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# Institutional Barriers to AI Adoption in Energy Utilities: A Theory-Driven Framework for Organizational Resistance, Capability Formation, and Strategic Transformation

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## Abstract

AI adoption in energy utilities is slower than anticipated despite its potential to support grid management, operational forecasting, asset optimization, and customer-facing services. Institutional forces, including regulations, professional norms, and organizational mental models, play a decisive but underexplored role in shaping this reluctance. The literature lacks a theory-driven framework that connects institutional barriers to organizational resistance, explains the process of capability formation, and outlines pathways for strategic transformation specifically for energy utilities. Existing discussions often treat AI adoption as a technical implementation issue rather than as an institutional and organizational transformation challenge. This article develops a theory-driven framework that identifies institutional barriers, analyses organizational resistance mechanisms, and proposes capability-building and transformation strategies for AI adoption in energy utilities. The framework links organizational resistance, capability formation, and strategic transformation as mutually reinforcing processes. The framework is built through conceptual integration of institutional theory, dynamic capabilities, organizational change management, and energy sector studies. No empirical data, experiments, surveys, simulations, or quantitative analyses are used. The framework classifies institutional barriers into regulative, normative, and cultural-cognitive types, each linked to specific resistance mechanisms. It further defines capability formation stages and strategic transformation pathways, while two analytical tables provide a barrier typology and a transformation roadmap. Accelerating AI adoption in energy utilities requires addressing institutional barriers head-on, building absorptive capacity, and pursuing context-sensitive strategic transformation. The framework offers a diagnostic and prescriptive tool for utility managers and policymakers.

**Keywords** Energy utilities, AI adoption, Institutional barriers, Organizational resistance, Capability formation, Strategic transformation

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## Introduction

AI is increasingly positioned as a strategic technology for energy utilities because it can support predictive maintenance, smart grid optimization, demand response, customer analytics, and operational decision support. Yet the pace of adoption often remains slower than the technical promise would suggest, especially in regulated utility environments where reliability, safety, compliance, and public accountability are central organizational concerns [1]. Digitalization studies show

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that energy organizations face distinctive barriers related to legacy infrastructures, regulatory uncertainty, fragmented data systems, and institutional risk aversion [2]. This article begins from the premise that AI adoption in utilities cannot be understood only as a question of algorithmic maturity or technical readiness.

The central argument is that institutional barriers tend to shape AI adoption more deeply than purely technological barriers. Regulatory lock-in can constrain experimentation, professional norms can privilege established engineering judgment, and cultural-cognitive assumptions can make algorithmic decision support appear risky or illegitimate [3]. Institutional contestation around smart grids demonstrates that energy transitions involve conflicts over organizational roles, authority, and accepted ways of operating rather than only the introduction of new technologies [4]. AI adoption in utilities therefore requires an institutional analysis that explains why organizations resist, delay, reinterpret, or selectively absorb new digital capabilities.

A theory-driven framework is needed because current discussions of AI adoption often separate barriers, capabilities, and strategic transformation into disconnected themes. Research on AI readiness emphasizes organizational preparedness, leadership, skills, and data foundations, but these capabilities are shaped by institutional expectations and internal legitimacy struggles [5]. Dynamic capability theory further suggests that firms must sense technological opportunities, seize them through organizational investments, and transform routines over time. Bringing these perspectives together makes it possible to explain why the same AI tool may be interpreted as an efficiency opportunity, a compliance risk, or a threat to professional identity depending on the institutional setting.

This article contributes a conceptual framework for understanding institutional barriers to AI adoption in energy utilities through the interaction of organizational resistance, capability formation, and strategic transformation. It builds on energy-sector digitalization research, AI capability studies, and organizational theories of digital transformation to specify how barriers arise and how they could be overcome through staged capability development [6]. The article first reviews background literature, then develops a theoretical foundation, proposes a typology of institutional barriers, and examines resistance mechanisms. Part 2 extends the framework by detailing capability formation, strategic transformation pathways, integrative dynamics, implications, limitations, and conclusions.

# Background

## AI in energy utilities: applications and adoption status

AI applications in energy utilities can support forecasting, grid monitoring, asset management, customer segmentation, outage response, market operations, and energy efficiency services. Reviews of AI in sustainable energy show that the technology may improve planning and operational coordination, but also faces challenges related to data availability, interpretability, governance, and organizational integration [7]. More recent work on AI-enabled digital transformation in power networks frames AI as part of a broader Energy 4.0 transition, where sensors, analytics, automation, and platform infrastructures reshape utility operations [8]. However, adoption remains uneven because utilities must embed AI within highly reliable socio-technical systems rather than deploy it as a standalone digital tool.

## Institutional theory and organizational inertia

Institutional theory helps explain why energy utilities may preserve existing practices even when alternative technologies appear technically attractive. Digital transformation studies in the energy sector identify path dependency, regulatory rigidity, organizational inertia, and legacy routines as recurring constraints on innovation [1]. In smart grid contexts, institutional change is often contested because new technologies redistribute authority among utilities, regulators, technology vendors, aggregators, and customers [4]. AI adoption therefore tends to challenge established rule systems, professional jurisdictions, and cognitive frames that define what counts as safe, legitimate, and responsible utility practice.

## Organizational resistance to technological change

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Organizational resistance to AI can emerge through passive delay, active opposition, selective compliance, or symbolic adoption without meaningful transformation. Research on algorithms at work shows that algorithmic systems may become contested because they alter control, autonomy, accountability, and the visibility of professional performance [9]. The automation–augmentation paradox further indicates that AI can be framed simultaneously as a support tool and as a threat to managerial or expert judgment [10]. In energy utilities, such resistance may be intensified by operational cultures that prioritize reliability and risk minimization over experimentation.

### Capability formation and dynamic capabilities

Capability formation for AI adoption involves more than acquiring software or hiring data scientists; it requires learning processes that connect technical knowledge, domain expertise, data governance, and organizational routines. AI capability research defines organizational value as dependent on complementary resources, including data quality, analytical skills, managerial commitment, and cross-functional coordination [6]. Studies of digital transformation emphasize that dynamic capabilities develop through ongoing strategic renewal rather than one-time technology implementation [11]. For utilities, this means that AI capability formation must be institutionally embedded in regulatory compliance, operational reliability, and long-term infrastructure planning.

### Strategic transformation of incumbents

Energy utilities are incumbent organizations whose transformation is shaped by regulated business models, asset-intensive operations, and public service obligations. Studies of utility business models show that the growth of renewable energy, distributed resources, and digital platforms pressures traditional utilities to reconsider their value propositions and organizational roles [12]. Work on European energy industry transformation similarly shows that utilities face simultaneous climate, market, and digital pressures that require strategic adaptation rather than incremental technical upgrading [13]. AI adoption should therefore be understood as part of a broader transformation of how utilities sense change, allocate resources, collaborate with external actors, and justify innovation to regulators and society.

## Theoretical Foundation

### An institutional-capability framework

The proposed framework integrates institutional theory with dynamic capability theory to explain AI adoption as a process shaped by external rules, internal norms, and strategic resource formation. Institutional barriers define what utilities perceive as permissible, legitimate, and meaningful, while dynamic capabilities determine whether organizations can convert AI opportunities into operational and strategic change [11]. AI readiness research shows that organizations require technical, organizational, and cultural preparation before AI can generate business value [5]. This article conceptualizes AI adoption as the result of alignment or misalignment among institutional pressures, resistance mechanisms, capability-building processes, and strategic transformation pathways.

### Defining key constructs

Institutional barriers are defined here as regulative, normative, and cultural-cognitive constraints that slow, redirect, or delegitimize AI adoption in energy utilities. Organizational resistance refers to individual, group, and structural responses that protect existing routines, authority relations, professional identities, or resource allocations when AI threatens established arrangements [14]. Capability formation denotes the development of absorptive capacity, data governance maturity, workforce skills, leadership commitment, and cross-functional routines needed to use AI responsibly and strategically [6]. Strategic transformation refers to the reconfiguration of business models, organizational structures, operational processes, and stakeholder relationships through which utilities integrate AI into long-term institutional adaptation.

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## The institutional-cognitive-strategic chain

The framework proposes an institutional-cognitive-strategic chain in which external and internal institutions shape how AI is interpreted, those interpretations generate resistance or support, and organizational responses determine whether capability formation occurs. Digital transformation research shows that technological change disrupts organizational identity, routines, value creation logics, and strategic assumptions [15]. In utilities, regulatory expectations, engineering norms, and public accountability demands can cause AI to be cognitively framed as risky, opaque, or misaligned with service obligations [2]. Strategic transformation becomes possible when leaders reframe AI from a disruptive external technology into a legitimate organizational capability aligned with reliability, affordability, sustainability, and public value.

**Figure 1** presents the proposed organizational transformation framework, showing how institutional barriers trigger resistance mechanisms, shape capability formation, and enable strategic transformation pathways for AI adoption in energy utilities.

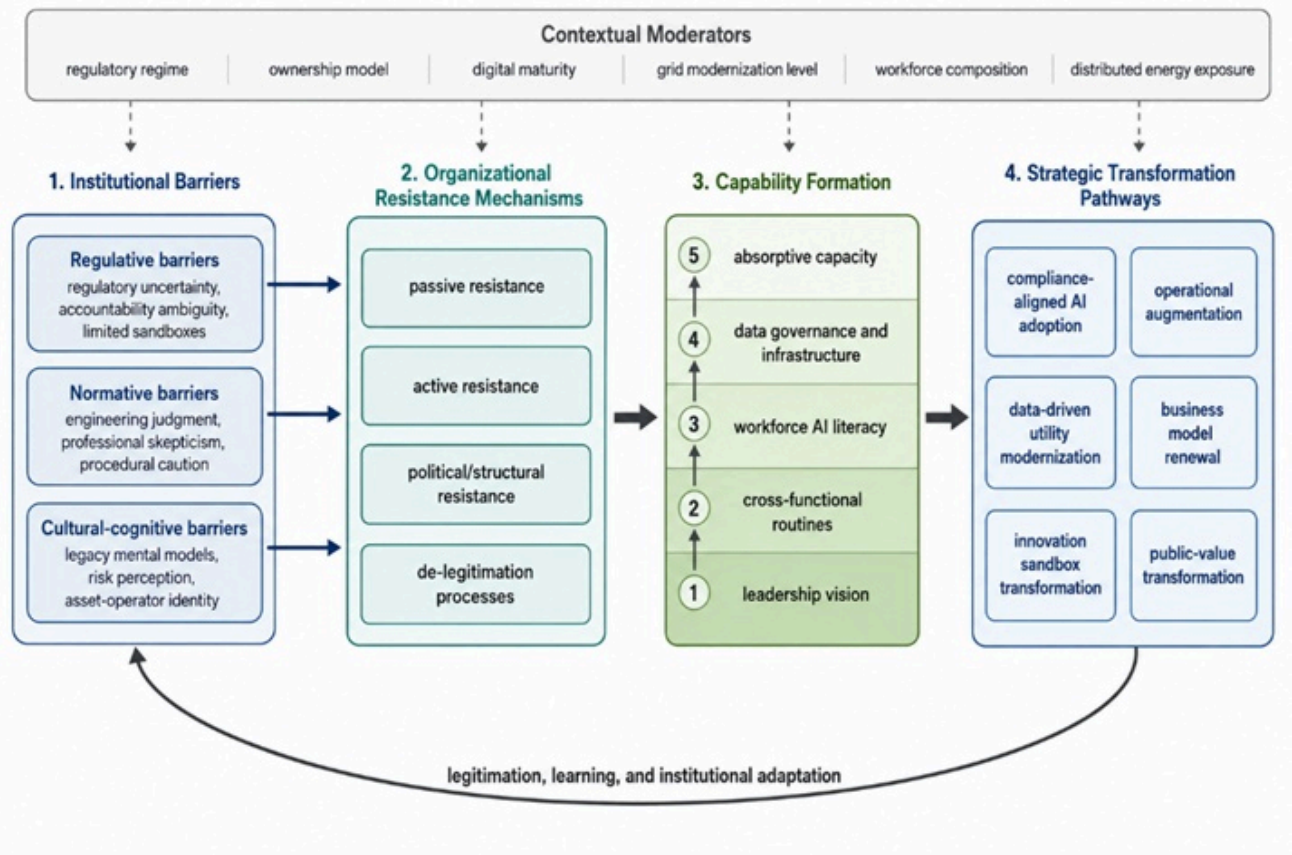



**Figure 1.** Organizational Transformation Framework for AI Adoption in Energy Utilities

# A Typology of Institutional Barriers in Energy Utilities

## Regulative barriers

Regulative barriers arise from formal rules, regulatory incentives, compliance obligations, and accountability structures that shape how utilities evaluate AI risk. Regulatory uncertainty around AI in smart grids can discourage investment because utilities may be unsure how algorithmic decisions will be assessed by regulators, customers, or legal institutions [16]. Energy regulatory sandboxes have been proposed as a way to create controlled spaces for innovation, suggesting that conventional regulatory arrangements may not always support experimentation with novel digital tools [17]. In this

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framework, regulative barriers affect AI adoption by limiting the organizational legitimacy of experimentation before technical feasibility is fully assessed.

## Normative barriers

Normative barriers emerge from professional standards, industry expectations, engineering cultures, and managerial assumptions about responsible utility operation. Energy utilities often operate within cultures that privilege caution, procedural compliance, and expert judgment, which can make AI systems appear insufficiently transparent or insufficiently aligned with established professional responsibility [7]. Research on algorithmic work shows that professional groups may resist technologies that alter discretion, accountability, or status hierarchies [9]. In utilities, normative resistance may therefore appear as skepticism toward AI recommendations, insistence on manual verification, or preference for established vendor and engineering practices.

## Cultural-cognitive barriers

Cultural-cognitive barriers involve taken-for-granted beliefs about what utilities are, how they should operate, and what forms of knowledge are considered trustworthy. Digital transformation literature shows that organizations often struggle not because they lack technology, but because existing mental models constrain how digital possibilities are interpreted [18]. In energy-sector digitalization, legacy assumptions about centralized control, asset ownership, and infrastructure stability can limit acceptance of data-driven, adaptive, and decentralized AI-enabled operations [3]. These barriers are particularly powerful because they are rarely experienced as resistance; they appear instead as common sense about reliability, prudence, and the proper boundaries of utility work. **Table 1** summarizes the major regulative, normative, and cultural-cognitive barriers that influence AI adoption across different stages of implementation in energy utility organizations.

**Table 1.** Typology of Institutional Barriers to AI Adoption in Energy Utilities

| Barrier Type | Specific Manifestation | AI Adoption Stage Affected | Organizational Impact |
|---|---|---|---|
| Regulative barrier | Unclear accountability for AI-supported operational decisions in grid management, customer prioritization, asset maintenance, or market-facing functions | Problem framing and approval | AI initiatives are delayed because managers cannot determine whether algorithmic recommendations will be accepted by regulators or auditors |
| Regulative barrier | Incentive regulation that rewards conventional capital investment more clearly than data, analytics, experimentation, or organizational learning | Investment justification | AI is framed as discretionary innovation rather than as a legitimate utility capability, weakening strategic commitment |
| Regulative barrier | Limited use of regulatory sandboxes or controlled experimentation mechanisms for high-reliability utility environments | Pilot design and testing | Utilities avoid iterative learning and restrict AI to low-risk peripheral functions rather than core operational processes |
| Normative barrier | Professional preference for engineering judgment, manual validation, and established operational routines | User acceptance and workflow integration | AI outputs are treated as supplementary information rather than as actionable decision support |

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| | | | |
|---|---|---|---|
| Normative barrier | Internal belief that responsible utility management requires minimizing visible experimentation and avoiding reputational risk | Scaling and institutionalization | Successful pilots may remain isolated because organizational actors fear public criticism if AI-supported decisions fail |
| Normative barrier | Departmental norms separating IT, operations, regulatory affairs, customer service, and strategic planning | Cross-functional deployment | AI capability remains fragmented, with limited translation between technical models and operational decision contexts |
| Cultural-cognitive barrier | Taken-for-granted assumption that utilities are infrastructure operators rather than data-driven service orchestrators | Strategic sensemaking | AI is interpreted as a technical add-on rather than as a basis for strategic transformation |
| Cultural-cognitive barrier | Legacy mental models emphasizing centralized control, stable demand patterns, and linear planning | Model design and organizational learning | Adaptive AI tools are rejected or constrained because they conflict with inherited planning assumptions |
| Cultural-cognitive barrier | Suspicion that algorithmic decisions are inherently opaque, risky, or misaligned with public service obligations | Legitimation and stakeholder communication | AI adoption loses internal and external legitimacy even when technical performance appears promising |

# Organizational Resistance Mechanisms

## Passive and active resistance

Organizational resistance to AI may appear passively through delayed approvals, lack of data sharing, limited participation in pilots, or repeated demands for additional validation. It may also appear actively through open criticism, professional contestation, or efforts to restrict AI tools to marginal tasks where they cannot challenge existing decision authority [14]. Studies of AI and management suggest that resistance often reflects uncertainty about whether AI will augment or automate human work, making its organizational meaning ambiguous [10]. In utilities, passive and active resistance can be explained by the tension between innovation ambitions and institutionalized commitments to reliability, accountability, and procedural control.

## Political and structural resistance

Political and structural resistance emerges when AI adoption redistributes resources, authority, and visibility across organizational units. Algorithms at work can create new forms of control by making performance measurable and by shifting decision rights from professional groups to data-driven systems [9]. Utility organizations may also experience resistance from silos because AI initiatives require integration among operations, IT, regulatory affairs, cybersecurity, customer management, and executive strategy [19]. Such resistance is not merely irrational opposition; it tends to emerge from real conflicts over expertise, budgets, accountability, and organizational status.

## Legitimation and de-legitimation processes

AI adoption in energy utilities depends on whether organizational actors can legitimate AI as consistent with public service, operational safety, professional responsibility, and regulatory compliance. AI may be de-legitimated when opponents frame it as opaque, risky, vendor-driven, job-threatening, or incompatible with utility obligations [20]. Conversely, AI may become legitimate when it is framed as a capability for improving resilience, sustainability, customer service, and informed human decision-making rather than as a replacement for professional judgment [21]. The

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institutional challenge is therefore not simply to reduce resistance, but to construct credible narratives, governance mechanisms, and capability-building processes that make AI adoption organizationally and socially acceptable.

# Capability Formation for AI Adoption

## Absorptive capacity and AI knowledge

Capability formation begins with absorptive capacity, because utilities must first recognize, interpret, and translate AI knowledge before it can be embedded in operations. AI adoption tends to require boundary-spanning learning between data scientists, engineers, regulators, cybersecurity teams, customer service units, and executive decision-makers [6]. General AI readiness research suggests that organizations must develop shared understanding of AI opportunities, risks, data requirements, and implementation conditions before adoption can progress beyond isolated pilots [5]. In energy utilities, absorptive capacity therefore can be explained by the organization's ability to connect external AI knowledge with internal operational expertise and institutional obligations. **Figure 2** illustrates how absorptive capacity enables energy utilities to convert external AI knowledge into operationally meaningful capabilities through boundary-spanning learning across technical, regulatory, cybersecurity, customer-facing, and executive domains.

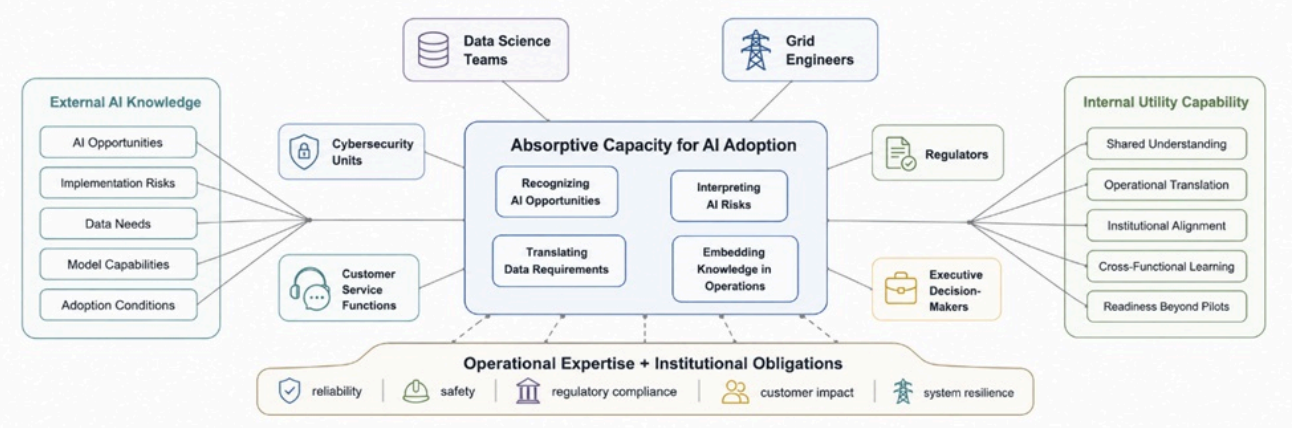



**Figure 2.** Absorptive Capacity as the Foundation for AI Capability Formation in Energy Utilities

## Data governance and infrastructure

AI capability formation also depends on data governance and infrastructure because utilities often operate with fragmented legacy systems, heterogeneous operational data, and strict reliability requirements. Digitalization barriers in power distribution grids show that data access, interoperability, cybersecurity, and legacy system constraints can limit the transition from digital ambition to operational deployment [2]. AI in smart grids may require stronger governance over data quality, model accountability, system integration, and compliance with emerging legal expectations [16]. Data infrastructure is therefore not only a technical precondition but also an institutional capability that determines whether AI can be trusted, audited, and scaled.

## Workforce skills and cultural change

Workforce capability formation requires utilities to cultivate AI literacy, domain-specific data interpretation, cross-functional collaboration, and confidence in human-AI decision processes. AI adoption challenges in the energy sector suggest that workforce skills, organizational readiness, and trust in AI systems must develop together rather than sequentially [22]. Organizational studies of learning algorithms show that employees may reinterpret their roles when algorithmic systems enter work processes, making cultural change inseparable from technical training [14]. Utilities therefore may need to treat AI skills as part of a broader cultural transition from procedural expertise alone toward hybrid expertise that

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combines engineering judgment, institutional knowledge, and algorithmic reasoning. **Table 2** outlines the major capability formation and strategic transformation pathways through which utilities can institutionalize AI adoption while overcoming regulatory, operational, organizational, and cultural barriers.

**Table 2.** Capability Formation and Strategic Transformation Pathways

| Transformation Pathway | Required Capabilities | Key Barriers Overcome | Strategic Outcome |
|---|---|---|---|
| Compliance-aligned AI adoption | Regulatory interpretation capability, audit-ready data governance, explainability protocols, documentation routines | Regulative uncertainty, fear of non-compliance, unclear accountability for AI-supported decisions | AI becomes institutionally legitimate as a controlled decision-support capability aligned with regulatory expectations |
| Operational augmentation | Workforce AI literacy, human-in-the-loop workflow design, model interpretation skills, operational validation routines | Professional skepticism, fear of automation, preference for manual judgment | AI supports expert decision-making without undermining professional authority or operational responsibility |
| Data-driven utility modernization | Enterprise data architecture, interoperability capability, cybersecurity governance, cross-unit data stewardship | Legacy systems, fragmented data ownership, departmental silos | AI moves from isolated pilots into scalable infrastructure for maintenance, planning, customer service, and grid operations |
| Strategic business model renewal | Dynamic capabilities, ecosystem partnership management, digital service design, customer analytics capability | Incumbent inertia, narrow asset-operator identity, resistance to new value propositions | The utility repositions itself as a data-enabled energy service and coordination organization |
| Innovation sandbox transformation | Experimentation governance, regulator engagement, risk-bounded piloting, learning evaluation mechanisms | Regulatory rigidity, reputational risk aversion, limited tolerance for experimentation | AI innovation becomes possible within protected institutional spaces that support learning without abandoning public accountability |
| Public-value transformation | Stakeholder engagement capability, fairness assessment, transparency communication, sustainability alignment | Cultural suspicion of AI, legitimacy deficits, concern about unequal benefits | AI adoption is framed as serving reliability, affordability, equity, decarbonization, and public trust |

## The role of leadership and vision

Leadership is central to capability formation because AI adoption requires an organizational narrative that connects institutional legitimacy with strategic renewal. Research on digital transformation emphasizes that leaders must coordinate strategic vision, resource allocation, cultural change, and organizational redesign over time [15]. In utilities, leadership may also need to mediate between regulatory caution and innovation pressure, ensuring that AI initiatives are neither reckless experiments nor symbolic projects without operational consequences [23]. A credible leadership vision can therefore convert AI from a contested technology into a structured transformation agenda grounded in reliability, accountability, and public value.

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# Strategic Transformation Pathways

## Incremental vs. radical transformation

Strategic transformation in energy utilities may follow incremental or radical pathways depending on institutional constraints, organizational readiness, and external pressures. Incremental transformation can begin with bounded applications such as maintenance analytics, customer service automation, or internal forecasting, while radical transformation may involve reconfiguring utility business models around digital platforms, distributed energy coordination, and data-enabled services [12]. Digital transformation research shows that firms often move through ongoing strategic renewal rather than a single disruptive shift [11]. For utilities, the central strategic challenge is to determine when gradual AI integration is sufficient and when institutional conditions require deeper reconfiguration of routines, capabilities, and organizational identity.

## Leveraging regulatory sandboxes and pilot projects

Regulatory sandboxes and pilot projects can provide utilities with controlled environments in which AI experimentation becomes institutionally acceptable. Work on energy regulatory sandboxes shows that experimental regulatory spaces may help organizations test innovations while managing legal uncertainty and public accountability concerns [17]. Vehicle-to-grid implementation research similarly demonstrates that institutional barriers can slow adoption when regulatory roles, market arrangements, and operational responsibilities remain unclear [24]. AI pilot projects should therefore be designed not merely to test technical feasibility but to generate institutional learning about accountability, user acceptance, regulatory fit, and organizational capability needs.

## Partnerships, ecosystems, and open innovation

Energy utilities may overcome internal capability gaps through partnerships with technology firms, universities, regulators, startups, aggregators, and other ecosystem actors. Business model innovation research in demand response firms indicates that energy innovation often emerges across organizational boundaries rather than within incumbent firms alone [25]. Digital transformation overviews also emphasize that ecosystem participation, platform logic, and external knowledge integration are increasingly central to organizational renewal [26]. For utilities, partnerships can accelerate AI adoption, but they also require governance mechanisms to manage data ownership, vendor dependence, cybersecurity, accountability, and the preservation of public service obligations.

## Aligning transformation with public value

Strategic transformation through AI must be aligned with public value because energy utilities operate in sectors where affordability, reliability, sustainability, safety, and equity are central expectations. AI in the sustainable energy industry has been associated with opportunities for improved efficiency and environmental performance, but also with governance and implementation challenges that require responsible design [7]. European energy transformation research shows that utilities face intertwined climate, digital, and market pressures that cannot be addressed through narrow operational optimization alone [13]. AI adoption should therefore be framed as a public-value transformation rather than only as a productivity or cost-reduction strategy.

# Integrating Resistance, Capabilities, and Transformation

## The dynamic feedback loop

The proposed framework integrates resistance, capability formation, and strategic transformation as a dynamic feedback loop rather than as linear stages. Institutional barriers tend to generate resistance, resistance can slow capability formation, weak capabilities can reinforce skepticism, and failed or symbolic AI initiatives can further strengthen institutional inertia [1]. Conversely, successful capability-building can reduce uncertainty, increase legitimacy, and create

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strategic momentum for broader transformation. This feedback logic explains why AI adoption in utilities may stall even when technical tools are available, and why early capability-building must be connected to institutional sensemaking and transformation strategy.

### Contextual contingencies

The framework is moderated by contextual contingencies, including regulatory regime, utility ownership model, grid modernization level, workforce composition, digital maturity, and exposure to distributed energy resources. Digital transformation in energy is not uniform, because utilities differ in legacy assets, data infrastructures, regulatory incentives, and organizational cultures [3]. Studies of AI and business value also suggest that AI outcomes depend on complementary organizational resources rather than on technology alone [20]. Therefore, the framework should be interpreted as a conceptual diagnostic model whose pathways may vary across investor-owned utilities, public utilities, distribution operators, transmission operators, and integrated energy companies.

## Implications for Management, Policy, and Regulation

### Managerial recommendations

Managers should diagnose AI adoption barriers institutionally before treating them as technical implementation problems. AI readiness work suggests that organizations need coordinated attention to strategy, data, skills, governance, and culture, but utility managers must additionally assess how regulation, professional norms, and inherited assumptions shape willingness to adopt AI [5]. The barrier typology in **Table 1** can support managerial diagnosis by distinguishing whether resistance arises from formal uncertainty, professional legitimacy concerns, or cultural-cognitive assumptions. Managers can then use the capability roadmap in **Table 2** to connect barrier reduction with staged capability formation and strategic outcomes.

### Policy and regulatory enablers

Policymakers and regulators can enable responsible AI adoption by creating clearer expectations for algorithmic accountability, explainability, data governance, cybersecurity, and pilot experimentation in energy utilities. Regulatory barriers to smart grid AI suggest that unclear legal and institutional conditions can discourage adoption even when stakeholder benefits are plausible [16]. Innovation allowances, sandbox mechanisms, and performance-based regulatory incentives may help utilities invest in AI capabilities without abandoning public accountability [17]. Regulation should therefore not merely constrain AI risk after deployment, but actively shape the institutional conditions under which responsible experimentation and capability formation become legitimate.

### Research agenda

Future research should empirically investigate how institutional barriers, resistance mechanisms, and capability formation interact across different types of energy utilities and regulatory systems. Studies on AI utilization in the energy sector identify broad challenges, but further research is needed to explain how organizational cultures, professional identities, and regulatory environments shape adoption trajectories [27]. Digital transformation research also calls for more integrated analysis of strategy, organization, technology, and institutional context [18]. Future work could compare utilities across governance models, examine how AI pilots become institutionalized, and test whether the proposed framework explains variation in adoption readiness and transformation outcomes.

## Limitations

### Conceptual nature and generalizability

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This article is conceptual and does not test the proposed framework through interviews, surveys, case studies, adoption metrics, or performance data. Its explanatory claims are grounded in theoretical integration and prior literature on digital transformation, AI capability, energy innovation, and institutional barriers rather than empirical validation within a specific utility setting [6]. Because energy utilities differ across regulatory regimes, ownership structures, national contexts, and grid responsibilities, the framework should not be interpreted as universally predictive. It should instead be used as a theory-driven diagnostic model requiring further empirical investigation and contextual refinement.

### Evolving technological and institutional landscapes

A second limitation is that AI technologies, regulatory expectations, energy markets, and utility business models are evolving rapidly. Reviews of digital transformation show that organizational change is an ongoing process in which technologies, strategies, and institutional arrangements continuously reshape one another. The rise of generative AI, autonomous grid management, distributed energy platforms, and more stringent AI governance rules may create new barriers not fully captured by the present framework [19]. Future versions of the framework may therefore need to incorporate emerging forms of algorithmic governance, public trust management, and cross-sector infrastructure regulation.

## Conclusion

This article developed a theory-driven framework for understanding institutional barriers to AI adoption in energy utilities. The framework argued that AI adoption is not merely a technical or economic challenge, but a process shaped by regulative structures, professional norms, cultural-cognitive assumptions, organizational resistance, capability formation, and strategic transformation.

The central contribution is the integration of institutional theory, organizational resistance, dynamic capabilities, and strategic management into a single conceptual explanation. This integration shows that utilities may resist AI not because the technology lacks promise, but because AI unsettles established routines, accountability structures, professional identities, and assumptions about responsible utility work.

The framework calls for empirical testing, managerial experimentation, and regulatory collaboration. Advancing AI adoption in energy utilities will require utilities, regulators, technology providers, employees, and public stakeholders to work together in building AI systems that are capable, legitimate, accountable, and strategically aligned with the public role of the energy sector.

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