connections were treated cautiously and were not used as evidence of causal relationships.

Only participant-stated linkages and clearly supported within-case sequences were therefore used to substantiate cross-domain constraint propagation in the results. Researcher inference alone was not treated as evidence of a causal connection.

Trustworthiness was further supported through systematic within-case and cross-case comparison, retention of negative or disconfirming evidence, transparent distinction between participant-stated relationships and analytical interpretation, and the use of participant quotations to demonstrate the empirical basis of the principal mechanisms (Shenton, 2004).

Ethics and Informed Consent

Ethical approval for this study was obtained from the relevant university ethics committee prior to data collection. All participants provided informed consent, and participant and organizational identities were anonymized throughout the study.

RESULTS

Cross-Domain Propagation of AI Adoption Constraints

Important AI adoption constraints did not remain confined to a single TOE domain. Participants described sequences in which an organizational constraint generated a technological consequence that subsequently produced additional organizational difficulties. A recurrent example concerned specialized skills. Insufficient data-engineering capacity reduced the time and expertise available for data preparation; inadequate preparation lowered model reliability; and unreliable outputs weakened business confidence in AI initiatives.

A participant from Operator B described this sequence explicitly: “The shortage of skills worsened the poor quality of the data. Because we did not have enough data engineers, we under-invested in data preparation. So the models were less reliable. Then the business teams lost confidence. Then adoption slowed. It is a chain.” (B2, translated).

A participant from Operator A reported a similar sequence: “We did not have enough resources to prepare the data properly; the models were less reliable, the business teams lost confidence, and adoption slowed. It is a sequence we really experienced.” (A2, translated).

Legacy systems and data silos generated another recurrent pathway. Fragmented information across CRM, billing, network and operational systems increased cleaning and integration work. Participants associated incomplete or inconsistent data with lower model usefulness, implementation delays, additional costs and difficulties in maintaining business confidence. Similar patterns were identified across the three operators, although the projects and operational contexts differed.

Environmental Pressures are Translated into Internal Requirements

Environmental constraints became consequential when they were translated into internal technological and organizational requirements. Participants referred particularly to regulation, labor-market conditions, vendors and competitive pressure.

Data-protection requirements were frequently associated with architectural and organizational changes. Participants described additional encryption, access controls, security measures and legal validation. One participant explained that regulation “forced us to review certain architectures, strengthen encryption, and add legal validations. It slowed some projects, but it also strengthened the confidence of clients and authorities” (B3, translated).

Labor-market conditions generated a different pattern. Difficulties in recruiting and retaining data engineers, data scientists and MLOps specialists reduced internal implementation capacity and increased reliance on

external providers or on a limited number of internal experts. Competitive pressure sometimes accelerated AI project decisions, but participants also reported tensions around project priorities and budget allocation.

Across the cases, external pressures therefore became visible in concrete internal requirements concerning architecture, expertise, coordination, security and financial resources.

Organizational Responses Mitigate Constraints But Generate Secondary Constraints

Organizations responded to AI adoption constraints through data centralization, recruitment, governance arrangements, training, MLOps development, cloud infrastructure and external partnerships. Participants generally described these interventions as necessary, but they also identified new dependencies or burdens associated with them.

Centralized data platforms improved data access, consistency and integration but increased dependence on a limited number of specialized employees. Cloud solutions improved scalability while increasing recurring costs and vendor dependence. Governance committees clarified decision responsibilities but introduced additional validation and coordination requirements. Training supported employee acceptance but required managerial and employee time.

A participant from Operator C summarized this pattern: “We move the problem. We do not eliminate it.” (C2, translated).

A participant from Operator A reported a similar trade-off: the centralized data platform improved data quality but concentrated reliance on a few experts, while cloud-based industrialization improved scalability but increased cost and vendor dependence (A2).

Across the cases, mitigation actions therefore reduced particular initial constraints while generating additional dependencies, costs or coordination requirements. These response-induced effects are referred to in this study as secondary constraints.

Differentiated AI Adoption Trajectories

AI adoption did not emerge as a binary outcome. Projects progressed unevenly from proof of concept to pilot, partial operational use and broader deployment. Further scaling remained conditional on data quality, systems integration, governance, budget and demonstrated business value.

A churn project, for example, progressed from a limited proof of concept to a pilot and partial operational use, while broader deployment remained dependent on CRM integration and additional scaling resources. A network anomaly-detection initiative followed a similar trajectory: the model was used on some equipment, while wider deployment depended on further integration with supervision systems and additional resources.

In Operator C, one participant described a model already used for selected network dashboards and marketing recommendations, while wider deployment remained dependent on additional integration and budget: “We are moving, but slowly.” (C2, translated).

A contrasting case involved fraud detection. The model operated on a restricted perimeter, but wider deployment remained uncertain following difficulties related to data, integration, suppliers and compliance. The participant explained: “Today, the model is running, but on a limited scope. We have not generalized it. I do not know whether we will generalize it. The cost–benefit ratio is not obvious.” (B6, translated).

Across the cases, the observed trajectories therefore included partial deployment, continued implementation, wider scaling and uncertain non-scaling.

Cross-Case Synthesis of Results

Cross-case comparison identified a recurring sequence across the three operators. An initial technological, organizational or environmental constraint could generate consequences in another TOE domain. Organizations responded through capability development, infrastructure investment, governance, training or external expertise. These responses often mitigated part of the initial difficulty while sometimes generating additional dependencies, costs or coordination requirements. Subsequent reassessment of technical feasibility, organizational capacity, risk and business value influenced whether projects progressed toward wider scaling, remained partially deployed, continued in implementation or were not generalized. The sequence was not observed identically in every project. Some constraints remained relatively isolated, and some organizational responses resolved problems without generating consequential secondary constraints. The cross-case pattern therefore represents a recurrent mechanism rather than a deterministic adoption cycle.

Table 2. Cross-case synthesis of results

Cross-case finding	Empirical pattern	Organizational response	Adoption consequence
Cross-domain constraint propagation	Skills shortage → weak data preparation → lower model reliability → reduced business trust	Recruitment; data data engineering; platforms; training	Delay, additional cost and slower adoption
Environmental-to-internal translation	Regulation → architecture/compliance requirements; labor market → capability shortage; competition → priority tension	Governance; legal security; validation; sourcing	Implementation burden, but sometimes stronger legitimacy/trust
Response-induced secondary constraints	Data platforms, cloud and committees solve immediate problems but create new dependencies or burden	Centralization; vendors; cloud; governance; training	Expert dependence, vendor dependence, cost, bureaucracy
Differentiated trajectories	Projects progress unevenly from POC to pilot and operational use	Continued integration, capability building and reassessment	Scaling, partial deployment, prolonged pilot or non-scaling

Source: Authors' own elaboration.

To make the empirical basis of the proposed mechanisms more explicit, Table 3 links each principal mechanism to illustrative evidence and indicates the evidentiary status of the relationship. Consistent with the analytical standards described above, simple co-occurrence is not treated as interaction, and researcher inference alone is not used to substantiate a causal relationship.

Table 3. Illustrative empirical evidence for the principal mechanisms

Mechanism	Participant	Illustrative empirical evidence	Evidence status	Analytical scope
Cross-domain constraint	B2	"The shortage of skills worsened the poor quality of the data... the models were	Participant-stated linkage	Direct evidence of a chain linking skills, data preparation,

propagation		less reliable. Then the business teams lost confidence. Then adoption slowed. It is a chain.”		model reliability, business trust and adoption.
Cross-domain constraint propagation	A2	“We did not have enough resources to prepare the data properly; the models were less reliable, the business teams lost confidence, and adoption slowed. It is a sequence we really experienced.”	Participant-stated linkage	A similar mechanism reported in a second operator.
Environmental-to-internal translation	B3	Regulation “forced us to review certain architectures, strengthen encryption, and add legal validations.”	Participant-stated linkage	Shows how an external regulatory pressure becomes an internal technological and organizational requirement.
Secondary constraints	C2	“We move the problem. We do not eliminate it.”	Participant-stated linkage	Supports the possibility that mitigation displaces rather than fully removes a constraint.
Secondary constraints	A2	A centralized data platform improved data quality but concentrated reliance on a few experts; cloud-based industrialization improved scalability but increased cost and vendor dependence.	Within-case sequence	Shows how a response to an initial constraint may create a new dependence or cost.
Partial/progressive trajectory	C2	“We are moving, but slowly.” Wider deployment remained dependent on additional integration and budget.	Participant statement supported by case sequence	Illustrates conditional progression from limited operational use toward possible wider deployment.
Possible non-scaling	B6	“Today, the model is running, but on a limited scope... The cost–benefit ratio is not obvious.”	Participant-stated linkage	Shows that technical operation does not necessarily lead to wider generalization.

Source: Authors’ own elaboration from the interview data.

The cross-case comparison in Table 4 highlights both recurrent mechanisms and differentiated configurations. The comparisons are limited to patterns directly supported by the interview material and should not be read as permanent organizational characteristics of the three operators.

Table 4. Cross-case comparison of constraint configurations and AI adoption trajectories

Dimension	Operator A	Operator B	Operator C
Observed constraint configuration	Insufficient resources for data preparation, associated with lower model reliability and reduced business confidence.	Data-engineering skill shortages; regulatory and compliance requirements; data, integration and supplier difficulties in some projects.	Integration and budget constraints affecting the extension of some AI uses.
Interaction pattern	Insufficient resources → inadequate data preparation → lower model reliability → reduced business trust → slower adoption.	Skills shortage → weaker data preparation → lower reliability → reduced trust. Regulation also translated into architecture, security and legal-validation requirements.	Integration and budget conditions constrained wider deployment of AI uses already in operation.
Documented organizational responses	Data centralization and cloud-based industrialization to improve data quality and scalability.	Architecture review, stronger encryption and additional legal validation in response to regulatory requirements.	Continued integration and gradual deployment before wider scaling.
Observed secondary constraints	Centralization concentrated dependence on a few experts; cloud increased recurring costs and vendor dependence.	Security and compliance requirements increased validation and implementation burden; economic viability constrained wider fraud-detection deployment.	Some responses were described as displacing rather than eliminating problems; wider deployment remained dependent on integration resources and budget.
Documented trajectory	The available evidence primarily documents propagation and response-induced dependencies; the current material does not support assigning a single project trajectory as precisely as in B and C.	A fraud-detection model remained operational on a limited scope, with wider generalization uncertain partly because of the cost–benefit relationship.	Some models were used for selected network dashboards and marketing recommendations, while wider deployment remained dependent on integration and budget.

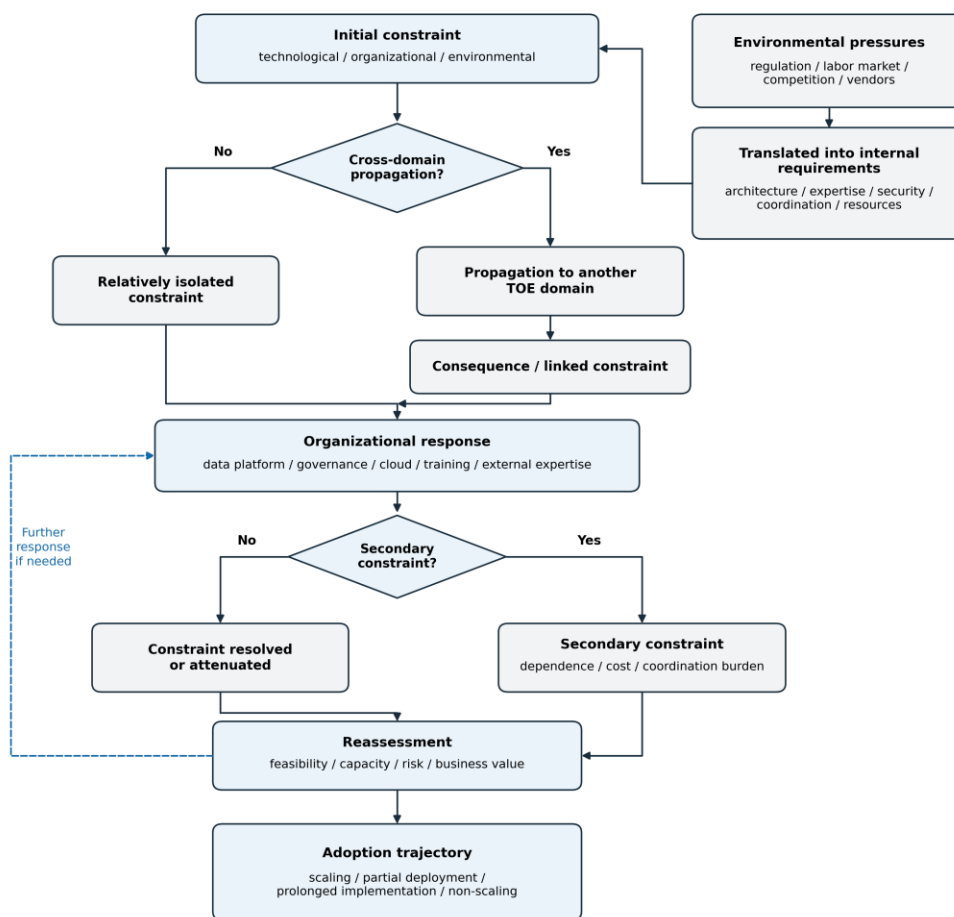
Source: Authors' own elaboration from the cross-case analysis.

Across the three operators, constraints did not remain isolated, but their configurations, organizational responses and adoption consequences differed. In Operator A, the evidence primarily documents a capability-data preparation chain and the dependencies created by data centralization and cloud-based industrialization. In Operator B, capability shortages were combined with regulatory, integration and supplier-related requirements, while the fraud-detection case also introduced explicit concerns about economic viability for wider deployment. Operator C, by contrast, was characterized in the available material by a more gradual deployment pattern in which some AI uses were already operational but wider extension remained conditional on additional integration and budget. These differences can therefore be

understood in relation to the specific constraint configurations and response patterns documented in the initiatives examined, rather than as fixed characteristics of the three organizations.

Figure 1 should be interpreted as a conditional rather than automatic recursive mechanism. Recursion occurs when a response introduced to mitigate an initial constraint generates or intensifies a new dependency, cost or organizational burden, prompting further reassessment. By contrast, some constraints may remain relatively isolated, and some responses may resolve or attenuate a difficulty without generating a consequential secondary constraint. The arrows therefore represent mechanisms observed in particular cases rather than universal causal relations.

Figure 1. Conditional recursive constraint–response model of organizational AI adoption



Conditional model: some constraints remain isolated, and some responses do not generate secondary constraints.

Source: Authors' own elaboration based on the cross-case analysis.

DISCUSSION

From isolated TOE Factors to Cross-Domain Constraint Propagation

The findings confirm the relevance of technological, organizational and environmental conditions identified in prior AI adoption research, but shift analytical attention from individual factors to the relationships connecting them. Previous studies have emphasized technical capability, organizational readiness, managerial support, competitive pressure, regulation and vendor relationships (Chen et al., 2021; Chatterjee et al., 2021; Yang et al., 2024; Wong and Ngai, 2025). The present study extends this perspective by showing that some adoption constraints become consequential through sequences that cross TOE domains.

This distinction adds a relational layer to TOE. Jöhnk et al. (2021) emphasize combinations of AI readiness dimensions; the present findings suggest that some of these combinations are not merely additive but sequential. Cross-domain constraint propagation therefore captures situations in which a condition located in one TOE domain alters conditions in another. TOE remains a contextual framework rather than a process theory, but its explanatory use can be extended by examining the relationships and sequences connecting its domains.

Environmental Constraints Operate Through Organizational Translation

A second contribution concerns how environmental conditions become consequential during implementation. TOE-based research recognizes regulation, competitive pressure, government involvement and external actors as relevant environmental influences on AI adoption (Chen et al., 2021; Yang et al., 2024). The present findings add process detail by showing that such pressures can become consequential through their translation into internal technological and organizational requirements.

Institutional theory helps specify this mechanism. Regulatory requirements can be interpreted as coercive pressures in the sense of DiMaggio and Powell (1983), but the findings do not imply that organizations respond mechanically to such pressures. Consistent with Oliver (1991), external demands acquire organizational consequences through the ways in which firms interpret and incorporate them into internal structures and processes. The contribution therefore lies less in identifying environmental pressures themselves than in showing how they become internal implementation requirements.

Organizational Responses are Endogenous to the Adoption Process

The findings also qualify the conventional distinction between barriers and facilitators. AI readiness research appropriately treats capabilities, governance, infrastructure, skills and external partnerships as mechanisms supporting implementation (Jöhnk et al., 2021; Mikalef and Gupta, 2021). The present study suggests, however, that an intervention can mitigate an initial constraint while simultaneously reconfiguring subsequent dependencies, costs or coordination requirements.

This provides the basis for the concept of secondary constraints. Such constraints should not be interpreted as evidence that an organizational response has failed; rather, they capture trade-offs that emerge when mitigation changes the configuration surrounding an AI initiative. Organizational responses can therefore become endogenous to the adoption process, making recursive sequences possible under particular conditions rather than inevitable.

Resource dependence theory helps specify this mechanism. Reliance on external providers or specialized expertise can give organizations access to resources that are insufficiently available internally while simultaneously increasing dependence on actors controlling those resources (Pfeffer and Salancik, 1978; Hillman et al., 2009). A response to an initial capability constraint may therefore reconfigure the dependencies surrounding the initiative and, under some conditions, contribute to a secondary constraint.

An alternative explanation must nevertheless be considered. Some constraints described as secondary may reflect limitations already present in the initial project design, including insufficient anticipation of costs, integration requirements, capabilities or technological dependencies. Because the evidence is retrospective, the study cannot always distinguish definitively between a constraint generated by an organizational response and a pre-existing condition that became more visible during implementation. The notion of secondary constraint is therefore applied conditionally and only when the relationship with the preceding response is sufficiently supported. Poor initial planning and response-induced effects should consequently be treated as competing, and in some cases complementary, explanations.

AI adoption as a Contingent Trajectory

Finally, the findings support a trajectory-based understanding of organizational AI adoption. Uren and

Edwards (2023) conceptualize AI adoption as an organizational journey in which readiness requirements evolve over time. The present study extends this perspective by connecting differentiated trajectories to changing configurations of constraints, organizational responses and subsequent reassessment.

Technical operation should therefore not be equated automatically with organizational scaling, nor should restricted expansion necessarily be interpreted as technical failure. Scaling decisions can depend on repeated assessments of technical feasibility, organizational capacity, environmental requirements, risk and business value. Scaling, partial deployment, prolonged implementation and non-scaling are consequently treated as different possible states within a contingent trajectory rather than as simple success-failure categories.

Taken together, the findings support a relational and conditional interpretation of organizational AI adoption. TOE identifies the contextual domains in which adoption conditions arise, while the present analysis highlights how some constraints propagate across those domains, how organizational responses can reconfigure subsequent conditions, and how these configurations contribute to differentiated adoption trajectories. The resulting perspective is recursive only when the empirical conditions for such recursion are present, rather than being a deterministic cycle.

CONTRIBUTIONS AND IMPLICATIONS

Theoretical Contributions

This study makes three theoretical contributions to research on organizational AI adoption.

First, the study develops a relational use of the Technology–Organization–Environment framework by focusing on connections among constraints located in different domains. The contribution is not to redefine TOE as a process theory, but to show that its explanatory value can be extended when analysis addresses not only technological, organizational and environmental factors but also the relationships and sequences connecting them. Cross-domain constraint propagation therefore refers to situations in which the consequences of a constraint arising in one domain affect conditions in another.

Second, the study specifies the role of organizational responses in the adoption process. Capabilities, infrastructure, governance arrangements and external partnerships are not treated only as facilitators. Some interventions may simultaneously reduce an initial constraint and reconfigure the dependencies, costs or coordination requirements surrounding the project. The concept of secondary constraint captures these effects when a sufficiently supported relationship can be established between an organizational response and a subsequent difficulty. This contribution is explicitly conditional: not all responses generate secondary constraints, and some later difficulties may also reflect initial conditions that were insufficiently anticipated.

Third, the study links these evolving configurations to differentiated adoption trajectories. Scaling, partial deployment, prolonged implementation and non-scaling are not treated as simple success–failure categories. They can represent organizational states emerging from repeated reassessments of technical feasibility, organizational capacity, environmental requirements, risk and business value. This perspective helps explain why technically promising AI initiatives may follow different organizational trajectories even when they confront apparently similar adoption conditions.

Practical implications

The findings have several implications for managers responsible for AI initiatives.

First, organizations should diagnose chains of constraints rather than isolated barriers. A shortage of specialized skills, for example, should not be treated exclusively as a human-resource issue if it subsequently affects data preparation, model reliability and business trust. Mapping these relationships can help managers identify intervention points where addressing one constraint may prevent several downstream difficulties.

Second, managers should assess the secondary consequences of mitigation actions before implementation. External partnerships should be evaluated not only for the expertise they provide but also for knowledge transfer and vendor-dependence risks. Cloud decisions should incorporate recurring cost and dependency scenarios. Centralized data platforms should include mechanisms for knowledge diffusion and succession, while governance arrangements should balance accountability with decision speed.

Third, decisions about wider AI deployment should rely on stage-specific scaling criteria. Technical performance alone is insufficient to justify enterprise-level implementation. Organizations should also assess data readiness, systems integration, maintainability, governance requirements, user adoption, regulatory compliance and business viability before progressing from proof of concept or pilot to broader deployment.

More broadly, mitigation actions should be treated as organizational design choices with both intended and unintended consequences. Anticipating these trade-offs can help firms reduce repeated cycles of problem displacement and make more informed decisions about whether, when and how AI initiatives should scale.

LIMITATIONS AND FUTURE RESEARCH

This study has several limitations that should be considered when interpreting its findings. First, it relies on retrospective participant accounts. Such accounts are appropriate for reconstructing perceived experiences, constraints and organizational responses, but they remain vulnerable to memory error, post-hoc reconstruction and retrospective rationalization. This limitation is particularly important in the present study because the analysis concerns sequences linking constraints, consequences and organizational responses. As Golden (1992) notes, retrospective accounts may differ from descriptions produced closer to the time of the events.

Several precautions were used to reduce the risk of overinterpretation. Relational claims were retained only when participants explicitly connected two conditions or when a sequence was supported by multiple passages within the same case. Researcher inference alone was not treated as evidence of a causal relationship. Within-case analysis preceded cross-case comparison, negative or disconfirming evidence was retained, and participant quotations were used to make the empirical basis of the proposed mechanisms visible. These procedures strengthen interpretive credibility, but they cannot eliminate the limitations inherent in retrospective accounts.

Second, the absence of longitudinal observation limits the ability to observe directly how constraints and responses evolve over time. The mechanisms identified should therefore be understood as reconstructed process patterns rather than as causal sequences observed prospectively. Future longitudinal research could follow AI initiatives from experimentation through operational use and scaling decisions to examine the recursive dynamics more directly.

Third, the empirical setting is limited to 17 participants across three telecommunications operators in one country. The objective was not statistical generalization but the identification and comparison of mechanisms within a specific organizational and institutional context. The findings may be particularly relevant to organizations characterized by data-intensive operations, complex technological infrastructures, legacy systems, regulatory requirements and dependence on specialized skills. Transferability to less regulated, less data-intensive sectors or organizations with substantially different technological resources should therefore be examined empirically.

Fourth, Tunisia provides an emerging-economy setting in which resource constraints, specialized labor-market conditions and regulatory requirements shaped the context examined in this study. Vendor dependence, skill availability and the translation of regulatory requirements may be configured differently in other institutional environments. Comparative research across countries, sectors and organization types could therefore identify the boundary conditions under which cross-domain propagation and secondary constraints are more or less likely to occur. These contextual characteristics should therefore be treated as

boundary conditions of the present findings rather than as universally applicable features of organizational AI adoption.

Finally, TOE was used as a sensitizing analytical framework. Although the abductive design allowed open coding and relational mechanisms to emerge from the data, TOE inevitably oriented analytical attention toward technological, organizational and environmental conditions. Future studies could combine TOE with complementary perspectives or use configurational and quantitative designs to test whether particular combinations or sequences of conditions are associated with differentiated adoption trajectories.

CONCLUSION

This study examined how technological, organizational and environmental constraints may interact during organizational AI adoption and how firms respond to these interdependencies in Tunisian telecommunications. The findings show that, in the cases studied, some constraints did not remain confined to a single TOE domain: their consequences extended into other technological or organizational conditions. Some environmental pressures also became consequential when translated into internal architectural, capability, security or coordination requirements.

The study also shows that organizational responses should not be understood exclusively as mechanisms of resolution. In some configurations, an intervention introduced to mitigate an initial constraint reconfigured costs, dependencies or coordination requirements and contributed to a secondary constraint. This dynamic is neither automatic nor universal: some constraints remained relatively isolated and some responses resolved or attenuated difficulties without generating a consequential secondary constraint.

These configurations help explain why the AI initiatives examined followed differentiated trajectories. Some progressed toward wider deployment, whereas others remained partially deployed, continued through prolonged implementation or were not generalized. Organizational AI adoption can therefore be understood as a conditional process of reconfiguration and reassessment rather than as a linear transition from an adoption decision to enterprise-wide deployment. Theoretically, the study offers a relational and conditional use of TOE centered on cross-domain propagation, the potential secondary effects of organizational responses and differentiated adoption trajectories. Managerially, it highlights the value of examining relationships among constraints and anticipating the possible consequences of mitigation choices before scaling decisions are made.

Conflict of Interest

The authors declare no conflict of interest.

Data Availability

The interview data are not publicly available in order to protect participant and organizational confidentiality.

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