Applied Chemical Engineering (2026) Volume 9 Issue 2 ISSN: 2578-2010 (O)
doi: 10.59429/ace.v9i2.5938

ORIGINAL RESEARCH ARTICLE

AI governance and digital transformation in public utilities: Evidence from Morocco's national electric grid

Nissrine MAJIT[1,*], Naila AMROUS[1], Jamal MABROUKI[2]

[1] *Laboratory of Mediation, Information, Knowledge and Society- MIKS: School of Information Sciences, Avenue Allal Al Fassi, Madinat AL Irfane, BP 6204, Rabat Institute, Morocco*

[2] *Laboratory of Spectroscopy, Molecular Modelling, Materials, Nanomaterials, Water and Environment, CERN2D, Mohammed V University in Rabat, Faculty of Science, AV Ibn Battouta, Agdal, Rabat 10106, Morocco*

***Corresponding author:** Nissrine MAJIT, nissrine.majit@esi.ac.ma

ABSTRACT

Artificial Intelligence (AI) is increasingly used to support the digital transformation of critical energy infrastructures by improving forecasting, grid monitoring, predictive maintenance, and operational decision-making. However, AI deployment in public utilities faces challenges related to institutional acceptance, digital maturity, institutional trust, and governance mechanisms. This article investigates how these factors interact within Morocco's National Office of Electricity and Drinking Water (ONEE). The methodology is based on 29 semi-structured interviews, thematic coding using NVivo, and an exploratory quantitative synthesis. The analytical framework combines a condensed UTAUT2 framework, the McKinsey AI Maturity Model, and selected AI governance dimensions related to accountability and interoperability. The findings suggest a positive association between AI maturity and organisational acceptability, with governance strengthening this relationship. However, given the qualitative-dominant design, the small sample size, and the exploratory scoring procedure, the correlation results are interpreted as indicative rather than confirmatory. The study contributes to applied infrastructure and utility governance research by showing that responsible AI deployment in critical energy systems requires not only digital capabilities but also transparent governance, regulatory clarity, cybersecurity safeguards, and internal stakeholder trust.

Keywords: artificial intelligence; AI governance; smart grids; organisational acceptability; digital maturity; public utilities; critical energy infrastructure; Morocco

ARTICLE INFO

Received: 11 March 2026
Accepted: 1 May 2026
Available online: 18 May 2026

1. Introduction

Decarbonisation and digitisation are two central dimensions of the global energy transition[1]. In critical energy infrastructures, AI is increasingly used to improve demand forecasting, grid monitoring, operational optimisation, predictive maintenance, and system resilience[2].

However, in developing countries, the integration of AI technologies in public utilities faces many challenges: inconsistent institutional digital maturity, ambiguous organisational acceptance among internal stakeholders, and governance frameworks that are only partially structured, particularly regarding interoperability and accountability. These factors are necessary to ensure a credible and legitimate socio-technical transition[3].

In Morocco, since 2016, the National Office of Electricity and Drinking Water (ONEE) has progressively integrated AI into the very high-voltage and high-voltage segments of its national grid. AI-related applications are associated with:

- Demand forecasting, using machine learning to refine daily supply – demand balancing;

- Predictive maintenance to anticipate failures in HV/MV substations;

- Grid optimisation through anomaly detection and automated control algorithms that reduce technical losses.

Alongside these deployments, several applications remain in pilot or experimental phases, such as real-time optimisation of renewable generation, intelligent load management in selected regional substations, natural language processing (NLP)-based customer interaction tools, and meter system interoperability tests within the smart meter (AMI) program[4]. These projects are being developed under a stricter set of rules, including Law 82.21 on electrical self-generation and its 2025 implementing decree[5], as well as the 2024 Smart Meters Decree, which reinforces requirements for transparency, interoperability, and institutional control[6]. Even with these technological and legislative improvements, perceptions of AI at the ONEE vary by hierarchical level within the institution. This raises the following research question: How does AI governance influence the relationship between digital maturity and organisational acceptability within a critical public energy utility?

This study contributes to applied infrastructure and engineering-oriented research by examining the governance conditions required for the responsible deployment of AI-based digital systems in critical public energy utilities. Although the empirical case focuses on Morocco's national electric grid, the study addresses a broader infrastructure challenge: How AI-enabled digital transformation can be governed in complex energy systems where operational reliability, data quality, cybersecurity, interoperability, regulatory alignment, and organisational readiness are essential. Accordingly, two hypotheses guide the study:

1. H1 AI maturity is positively associated with organisational acceptability within ONEE.
2. H2 AI governance AI governance is expected to strengthen the relationship between AI maturity and organisational acceptability.

This study is organised as follows. Section 1 presents the research context, the conceptual and analytical framework, and the main prior research. Section 2 describes the methodological framework. Section 3 reports the empirical results. Section 4 discusses the theoretical and practical implications of the findings. Finally, Section 5 concludes the article by summarising the main contributions, limitations, and avenues for future research.

1.1. Literature Review and Theoretical Framework

1.1.1. Smart Grids and Governance

Smart grids are a major transformation in contemporary energy systems, because they combine traditional electrical infrastructure with digital technologies, data-driven monitoring, automation, and intelligent decision-support systems[7]. AI contributes to this transformation by supporting demand forecasting, predictive maintenance, anomaly detection, automated control, and real-time optimization[8]. However, energy literature increasingly shows that the smart grid deployment cannot be reduced to technical performance alone. The success of smart grid projects also depends on governance mechanisms that assure transparency, accountability, and institutional trust in sociotechnical transitions[9]. In this way, Smart grids should be understood as socio-technical systems, and their effectiveness depends not only on the quality of algorithms and infrastructure, but also on the organisational and institutional conditions that make these technologies usable, legitimate, and accepted by internal and external actors.

1.1.2. Organisational Digital Maturity in Energy utilities

Digital maturity refers to the organisational capacity to align advanced and intelligent technologies with its strategic goals, operational processes, skills, data infrastructure, and governance arrangements[10]. The McKinsey AI Maturity Model provides a useful framework for assessing this transition through dimensions such as strategy, culture, data, technology, and governance[2,10]. In energy utilities, digital maturity extends beyond the availability of digital tools. It also includes the clear allocation of responsibilities, data quality, cybersecurity preparedness, and the interoperability of legacy operational technologies with AI-enabled information systems[12]. In developing economies, uneven digital maturity may result in fragmented data practices, siloed projects, and weak alignment between strategic intent, technical capabilities, and governance arrangements[13].

1.1.3. AI Acceptability and UTAUT2 framework

Technology acceptance models emphasise that user perceptions strongly influence the adoption and use of digital systems[14]. UTAUT and UTAUT2 extend earlier acceptance models by integrating dimensions such as performance expectancy, effort expectancy, social influence, facilitating conditions, and user-related factors[14]. In public utilities, however, AI acceptability cannot be reduced to individual intention alone. It is also shaped by institutional trust, perceived legitimacy, training, and the perceived alignment between AI systems and organisational missions. In the context of AI-enabled smart grids, employees' perceptions of usefulness, ease of use, and institutional trust are therefore critical determinants of whether AI systems are accepted, integrated, or resisted[15].

1.1.4. AI Governance

AI governance refers to the set of institutional, technical, legal, and organisational mechanisms through which AI systems are designed, deployed, monitored, and controlled. In the public sector and infrastructure context, AI governance frameworks emphasise that AI systems should be transparent, robust, accountable, human-centred, and aligned with public values[16].

International AI governance frameworks emphasise several key principles for trustworthy AI, including transparency, accountability, data protection, inclusion, human oversight, and institutional capacity[17]. For public energy utilities, two governance dimensions are especially critical: accountability and interoperability. Accountability clarifies who is responsible when AI-supported decisions influence operational or managerial processes. Interoperability ensures that AI applications can function across legacy infrastructure, sensors, legacy systems, data platforms, operational technologies, and information systems[18].

1.1.5. Toward an Integrated Conceptual Model

Although prior research has examined digital maturity, organisational acceptability, and AI governance separately, their interaction remains under-theorised in the context of public energy utilities. Few studies explicitly conceptualize how governance mechanisms condition the way institutional readiness for AI translates into internal acceptance of AI-enabled systems[19].

To address this gap, the present study develops an integrated conceptual framework that combines three complementary lenses: the McKinsey AI Maturity Model, a condensed UTAUT2, and selected AI governance dimensions inspired by international responsible AI governance frameworks. Institutional AI maturity is conceptualised as the structural enabler capturing ONEE's strategic alignment and organisational culture regarding AI (**Figure 1**). Organisational acceptability is understood as the perceptual response of staff, reflected in perceived usefulness, ease of use, and institutional trust. AI governance, operationalised here through accountability and interoperability, is theorised as a potential moderating mechanism that may shape the strength of the relationship between maturity and acceptability in smart grid settings.

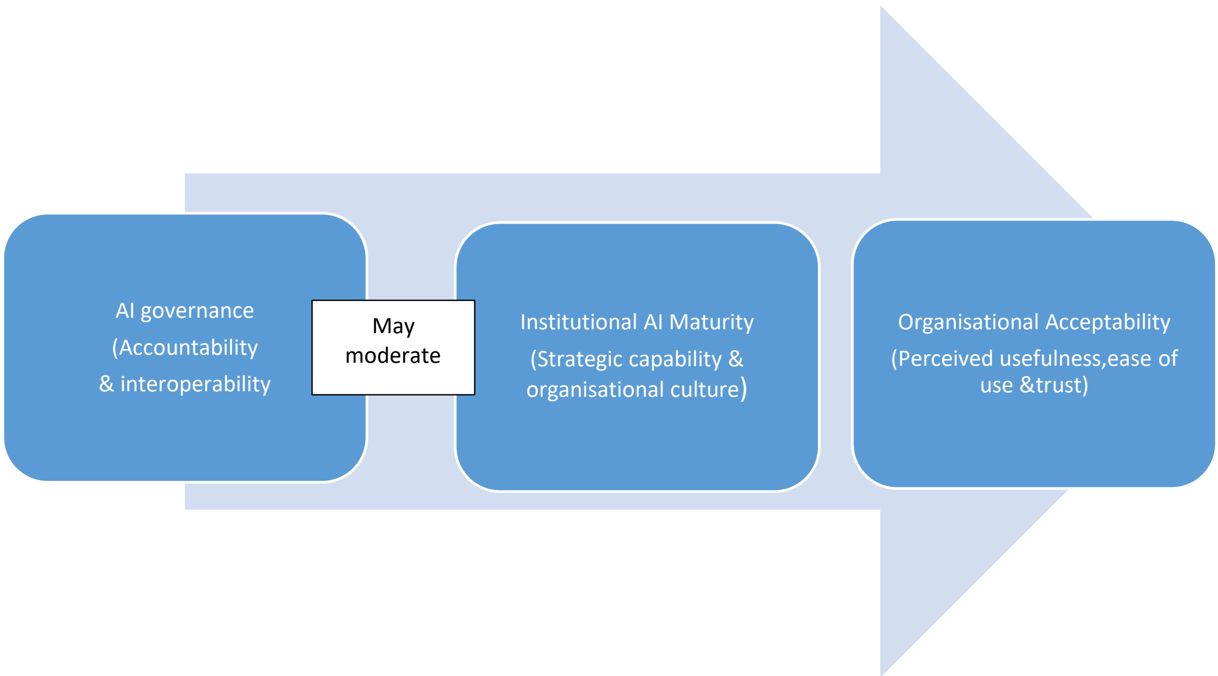

Figure 1. Conceptual framework of the potential moderating role of AI governance in the relationship between institutional AI maturity and organisational acceptability.

This framework is used as an analytical guide for the empirical study. The potential moderating role of AI governance is examined exploratorily through qualitative coding and descriptive correlation analysis, without claiming confirmatory statistical validation.

1.1.6. Prior research in public energy institutions and research gap

The integration of AI into energy systems no longer concerns technical performance alone. It also entails organisational, institutional, and governance changes[19]. Early work on AI in energy focused on predictive maintenance, anomaly detection, and network automation. More recent literature highlights three critical conditions for successful deployment: institutional digital maturity, social legitimacy, and governance of algorithmic systems[20].

In mature markets such as the United States and Germany, empirical studies report persistent challenges linked to regulatory fragmentation, ethical uncertainty, and declining public trust in AI technologies[21]. According to the ENERDATA report, issued in 2022, China, despite its progress in optimizing its power grids, still continues to confront constraints and limits due to the opacity of AI algorithms and the weak governance of data flowing on its networks[22].

However, in the African setting, Melani and Tabaa highlight structural obstacles such as the limitation of digital infrastructure, the poor interoperability, and the shaky governance frameworks that hinder the implementation of AI in energy public services[23].

Morocco holds a particular hybrid position. The African country hosting COP 22 is committed to energy transition and sustainable development goals. Morocco has structural issues characteristic of growing economies, while maintaining a generally stable and dedicated institutional architecture that is yet inadequate. Even though Morocco has a public monopoly on energy, it reveals aspects of modernization and openness to technology through its smart grid and smart meter projects, and the ONEE research laboratory, which is working on energy AI technologies. However, Morocco remains exposed to organisational inertia, unlike public energy services that depend on external donors, like the Senegal and Mali cases, or like countries with completely liberalized energy systems, such as South Africa[24].

Previous research has examined the AI maturity, governance, and AI acceptability as separate concepts. Empirical studies that integrate these dimensions into a unified framework remain rare, particularly in monopolised energy services in emerging economies. The study of Rhardas and Habachi and their teams highlights that the gap between technological readiness and social acceptance is often caused by the absence of effective governance mechanisms capable of bridging these domains, and that the emergence of AI as a pillar of socio-technical projects makes this governance even less obvious[25,26].

This study addresses this gap by analysing how AI governance processes, particularly accountability and interoperability, may influence the relationship between AI maturity and organisational acceptability within Morocco's national electric utility. In doing so, it will contribute to offering practical advice for critical energy systems in emerging economies.

2. Materials and methods

2.1. Research design and conceptual framework

This study adopts an exploratory single-case study focusing on ONEE, a vertically integrated public utility engaged in smart grid transformation. A qualitative-dominant mixed-methods strategy was used. Qualitative interview analysis constitutes the primary empirical basis of the study, while quantitative synthesis is used only as a complementary exploratory tool to identify broad patterns across organisational levels.

The study does not aim to produce statistically generalisable findings. Rather, it seeks to generate analytically transferable insights into the governance conditions that shape AI deployment in critical public energy infrastructure.

The research pursues three objectives: (1) to assess ONEE's AI maturity; (2) to analyse internal perceptions of AI in the smart grid context; and (3) to explore the role of AI governance in the relationship between institutional maturity and organisational acceptability. The conceptual framework combines three complementary models that informed both the interview guide and the coding scheme: (1) the McKinsey AI Maturity Model, used to assess institutional readiness through strategy, culture, and digital capabilities; (2) a condensed UTAUT2 framework, focused on perceived usefulness, ease of use, and institutional trust; and (3) selected AI governance dimensions related to accountability and interoperability. These dimensions were selected because they are particularly relevant in early-stage AI deployment within critical energy infrastructures and were consistently reflected in the empirical material.

Together, these models structured seven main analytical dimensions (NVivo nodes): AI Strategy, Organisational Culture, Perceived Usefulness, Ease of Use, Institutional Trust, Accountability, and Interoperability.

2.2. Data Collection and Participants

Fieldwork was conducted at ONEE between October 2022 and October 2025. Institutional access was facilitated by long-standing collaboration with the Ministry of Energy Transition and Sustainable Development and prior academic partnerships with ONEE.

A purposive sampling strategy was adopted. Participants were selected because of their direct or indirect involvement in digital transformation, smart grid deployment, AI-related initiatives, data systems, grid operations, or technical maintenance. The objective was to capture different organisational viewpoints across strategic, technical, and operational levels. In total, 29 semi-structured interviews were conducted with internal actors occupying different positions within the organisation:

Table 1. Profile of interview participants.

Participants category	Number of participants	Organisational level	Relevance to the study
Senior managers and decision-makers	4	Strategic level	AI strategy, digital transformation priorities, governance and regulatory alignment
Middle managers/project coordinators	5	Strategic-technical level	Coordination of smart grid projects, implementation constraints and organisational readiness
Smart grids and electrical engineers	7	Technical level	AI integration, grid optimisation, operational technologies, interoperability, and cybersecurity
IT and data engineers	6	Technical level	Data infrastructure, AI tools, information systems, technical governance, and system interoperability
Maintenance technicians/operational staff	7	Operational level	Field implementation, training needs, perceived usefulness, and operational acceptability
Total	29	Multi-level sample	Internal perceptions of AI maturity, governance, and organisational acceptability

All interviews followed a semi-structured guide organised around the seven analytical dimensions derived from international frameworks mentioned above: AI strategy, organisational culture, perceived usefulness, ease of use, institutional trust, accountability, and interoperability (**Table 1**).

Interviews were fully transcribed and imported into the NVivo framework for thematic coding. The Excel was used for the subsequent quantitative analysis. Data were anonymised during the transcription stage.

2.3. Coding Procedure and Qualitative Analysis

A deductive thematic coding strategy was applied in the NVivo framework, using a pre-defined codebook structured around the seven parent nodes: AI Strategy, Organisational Culture, Perceived Usefulness, Ease of Use, Institutional Trust, Accountability, and Interoperability. The initial codebook was developed directly from the three international theoretical models used in the study and was tested on a small subset of transcripts.

After this pilot coding phase, the definitions and inclusion ‑ exclusion criteria of each code were refined to reduce overlap between categories and improve coding consistency.

In the first coding cycle, interview excerpts were assigned to these seven primary nodes. In the second coding cycle, we refined and regrouped emerging subthemes under each parent category.

To strengthen analytical reliability, a subset of transcripts was double-coded independently by two researchers. Coding differences were discussed during calibration sessions until agreement was reached on the interpretation of each category. The codebook was then stabilised and applied to the full corpus.

The calibration of the Likert-type scores was also conducted explicitly and systematically. After thematic coding, each parent node received a five-point score per interview, derived from an anchored rubric that combined the frequency, intensity, and valence of references in the coded data (from 1 = very low or negative to 5 = very high or positive).

Two researchers independently assigned preliminary scores for a subset of interviews, then compared and reconciled their assessments to harmonize the application of the rubric before scoring the full corpus. The resulting scores should therefore be understood as a structured synthesis of qualitative evidence rather than as survey-based measurements.

Thematic saturation was reached after 18 interviews, with fewer than 5% new codes emerging thereafter, in line with Guest et al. (2020). The qualitative analysis, therefore, provides the main empirical foundation of the study, while the quantitative synthesis serves only to visualise and compare patterns across organisational levels.

2.4. Scoring rubric, Spearman correlation and Exploratory Quantitative Synthesis

After thematic coding, each interview was assigned a 5-point score for each of the seven analytical dimensions (**Table 2**). To support cross-category comparison and identify broad patterns, the coded material was subjected to a quantitative synthesis. For each interview and each of the seven parent nodes, the calibrated 5-point scores described above were compiled in Excel. Mean scores were then aggregated by organisational level (strategic, technical, operational) to construct comparative profiles of AI maturity, perceptions, and governance.

Table 2. Scoring rubric used for qualitative-to-quantitative synthesis.

Score	Interpretation	Coding meaning
1	Very low	The theme is absent, weakly present, or expressed mainly through negative perceptions
2	Low	The theme is present but limited, fragmented, or associated with uncertainty
3	Moderate	The theme is clearly present but expressed with mixed or cautious perceptions
4	High	The theme is strongly present and generally positive
5	Very high	The theme is consistently present, strongly expressed, and positively evaluated

Spearman rank correlations were computed to explore the association between institutional AI maturity and organisational acceptability and to examine how these associations vary under different perceived levels of governance (accountability, interoperability). Governance scores were represented as a visual gradient in scatter plots to illustrate potential moderating patterns, without estimating formal interaction terms.

Given the limited sample size ($N = 29$), the non-probabilistic sampling strategy, and the qualitative-dominant design, these quantitative results are interpreted strictly as exploratory. Correlation coefficients and associated p-values are used as descriptive indicators of the strength and direction of associations, not as evidence of causality or as the basis for confirmatory statistical inference. The quantitative component thus complements the thematic analysis by highlighting internally consistent patterns rather than by testing hypotheses in a statistically generalisable way.

2.5. Ethical Considerations

The study received formal institutional approval from ONEE. All participants were informed of the study's scope, provided voluntary and written consent, and were assured of the confidentiality and anonymisation of all data. No personal identifiers were retained at any stage of analysis.

3. Results

In this section, we present the empirical results organised around three main dimensions: organisational profiles of AI maturity and perceptions, the exploratory association between AI maturity and organisational acceptability, and the role of governance as a potential moderating mechanism. The results are interpreted cautiously, in line with the exploratory nature of the study and the qualitative origin of the scoring procedure.

3.1. Organisational profiles of AI maturity and perceptions

The analysis reveals a clear hierarchical disparity in AI maturity and AI-related perceptions within ONEE. The strategic level participants obtained the highest scores across several dimensions, including AI maturity, institutional trust, accountability, and interoperability. This result reflects their active role in digital transformation strategies, regulatory discussions, and institutional narratives, presenting AI as a tool for grid modernisation and energy transition.

Technical level participants obtained intermediate scores. They recognize the usefulness of AI for the modernisation and improvement of the national power grid. However, they also identify persistent constraints related to interoperability between operational technologies (OT) and information technologies (IT). These constraints were perceived as limiting the effective integration of AI into Smart grid projects.

Operational level participants scored the lowest. They reported limited training on AI-related tools, insufficient communication about the purpose and implications of AI deployment, and limited transparency regarding AI-supported decision-making processes.

These responses suggest that operational acceptability remains fragile when employees do not clearly understand how AI systems will affect their roles, responsibilities, or daily work routines.

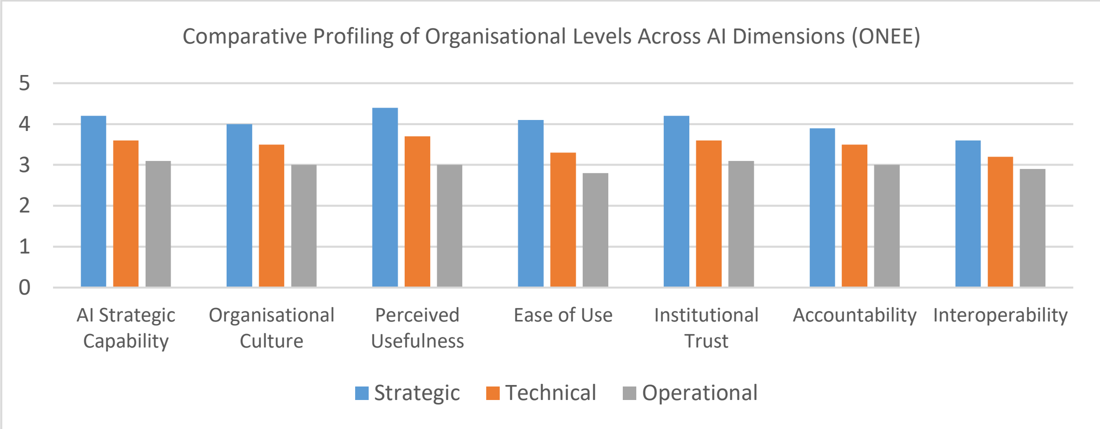

Figure 2. Comparative analysis of organisational levels across a range of AI-related dimensions.

These profiles indicate a hierarchical difference between strategic intent and operational implementation. In the ONEE's case study, the results reveal that AI is strongly supported at the strategic level but partially integrated by the personnel of the technical and operational levels (**Figure 2**). This gap may limit the effective deployment of an AI-enabled Smart grid system if it is not addressed through training, internal communication, clearer responsibility structures, and stronger interoperability mechanisms.

3.2. Relationship between AI maturity and organisational acceptability

The exploratory quantitative synthesis indicates a moderate positive association between institutional AI maturity and organisational acceptability (Spearman's $\rho = 0.58$). Units that report higher perceived maturity in terms of strategic alignment, cultural readiness, and digital capabilities also tend to express greater confidence in AI systems and a greater willingness to adopt them in their daily work.

This result suggests that organisational acceptability depends not only on individual attitudes towards AI, but also on how employees perceive the institution's overall readiness to support AI deployment.

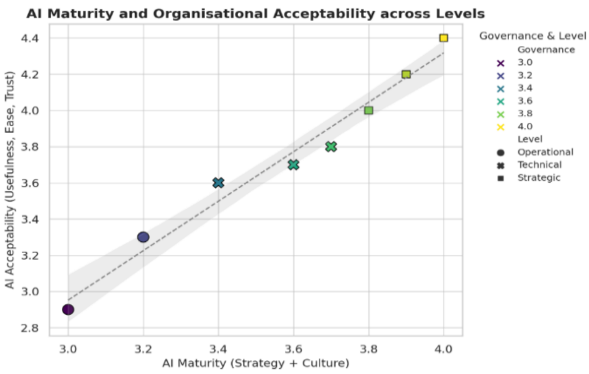

Figure 3. Relationship between AI maturity and organisational acceptability under governance conditions.

When observations are differentiated by perceived governance levels, particularly accountability and interoperability, the association between AI maturity and organisational acceptability appears stronger. This pattern provides preliminary exploratory support for H2 (**Figure 3**). However, because no formal interaction model was estimated, the study cannot claim to demonstrate a statistically robust moderation effect.

From a practical perspective, the findings suggest that digital maturity may be more likely to translate into organisational acceptability when employees perceive that AI deployment is accompanied by clear responsibility structures and technically coherent systems. In other words, governance may help translate AI maturity into organisational trust and acceptance, but this mechanism should be examined further through larger, more confirmatory studies.

3.3. Governance as a potential moderating mechanism: Thematic evidence

Qualitative findings suggest that governance acts as an important organisational catalyst for AI deployment. The interview results highlight two fundamental dimensions: accountability and interoperability. The first dimension, accountability, indicates that AI-related responsibilities must be clearly defined, including who is responsible for AI-supported decision-making processes. The second theme (interoperability) suggests that the successful integration of operational (OT) and information technologies (IT) through the generation of reliable data flows and stable interfaces between existing infrastructure and AI-enabled applications may facilitate the successful use of AI technologies within the organisation. The following interview excerpts illustrate these concerns:

- "AI technologies will be an enhancement to the strategic plan of ONEE; however, we still need to find ways to coordinate operations more effectively." (P1, P12)

- "The workforce at ONEE needs greater clarity on how AI will influence their current jobs and the jobs they will hold in the future." (P19)

- "The lack of interoperability between operational technology and information technology continues to create a major obstacle to the successful implementation of AI technologies. " (P7, P10)

Across organisational levels, accountability and interoperability appear closely related to perceived usefulness and institutional trust. When responsibilities are unclear or systems seem fragmented, employees may be reluctant to rely on AI-supported decisions. Conversely, clearer governance arrangements and better technical interoperability may strengthen internal trust and facilitate the organisational integration of AI in Smart grid transformation.

4. Discussion

This section discusses the main findings in relation to the study's conceptual framework and the literature on AI governance, digital maturity, and organisational acceptability in public utilities. It highlights the theoretical and practical implications of the results while taking into account the exploratory nature of the empirical analysis.

The findings show that AI deployment in critical energy infrastructure cannot be reduced to technical readiness alone. In the case of ONEE, strategic actors express stronger confidence in AI because they are more directly exposed to digital transformation priorities, policy objectives, and institutional modernisation narratives. By contrast, technical and operational actors appear more cautious because they are more directly confronted with implementation constraints, limited training, interoperability issues, and uncertainty regarding accountability.

This discrepancy highlights a central governance challenge: AI maturity at the strategic level does not automatically translate into organisational acceptability at the technical and operational levels. For AI-enabled Smart grid systems to become institutionally legitimate, employees need clear information about the purpose of AI tools, the rules governing data use, the distribution of responsibilities, and the technical compatibility between operational and information systems.

From an applied infrastructure perspective, accountability and interoperability should not be considered secondary governance concerns. They are operational conditions for responsible AI deployment. Accountability helps clarify decision-making responsibilities, while interoperability ensures that AI tools can be integrated into existing technical systems. Without these conditions, AI deployment may remain fragmented and weakly accepted by internal stakeholders.

The study also shows that governance may play a bridging role between digital maturity and organisational acceptability. Digital maturity creates the technical and organisational basis for AI adoption, but governance helps make this maturity understandable, legitimate, and usable for internal actors. This finding is particularly relevant for public utilities in emerging economies, where AI deployment often takes place within evolving regulatory frameworks, uneven digital capabilities, and complex institutional structures.

These findings contribute to the literature on AI-enabled digital transformation in public utilities by showing that the internal acceptability of AI depends on the interaction between technical maturity and governance conditions. They also extend technology acceptance perspectives by demonstrating that, in critical infrastructure contexts, perceived usefulness and ease of use are insufficient unless they are supported by institutional trust, accountability, and system interoperability.

5. Conclusion

This study examined the relationship between AI maturity, organisational acceptability, and AI governance in a national energy utility in Morocco. Based on 29 semi-structured interviews and a qualitative-dominant exploratory design, the findings suggest that AI-enabled digital transformation in public energy utilities depends not only on technical capabilities, but also on governance mechanisms, organisational trust, regulatory clarity, and system interoperability.

The results reveal a visible gap between strategic, technical, and operational perceptions of AI within ONEE. Strategic actors support the digital transformation and AI integration in Smart grid projects, while technical and operational staff remain more cautious due to concerns related to interoperability, accountability, training, transparency, and the practical integration of AI tools into existing work routines. This gap suggests that AI maturity at the institutional level does not automatically produce organisational acceptability unless it is supported by clear governance mechanisms.

The exploratory quantitative synthesis indicates a positive association between perceived AI maturity and organisational acceptability. This relationship appears stronger when governance mechanisms, particularly accountability and interoperability, are effectively mobilised in energy projects. However, these findings should be interpreted with caution. The Spearman correlation analysis was based on scores derived from qualitative coding and a small non-probabilistic sample. It therefore provides exploratory support rather than confirmatory statistical evidence or proof of causal moderation.

The main contribution of the study is to propose an integrated triangular model connecting AI maturity, organisational acceptability, and governance in a critical energy infrastructure context.

The study remains limited by its single-case design, its focus on internal organisational actors, and the absence of consumer-level data. Future research should extend this framework to other public utilities, compare different national contexts, and examine how AI governance affects both internal organisational acceptance and broader social acceptability of Smart grid technologies. Longitudinal research would also be useful to assess how governance mechanisms evolve as AI applications become more widely integrated into energy infrastructure management.

Conflict of interest

The authors declare no conflict of interest. No personal, financial, or institutional relationships influenced the design, analysis, interpretation, or reporting of this study.

References

1. OCDE, Vers le numérique : Forger des politiques au service de vies meilleures. OECD, 2019. doi: 10.1787 /7cba1873-fr.
2. G. Vial, « Understanding digital transformation: A review and a research agenda », The Journal of Strategic Information Systems, vol. 28, no 2, p. 118-144, juin 2019, doi: 10.1016/j.jsis.2019.01.003.
3. K. Schumacher, F. Krones, R. McKenna, et F. Schultmann, « Public acceptance of renewable energies and energy autonomy: A comparative study in the French, German and Swiss Upper Rhine region », Energy Policy, vol. 126, p. 315-332, mars 2019, doi: 10.1016/j.enpol.2018.11.032.
4. ONEE. Rapport d'activité 2022. Office National de l'Électricité et de l'Eau Potable, 2022.
5. Royaume du Maroc. Loi n° 82-21 relative à l'autoproduction d'énergie électrique. Bulletin Officiel du Royaume du Maroc, 2025.
6. Royaume du Maroc. Décret n° 2-24-804 relatif aux compteurs intelligents. Bulletin Officiel du Royaume du Maroc, 2024.
7. O. V. Mathisen, M. E. Sørbye, M. Rao, G. Tamm, et V. Stantchev, « Smart energy in smart cities », in Smart Cities: Issues and Challenges, Elsevier, 2019, p. 283-307. Consulté le: 7 février 2025. [En ligne]. Disponible sur: https://linkinghub.elsevier.com/retrieve/pii/B9780128166390000168
8. C. Prades-Gil, J. D. Viana-Fons, X. Masip, A. Cazorla-Marín, et T. Gómez-Navarro, « An agile heating and cooling energy demand model for residential buildings. Case study in a mediterranean city residential sector », Renewable and Sustainable Energy Reviews, vol. 175, p. 113166, avr. 2023, doi: 10.1016/j.rser.2023.113166.
9. J. Knauf et J. Le Maitre, « A matter of acceptability? Understanding citizen investment schemes in the context of onshore wind farm development », Renewable and Sustainable Energy Reviews, vol. 175, p. 113158, avr. 2023, doi: 10.1016/j.rser.2023.113158.
10. N. Hinov, « A Maturity-Based Framework for Assessing the Level of Digitalization in Smart Grids », in 2025 International Conference on Information Technologies (InfoTech), Sofia, Bulgaria: IEEE, sept. 2025, p. 1-5. doi: 10.1109/InfoTech67177.2025.11175970.
11. A. Alsheibani, Y. Cheung, and C. Messom, "Artificial intelligence adoption: AI-readiness at firm-level," PACIS 2018 Proceedings, 2018
12. M. J. Fell, D. Shipworth, G. M. Huebner, et C. A. Elwell, « Public acceptability of domestic demand-side response in Great Britain: The role of automation and direct load control », Energy Research & Social Science, vol. 9, p. 72-84, sept. 2015, doi: 10.1016/j.erss.2015.08.023.
13. M. Tabaa, K. Alami, A. Dandache, Z. Benabbou, B. Chouri, et K. Bousmar, « Initiation à la conception et ré alisation d'un réseau de capteurs intelligent : Maison Intelligente », J3eA, vol. 16, p. 1018, 2017, doi: 10.1051/j3ea/20171018.
14. Venkatesh, Morris, Davis, et Davis, « User Acceptance of Information Technology: Toward a Unified View », MIS Quarterly, vol. 27, no 3, p. 425, 2003, doi: 10.2307/30036540.
15. R. E. Freeman, Strategic management: a stakeholder approach, 2. [print.]. in Pitman series in business and public policy. Boston, Mass.: Pitman, 1984.
16. J. Gumz et D. C. Fettermann, « What improves smart meters' implementation? A statistical meta-analysis on smart meters' acceptance », SASBE, vol. 11, no 4, p. 1116-1136, déc. 2022, doi: 10.1108/SASBE-05-2021-0080.
17. OCDE, « Defining AI incidents and related terms », 2024.
18. S. S. S. R. Depuru, L. Wang, et V. Devabhaktuni, « Smart meters for power grid: Challenges, issues, advantages and status », Renewable and Sustainable Energy Reviews, vol. 15, no 6, p. 2736-2742, août 2011, doi: 10.1016/j.rser.2011.02.039.
19. T. Ahmad et al., « Artificial intelligence in sustainable energy industry: Status Quo, challenges and opportunities », Journal of Cleaner Production, vol. 289, p. 125834, mars 2021, doi: 10.1016/j.jclepro.2021.125834.
20. World Bank. Digital transformation and opportunities for African businesses. World Bank, 2024.[21] CRE, « Rapport d'activité de la CRE 2022 », 2022.
21. Enerdata. China Energy Report. Enerdata, 2022.

22. M. Meliani, A. El Barkany, I. El Abbassi, A. Moumen Darcherif, et M. Mahmoudi, « Smart grid implementation in Morocco: Case study », Materials Today: Proceedings, vol. 45, p. 7675-7679, 2021, doi: 10.1016/j.matpr.2021.03.176.
23. M. Meliani, A. El Barkany, I. El Abbassi, et M. Mahmoudi, « Smart Grid Challenges in Morocco and an Energy Demand Forecasting with Time Series », JERA, vol. 61, p. 195-215, juill. 2022, doi: 10.4028/p-2gufv6.
24. T. Rhardas et H. Rochdane, « Factors Affecting Citizen Intention to Use Smart City Services in Morocco: A Systematic Literature Review and Conceptual Framework », in Advances in Marketing, Customer Relationship Management, and E-Services, L. Alla, A. Hmioui, et B. Bentalha, Éd., IGI Global, 2024, p. 114-138. doi: 10.4018/979-8-3693-3172-9.ch006.
25. R. Habachi, A. Boulal, A. Touil, A. Charkaoui, et A. Echchatbi, « Barriers to the Adoption of Smart Grids in Morocco », in Advanced Intelligent Systems for Sustainable Development (AI2SD'2019), vol. 624, M. Ezziyyani, Éd., in Lecture Notes in Electrical Engineering, vol. 624. , Cham: Springer International Publishing, 2020, p. 34-42. doi: 10.1007/978-3-030-36475-5_4.