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Validation of an Artificial Intelligence Research and Development Governance Model with Emphasis on the Role of Policy–Investment–Innovation Convergence Capability

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Abstract

The present study aimed to validate a governance model for artificial intelligence research and development (AI R&D), with emphasis on the role of policy, investment, and innovation convergence capability, focusing on the Information and Communication Technology Research Institute. In terms of purpose, the study was applied, and methodologically, it employed an exploratory mixed-methods design with a qualitative–quantitative sequence. In the qualitative phase, 14 experts were selected through purposive and snowball sampling, and data obtained from semi-structured interviews were analyzed using thematic analysis and MAXQDA software. In the quantitative phase, data were collected using a researcher-developed questionnaire from 384 managers, researchers, and experts affiliated with the Institute and organizations related to the AI R&D ecosystem and were analyzed through partial least squares structural equation modeling (PLS-SEM) using SmartPLS. The qualitative findings resulted in the identification of 11 global themes, 45 organizing themes, and 130 basic themes. Convergence capability was conceptualized through four components: alignment of goals and priorities, joint decision-making and allocation, integration of information and processes, and feedback and adaptability. The quantitative results supported nine positive and statistically significant direct relationships in the model. Policy governance, with a path coefficient of 0.309, exhibited the largest coefficient among the antecedents of convergence capability, while convergence capability, with a path coefficient of 0.338, showed the largest coefficient among the antecedents of governance effectiveness. In addition, data and technical infrastructure governance, risk and lifecycle governance, and responsible AI were positively and significantly associated with governance effectiveness. The findings highlight the importance of an organization's capability to continuously connect policy priorities, resource-allocation decisions, and innovation activities. The proposed model can provide a basis for coordinating research, financial, and technical decisions and for strengthening learning and accountability in AI R&D governance.

Keywords: artificial intelligence governance, research and development, policymaking, investment, innovation

1. Introduction

Artificial intelligence (AI) has moved rapidly from a specialized technological domain to a strategic organizational and public-policy capability with profound implications for research and development (R&D), innovation systems, public administration, industrial competitiveness, and societal value creation. The expansion of AI applications has simultaneously increased the need for governance arrangements capable of coordinating technological development with institutional

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responsibilities, investment priorities, risk management, ethical requirements, and public objectives. Contemporary AI governance is therefore increasingly understood not merely as a collection of technical controls or ethical principles, but as a multidimensional system through which organizations define authority, allocate resources, establish accountability, manage data and algorithms, oversee innovation processes, and align AI initiatives with strategic goals (Batool et al., 2025; Berente et al., 2021; Birkstedt et al., 2023; Mäntymäki et al., 2022). This broader conception is particularly important in R&D-intensive environments, where uncertainty is high, technological trajectories evolve rapidly, and decisions concerning policy, funding, experimentation, infrastructure, intellectual property, and deployment are deeply interdependent.

The growing institutionalization of AI governance reflects the increasing recognition that the benefits of AI cannot be realized sustainably through technological capability alone. Organizational structures, decision rights, governance mechanisms, and management processes determine how AI is developed, evaluated, deployed, monitored, and revised over time. Research on organizational AI governance has emphasized the need to clarify roles, responsibilities, structures, and mechanisms that shape AI-related decision-making (Mäntymäki et al., 2022). At the same time, the literature has identified important gaps concerning how governance responsibilities are distributed within organizations and how formal governance roles emerge in practice (Frimpong & Botchey, 2026). These issues become more complex in research organizations because AI development often spans multiple units and professional domains, including scientific research, technology development, finance, legal affairs, data management, procurement, cybersecurity, ethics, commercialization, and external partnerships. Consequently, effective governance requires a coherent institutional architecture capable of linking these domains rather than treating them as separate administrative functions.

Systematic reviews of AI governance further indicate that the field has evolved toward more comprehensive and strategic frameworks, but remains fragmented in its conceptualization and implementation. Existing approaches address a wide range of concerns, including accountability, transparency, fairness, risk, organizational control, responsible innovation, and technical assurance, yet these elements are not always integrated into a unified governance logic (Bashir & Ravi, 2025; Batool et al., 2025). The fragmentation is especially significant when AI governance is considered in relation to R&D. Many frameworks focus on the governance of deployed AI systems, whereas R&D governance must also address upstream decisions concerning research agendas, investment portfolios, experimentation, access to data and computing resources, technological readiness, collaboration, and the transition from research outputs to scalable applications. Governance in this context must therefore operate across the entire innovation lifecycle rather than only at the point of implementation or regulatory compliance.

The strategic nature of AI R&D also places policymaking at the center of governance. National and organizational AI strategies increasingly define priority areas, research missions, infrastructure requirements, human-capital needs, innovation incentives, and regulatory expectations. Comparative research on AI policy has shown that governments use diverse policy goals and instruments to develop AI capabilities, ranging from R&D support and infrastructure investment to skills development, standards, data governance, and ecosystem-building measures (Alinaghian et al., 2021). Analysis of AI-enabled government strategies similarly demonstrates that national policy initiatives increasingly combine technological modernization with institutional reforms and public-sector capability development (van Noordt et al., 2025). In Iran, studies of AI governance and policy development likewise point to the growing importance of governance structures, national priorities, innovation ecosystems, and coordinated policy interventions (Aghayari & Karimmian, 2024; Safdari Ranjbar et al., 2023). The National Artificial Intelligence Document of the Islamic Republic of Iran also establishes a strategic framework for the development and governance of AI and reinforces the need for coordinated institutional action across research, technology, investment, and implementation domains (Supreme Council of the Cultural, 2024).

Policy governance, however, cannot be effective if priorities remain disconnected from resource allocation. AI research is increasingly capital-intensive because advanced development depends on specialized human resources, high-performance computing, cloud services, large and well-governed datasets, software engineering capabilities, cybersecurity, laboratories, and increasingly sophisticated operational infrastructures. The measurement of AI investment itself has therefore become an important policy and governance concern, as conventional categories of investment may fail to capture the multidimensional resources required for AI development (Fonteneau et al., 2025). For organizations engaged in AI R&D, investment governance must determine not only how much is spent, but also how funding is aligned with strategic priorities, distributed

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across research portfolios, staged according to technological maturity, and evaluated in terms of scientific, technological, economic, and public value. Without such alignment, organizations may experience a gap between declared policy priorities and the actual allocation of financial and technical resources.

The challenge of aligning policy and investment is closely related to the broader literature on mission-oriented and transformative innovation policy. Mission-oriented approaches emphasize the need to mobilize multiple policy instruments, organizational capabilities, and investment mechanisms around clearly defined societal or technological missions (Mazzucato, 2018). Such approaches require public organizations to develop capacities for strategic direction-setting, portfolio management, coordination, learning, experimentation, and adaptive implementation. Recent research on mission-oriented policy capacities has shown that successful implementation depends on the ability of institutions to connect strategic objectives with operational mechanisms and organizational capabilities (McLaren & Kattel, 2025). Similarly, the policy-mix literature highlights that complex innovation challenges cannot be addressed through isolated instruments; rather, they require coherent combinations of policy goals, instruments, processes, and institutional arrangements (Rogge & Reichardt, 2016). These insights are directly relevant to AI R&D governance because policy priorities, financial investments, innovation activities, and regulatory mechanisms must function as an interconnected system.

The evolution of innovation policy theory further supports the need for an integrated approach. Traditional R&D-oriented policy frameworks focused heavily on correcting market failures and increasing scientific and technological investment, while later innovation-system approaches emphasized networks, institutions, and interactions among firms, universities, government agencies, and other actors. More recent transformative innovation perspectives extend this logic by emphasizing directionality, societal challenges, institutional change, and systemic transformation (Schot & Steinmueller, 2018). AI development exhibits characteristics associated with all three perspectives. It requires sustained R&D investment, depends on complex innovation ecosystems, and raises transformative questions regarding economic structures, public services, employment, ethics, rights, security, and social inclusion. Therefore, governance mechanisms for AI R&D must be capable of integrating scientific research, innovation-system coordination, and strategic direction toward desired public outcomes.

Innovation governance constitutes another critical dimension because AI development is inherently experimental and iterative. Organizations need mechanisms for identifying opportunities, developing prototypes, conducting pilots, validating models, collaborating with users and external partners, and scaling successful solutions. At the same time, AI innovation generates paradoxical effects because the same technologies that create economic and social value may also produce new forms of risk, inequality, environmental pressure, opacity, and institutional dependency (Mancuso et al., 2025). This duality means that innovation governance cannot be evaluated solely in terms of speed, novelty, or commercialization. It must also incorporate responsible innovation, lifecycle oversight, stakeholder participation, and mechanisms for identifying and mitigating unintended consequences.

Responsible AI governance has therefore become an increasingly important field of research. The revised OECD Recommendation on Artificial Intelligence emphasizes principles such as inclusive growth, human-centered values, transparency, robustness, security, safety, and accountability, together with policy measures intended to support trustworthy AI ecosystems (Oecd, 2024). Similarly, contemporary responsible AI scholarship increasingly conceptualizes governance as an organizational capability rather than a static compliance framework (Haque, 2026). From this perspective, responsible governance depends on the organization's capacity to embed ethical, legal, social, and technical considerations into routine decisions, development processes, and monitoring practices. Papagiannidis et al. argue that responsible AI governance requires an integrated research agenda that links governance principles with organizational structures and implementation mechanisms (Papagiannidis et al., 2025). This capability-oriented perspective is particularly useful for AI R&D because governance must continuously adapt as research progresses, models change, data evolve, risks emerge, and technologies move from experimentation to deployment.

Lifecycle governance is especially important because AI risks are not confined to the deployment stage. Bias, privacy violations, security vulnerabilities, data-quality problems, model drift, lack of explainability, and accountability failures may originate at different points in the data and model lifecycle. The NIST Artificial Intelligence Risk Management Framework provides a structured approach for governing, mapping, measuring, and managing AI risks across organizational and technical

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processes (Tabassi, 2023). More recent work emphasizes the importance of embedding ethical requirements directly into the data lifecycle so that governance is incorporated into data collection, preparation, modeling, deployment, and monitoring rather than applied retrospectively (Huang et al., 2026). Wirtz et al. similarly propose an integrative governance approach based on risks and guidelines, illustrating the need to combine normative principles with operational controls (Wirtz et al., 2022). These perspectives suggest that AI R&D governance requires continuous feedback loops between technical performance, risk evaluation, organizational decisions, and policy adjustment.

Data and infrastructure governance are equally foundational because AI R&D depends heavily on access to reliable data, secure technical platforms, computing capacity, and reproducible research environments. Effective governance must clarify data ownership and stewardship, access rights, quality standards, provenance, security, model documentation, version control, and reproducibility. These requirements are becoming increasingly significant as organizations move from isolated AI experiments toward enterprise-level or institution-wide AI portfolios. Public organizations, in particular, face the challenge of translating high-level governance principles into workable organizational arrangements. Empirical research on the implementation of AI governance in public organizations demonstrates that implementation depends on institutional conditions, administrative processes, organizational capabilities, and practical mechanisms that convert principles into action (De Almeida & dos Santos Junior, 2025). Thus, governance effectiveness is likely to depend not only on the existence of policies, but also on their integration with operational, technical, and managerial systems.

The institutional maturity of AI governance has also become an important concern. Maturity-oriented approaches seek to assess whether organizations possess the structures, competencies, processes, and controls required to govern AI consistently and adaptively. In the context of smart cities, for example, an AI governance maturity model has been proposed to explain organizational transformation and progressive capability development in AI governance (Alrasbi & Ariaratnam, 2026). Such perspectives are useful because they shift attention from isolated governance practices toward organizational readiness and institutionalization. Governance maturity implies that roles are clearly defined, processes are repeatable, learning mechanisms exist, resources are coordinated, and governance practices become embedded in organizational routines rather than remaining dependent on individual initiatives.

Stakeholder and ecosystem governance represent another essential dimension of AI R&D. AI innovation rarely occurs within a single organization; instead, it involves universities, research centers, technology firms, startups, public agencies, investors, data providers, users, regulators, and other ecosystem actors. The development of the AI innovation ecosystem in Iran has likewise been associated with policies related to collaboration, infrastructure, financing, entrepreneurship, human capital, and institutional coordination (Safdari Ranjbar et al., 2023). Internationally, the governance of AI development increasingly emphasizes inclusive innovation and the distribution of benefits across countries and social groups. The United Nations Conference on Trade and Development has highlighted the importance of inclusive AI development and the need for technological progress to contribute to broader development objectives rather than intensify existing inequalities (United Nations Conference on & Development, 2025). Accordingly, stakeholder participation, co-creation, ecosystem coordination, and social legitimacy should be treated as governance mechanisms rather than peripheral considerations.

The geopolitical and strategic dimensions of AI governance further increase the importance of coordinated institutional capability. Analyses of U.S. approaches to AI governance illustrate how national strategies combine innovation promotion, security considerations, regulatory approaches, research investment, and technological leadership (Soleimanzadeh et al., 2024). These experiences indicate that AI governance is increasingly shaped by competition over technological capabilities, standards, infrastructure, talent, and strategic autonomy. Research institutes operating within national innovation systems must therefore simultaneously respond to scientific priorities, government policy, investment constraints, technological competition, and societal expectations. This complexity reinforces the need for governance models that can coordinate multiple decision domains rather than optimizing each domain independently.

Despite the rapid growth of AI governance scholarship, an important conceptual and practical gap remains in understanding how policymaking, investment, and innovation are jointly coordinated within AI R&D organizations. Existing frameworks frequently focus on principles, risks, ethics, public-sector adoption, organizational roles, or particular governance mechanisms (Bashir & Ravi, 2025; Birkstedt et al., 2023). Although these contributions provide important foundations, they do not fully

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explain the organizational capability through which policy priorities are translated into investment decisions and innovation portfolios, or how project outcomes are subsequently used to revise policy and resource allocation. This gap is especially consequential because misalignment among these domains may generate strategic inconsistency, fragmented investments, duplicated initiatives, delayed decision-making, and weak organizational learning.

The concept of convergence capability provides a useful way to address this gap. In the context of AI R&D governance, convergence capability can be understood as the organizational ability to align policy goals, investment decisions, and innovation activities through shared priorities, joint decision mechanisms, integrated information, coordinated processes, and continuous feedback. Such a capability is consistent with the view that AI governance should be treated as an integrated organizational system rather than a set of separate controls (Berente et al., 2021; Haque, 2026). It also responds to the policy-mix and mission-oriented innovation literature, which stresses coordination, coherence, directionality, and institutional learning (Mazzucato, 2018; McLaren & Kattel, 2025; Rogge & Reichardt, 2016). By integrating policy governance, investment governance, and innovation governance, convergence capability may provide the missing organizational mechanism that translates strategic direction into coordinated R&D action.

Such an integrated model should also recognize that convergence capability alone is insufficient unless supported by complementary organizational enablers. Institutional structure, managerial leadership, human capital, process maturity, stakeholder participation, ecosystem coordination, data governance, technical infrastructure, responsible AI, legal compliance, security, and lifecycle risk management all influence whether AI R&D decisions can be implemented effectively. Recent research suggests that governance must be embedded in organizational routines and supported by clearly allocated governance roles (Frimpong & Botchey, 2026), while responsible AI depends on institutional capabilities that link ethical expectations to operational processes (Haque, 2026; Papagiannidis et al., 2025). Similarly, public-sector governance studies demonstrate that formal governance principles must be translated into implementable organizational arrangements (De Almeida & dos Santos Junior, 2025). Therefore, a comprehensive AI R&D governance model should combine core governance domains, convergence mechanisms, organizational enablers, effectiveness criteria, and final scientific, technological, economic, and public-value outcomes.

The Information and Communication Technology Research Institute provides an appropriate context for examining such a model because research institutions occupy a distinctive position between public policy, scientific research, technology development, investment allocation, and innovation implementation. Their governance challenges differ from those of purely commercial organizations because they must often pursue multiple objectives simultaneously, including knowledge production, technological capability development, national strategic priorities, public value creation, collaboration with universities and industry, and responsible technology development. The increasing strategic importance of AI, combined with the institutional complexity of R&D governance, makes it necessary to empirically examine whether an integrated governance architecture can explain convergence capability and governance effectiveness within this organizational context.

Accordingly, the aim of this study is to validate an AI research and development governance model with emphasis on the role of policy–investment–innovation convergence capability in the Information and Communication Technology Research Institute.

2. Methods and Materials

The present study was applied in terms of purpose and employed an exploratory mixed-methods design with a qualitative–quantitative sequence. In the qualitative phase, the dimensions and components of the AI R&D governance model were identified and the measurement instrument was developed; subsequently, in the quantitative phase, the measurement properties and structural relationships of the model were evaluated with emphasis on policy, investment, and innovation convergence capability.

In the qualitative phase, the literature on AI governance, policymaking, investment, innovation, and related experiences was first reviewed, and the initial interview topics were developed. The participants consisted of 14 experts familiar with AI R&D governance and the organizational context of the study, who were selected through purposive and snowball sampling. Specialized familiarity with the subject, relevant professional experience, and the ability to explain organizational issues and

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processes were among the selection criteria. Data were collected through semi-structured interviews, and continuous comparison of codes and themes in the final interviews served as the basis for determining saturation and terminating data collection. Qualitative data were analyzed using MAXQDA 2020 and the thematic analysis procedure proposed by Braun and Clarke (2006), including familiarization with the data, coding, searching for themes, reviewing themes, defining and naming themes, and preparing the report. Related codes were compared and reviewed and were subsequently organized into basic, organizing, and global themes, which formed the basis for developing the model and questionnaire items. To enhance the trustworthiness of the findings, participant review of interpretations, comparison of documentary evidence with interview data, and examination of coding by a researcher familiar with qualitative methodology were employed. The statistical population of the quantitative phase comprised managers, researchers, and experts from the Information and Communication Technology Research Institute and organizations associated with the AI R&D ecosystem. The sample size was determined using Cochran's formula, and data from 384 respondents were included in the final analysis. The data collection instrument was a researcher-developed questionnaire based on the findings of the qualitative phase. The content validity of the questionnaire was assessed by evaluating the consistency of the items with the operational definitions of the constructs and extracted themes and by obtaining expert opinions. In the quantitative phase, instrument reliability was assessed using Cronbach's alpha and construct reliability indices. Convergent validity was evaluated using factor loadings and average variance extracted (AVE), while discriminant validity was assessed using the Fornell–Larcker criterion and the heterotrait–monotrait ratio of correlations (HTMT).

Quantitative data were analyzed using partial least squares structural equation modeling (PLS-SEM) in SmartPLS 3. First, the measurement model was assessed in terms of the reliability and validity of the measures, after which the structural relationships were analyzed by examining path coefficients, statistical significance of the relationships, coefficients of determination, predictive relevance indices, and model fit indices. Integration of the qualitative and quantitative phases was achieved by transforming the themes into measurable constructs and questionnaire items and empirically evaluating the proposed relationships.

3. Findings and Results

In this section, the demographic characteristics of the participants were first examined. Of the 14 participating experts, 11 were men and 3 were women. In terms of work experience, the group with 10–15 years of experience had the highest frequency, with 8 participants. With respect to age, the 30–40-year and 41–50-year age groups each included 5 participants and had the highest frequencies. In addition, 8 participants held master's degrees and 6 held doctoral degrees.

Data obtained from 14 semi-structured interviews with experts were analyzed using the thematic analysis method of Braun and Clarke (2006) and MAXQDA software.

a) **Initial Coding:** Following repeated examination of the interview transcripts and identification of meaning units related to AI R&D governance, 4,708 initial coding instances were recorded. Similar and related codes were then compared and reviewed and organized into basic, organizing, and global themes. The frequency of initial coding instances is presented in Table 1.

Table 1. **Frequency of Initial Coding Instances Across Interviews**

Interview	Number of Coding Instances
Interview 1	544
Interview 2	122
Interview 3	186
Interview 4	204
Interview 5	444
Interview 6	242
Interview 7	266
Interview 8	156
Interview 9	388
Interview 10	628
Interview 11	444
Interview 12	484
Interview 13	238

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Interview 14	362
Total	4,708

b) **Identification and Organization of Themes:** The initial codes were examined on the basis of their similarities, differences, and conceptual relationships and were classified at three levels: basic themes, organizing themes, and global themes.

c) **Review and Refinement of Themes:** The themes were reviewed in terms of internal coherence, conceptual distinctiveness, and consistency with the interview transcripts and research questions. Overlapping themes were merged, and themes requiring modification were redefined.

d) **Development of the Conceptual Framework of the Study:** The refined themes and the conceptual relationships among policymaking, investment, and innovation formed the basis for developing the AI R&D governance framework.

Table 2 presents the global, organizing, and basic themes of the AI R&D governance model based on the convergence of policymaking, investment, and innovation.

Table 2. **Themes of the Artificial Intelligence Research and Development Governance Model**

Global Themes	Organizing Themes	Basic Themes
Core Domain: AI R&D Policy Governance	Strategic orientation and prioritization	Existence of an approved AI R&D strategy and roadmap; alignment of priorities with the Institute's mission and national documents; clarity and measurability of objectives
	Adaptive regulation and standard-setting	Existence of clear rules regarding data, algorithms, intellectual property, and technology procurement; proportionality of regulations to risk level; use of regulatory sandboxes
	Evidence-based policymaking	Use of data, research, and actual needs in agenda-setting; establishment of policy evaluation indicators; policy revision based on feedback from project implementation
	Policy coordination and accountability	Clarity of the roles of institutions and organizational units; existence of a coordinating authority; designation of an accountable party for each policy
Core Domain: R&D Investment Governance	Alignment of budget and project portfolio	Linking budgets to strategic priorities; balance among basic, applied, and developmental research; stage-based allocation of resources according to technology readiness level
	Sustainability and diversity of financing	Availability of relatively stable multi-year budgets; joint financing by government, industry, and universities; attraction of venture capital
	Investment in strategic assets	Investment in computing capacity, cloud infrastructure, laboratories, and platforms; investment in data generation and preparation; investment in security and MLOps
	Financial transparency and efficiency	Transparency of budget allocation criteria; cost–benefit and public-value assessment; control of project costs, schedules, and outputs
Core Domain: AI Innovation Governance	Opportunity discovery and experimentation	Systematic identification of priority problems and needs; prototype development; use of pilots and sandboxes
	Open and collaborative innovation	Implementation of joint university–industry–government projects; collaboration with knowledge-based companies and startups; shared use of data and infrastructure
	Intellectual property and technology transfer	Existence of a clear intellectual property policy; registration and management of inventions, software, and data assets; market assessment and user-based product validation
	Adoption, scalability, and ambidexterity	Progression of projects across technology readiness levels; deployment in real-world environments; balance between exploratory and exploitative innovation
Central Mechanism: Policy–Investment–Innovation Convergence Capability	Alignment of goals and priorities	Translation of policy priorities into calls, budgets, and project portfolios; resolution of conflicts among policy, budget, and innovation programs
	Joint decision-making and allocation	Existence of a joint policy, investment, and innovation council; participation of specialized units in project selection; definition of joint decision gates
	Integration of information and processes	Existence of an integrated dashboard for policy, budget, projects, risk, and outcomes; decision traceability; linkage of financial data to technical progress and outcomes
	Feedback and adaptability	Integration of project results into policy-revision processes; budget adjustment based on performance and risk; periodic review of project portfolios
Enabler: Institutional Structure, Leadership, and Organizational Capacity	Structure, roles, and decision rights	Existence of an AI and R&D governance office or unit; designation of data, model, and project owners; transparency of the responsibility matrix
	Leadership and managerial commitment	Continuous support from senior management; active managerial participation in key decisions

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	Human capital and learning	Existence of a competency framework; continuous technical, managerial, legal, and ethical training; recruitment and retention of specialists
	Culture, readiness, and process maturity	Culture of innovation and learning from failure; periodic maturity assessment; existence of a continuous improvement program
Enabler: Data, Algorithm, and Technical Infrastructure Governance	Data governance	Designation of data owners and stewards; control of data quality and provenance; access and data-sharing rules
	Algorithm and model governance	Documentation and use of model cards; validation of accuracy, fairness, and explainability; version and model-change control
	Computational and operational infrastructure	Adequacy of computing resources, cloud infrastructure, and laboratories; existence of secure and interoperable platforms; implementation of MLOps processes
	Knowledge management and reproducibility	Existence of repositories for code, data, and documentation; reproducibility of research results; sharing and reuse of knowledge
Enabler: Responsible, Legal, and Ethical AI	Fairness and human rights	Assessment of bias and discrimination; observance of fairness and accessibility; preservation of human agency and oversight
	Transparency, explainability, and accountability	Provision of audience-appropriate explanations; documentation of algorithmic decisions; designation of accountable parties
	Legal and contractual compliance	Compliance with privacy, intellectual property, and data regulations; inclusion of liability, audit, and access clauses in contracts; preparedness for inspection and auditing
	Social legitimacy and sustainability	Assessment of stakeholder trust; participation of affected individuals; existence of mechanisms for complaints, appeals, and redress
Enabler: Stakeholder Participation and Ecosystem Governance	Stakeholder identification and inclusion	Stakeholder mapping; stakeholder engagement from the early stages of projects
	University–industry–government collaboration	Number and quality of joint projects; clarity of parties' roles; sharing of resources, knowledge, and infrastructure
	Co-creation with users and society	Identification of user needs; user participation in design and testing; assessment of satisfaction and acceptance
	Supplier governance and international collaboration	Assessment of supplier competence and risk; transparency, portability, and exit provisions in contracts; continuous monitoring of third parties
Enabler: Risk, Security, and Lifecycle Governance	Risk classification and impact assessment	Classification of projects according to application and risk level; AI and privacy impact assessment; recording of risks and designation of risk owners
	Testing, assurance, and auditing	Testing of accuracy, robustness, security, and bias; independent validation; approval prior to deployment
	Continuous monitoring and incident management	Monitoring performance degradation and data drift; incident and error reporting; existence of emergency shutdown and rollback mechanisms
	Resilience and control adaptation	Threat modeling; access control and protection of models and data; incident response and recovery
Intermediate Criterion: AI R&D Governance Effectiveness	Strategic coherence and alignment	Degree of consistency between decisions and priorities; reduction of conflicts among policy, budget, and projects; achievement of specified objectives
	Decision quality and agility	Decision-making speed; evidence-based decision-making; quality of decisions to continue, modify, or terminate projects
	Transparency, accountability, and coordination	Decision traceability; stakeholder satisfaction with coordination and accountability
	Resource efficiency and institutional learning	Efficient use of budgets and infrastructure; utilization of experience from previous projects; continuous process improvement
Final Outcome: R&D Outcomes and Public Value	Scientific and knowledge outcomes	Number and quality of publications; production of research data, code, and software; reproducibility of results
	Technological and innovation outcomes	Advancement of technology readiness levels; creation of products or spin-off companies; deployment and adoption rates
	Economic and investment outcomes	Amount of external resources attracted; economic return or value generated from investment; increased productivity and commercialization revenue
	Strategic and public value	Resolution of priority national and institutional challenges; improved service quality; enhanced trust, fairness, and inclusion
	Governance maturity and readiness	Improvement in maturity level relative to baseline; institutionalization of processes

To examine agreement in the classification of codes, Cohen's kappa coefficient was used. Another evaluator with expertise in the research domain independently classified the codes into concepts without being informed of how the researcher had merged the codes. The classifications of the two evaluators were then compared, and the kappa coefficient was calculated.

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Table 3. Kappa Agreement Coefficient for Code Classification

Measure	Statistic	Value	Standard Error	*T*	*p*
Agreement measure	Kappa	0.882	0.089	8.104	< .001
Number of codes		14			

The reported kappa coefficient was 0.882, which, according to the relevant interpretive guideline, represents an almost perfect level of agreement. This classification serves as a descriptive guideline for interpreting the degree of agreement.

A total of 384 individuals participated in the quantitative phase, including 244 men (63.5%), 130 women (33.9%), and 10 respondents (2.6%) who did not answer the gender question. The highest age-group frequency was observed among respondents aged 41–50 years, comprising 171 participants (44.5%). In terms of educational attainment, 180 respondents (46.9%) held master's degrees and 168 (43.8%) held doctoral degrees. In addition, respondents with 10–15 years of professional experience represented the largest group, comprising 113 participants (29.4%).

With respect to occupational role, researchers and faculty members, with 124 participants (32.3%), and senior experts, with 99 participants (25.8%), constituted the largest groups. Regarding organizational affiliation, 236 respondents (61.5%) were affiliated with the Institute, while the remaining respondents were drawn from governmental and regulatory bodies, universities, funding institutions and investors, industry, and knowledge-based companies. Among areas of expertise, data and model expertise had the highest frequency, with 101 participants (26.3%). Furthermore, among the reported categories of direct involvement in AI projects, respondents with experience in 3–5 projects represented the largest group, with 138 participants (35.9%).

Table 4. Reliability and Validity of the Research Variables

Variable	Cronbach's Alpha	Composite Reliability	Average Variance Extracted
Testing, assurance, and auditing	0.798	0.800	0.713
Strategic coherence and alignment	0.735	0.805	0.649
Legal and contractual compliance	0.807	0.808	0.721
Feedback and adaptability	0.762	0.769	0.677
Resource efficiency and institutional learning	0.773	0.800	0.684
Resilience and control adaptation	0.803	0.909	0.709
Joint decision-making and allocation	0.743	0.745	0.660
Adaptive regulation and standard-setting	0.732	0.735	0.651
Data, algorithm, and technical infrastructure governance enabler	0.700	0.701	0.714
Institutional structure, leadership, and organizational capacity enabler	0.798	0.798	0.768
Stakeholder participation and ecosystem governance enabler	0.793	0.793	0.765
Responsible, legal, and ethical AI enabler	0.749	0.750	0.740
Strategic orientation and prioritization	0.770	0.782	0.683
Algorithm and model governance	0.755	0.760	0.672
Supplier governance and external collaboration	0.757	0.760	0.673
Data governance	0.708	0.754	0.624
Leadership and managerial commitment	0.731	0.734	0.721
Computational and operational infrastructure	0.772	0.803	0.683
Structure, roles, and decision rights	0.776	0.822	0.688
Central mechanism of policy–investment–innovation convergence capability	0.729	0.730	0.729
Human capital and learning	0.793	0.798	0.619
Investment in strategic assets	0.788	0.814	0.700
Evidence-based policymaking	0.781	0.782	0.696
Financial transparency and efficiency	0.797	0.798	0.711
Transparency, explainability, and accountability	0.758	0.758	0.674
Transparency, accountability, and coordination	0.748	0.749	0.740
Stakeholder identification and inclusion	0.788	0.789	0.762
Risk classification and impact assessment	0.772	0.785	0.686
Fairness and human rights	0.744	0.747	0.661
Culture, readiness, and process maturity	0.793	0.796	0.707
Intellectual property and technology transfer	0.772	0.806	0.685
Knowledge management and reproducibility	0.783	0.783	0.698

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Social legitimacy and sustainability	0.732	0.757	0.646
Intermediate criterion of AI R&D governance effectiveness	0.769	0.773	0.751
Open and collaborative innovation	0.786	0.787	0.700
Core domain of R&D investment governance	0.792	0.792	0.710
Core domain of AI R&D policy governance	0.830	0.830	0.662
Core domain of AI innovation governance	0.734	0.734	0.790
Co-creation with users and society	0.773	0.793	0.685
Policy coordination and accountability	0.791	0.794	0.705
Alignment of goals and priorities	0.712	0.754	0.773
Alignment of budget and project portfolio	0.807	0.812	0.721
University–industry–government collaboration	0.769	0.770	0.684
Sustainability and diversity of financing	0.732	0.776	0.644
Continuous monitoring and incident management	0.745	0.749	0.663
Adoption, scalability, and ambidexterity	0.791	0.824	0.703
Opportunity discovery and experimentation	0.783	0.783	0.697
Decision quality and agility	0.735	0.736	0.654
Integration of information and processes	0.763	0.792	0.674

Cronbach's alpha and composite reliability values for all research variables exceeded 0.70 and were higher than 0.705, indicating satisfactory reliability of the study variables. The results also showed that the AVE coefficients of all study variables were greater than 0.50, indicating satisfactory convergent validity.

Figure 1 presents the model output together with path coefficients and factor loadings, while Figure 2 presents the bootstrapping results together with the *t* statistics. The structural model contains two principal endogenous constructs: convergence capability, with five antecedents, and governance effectiveness, with four antecedents. The values displayed within the two principal endogenous constructs represent their coefficients of determination.

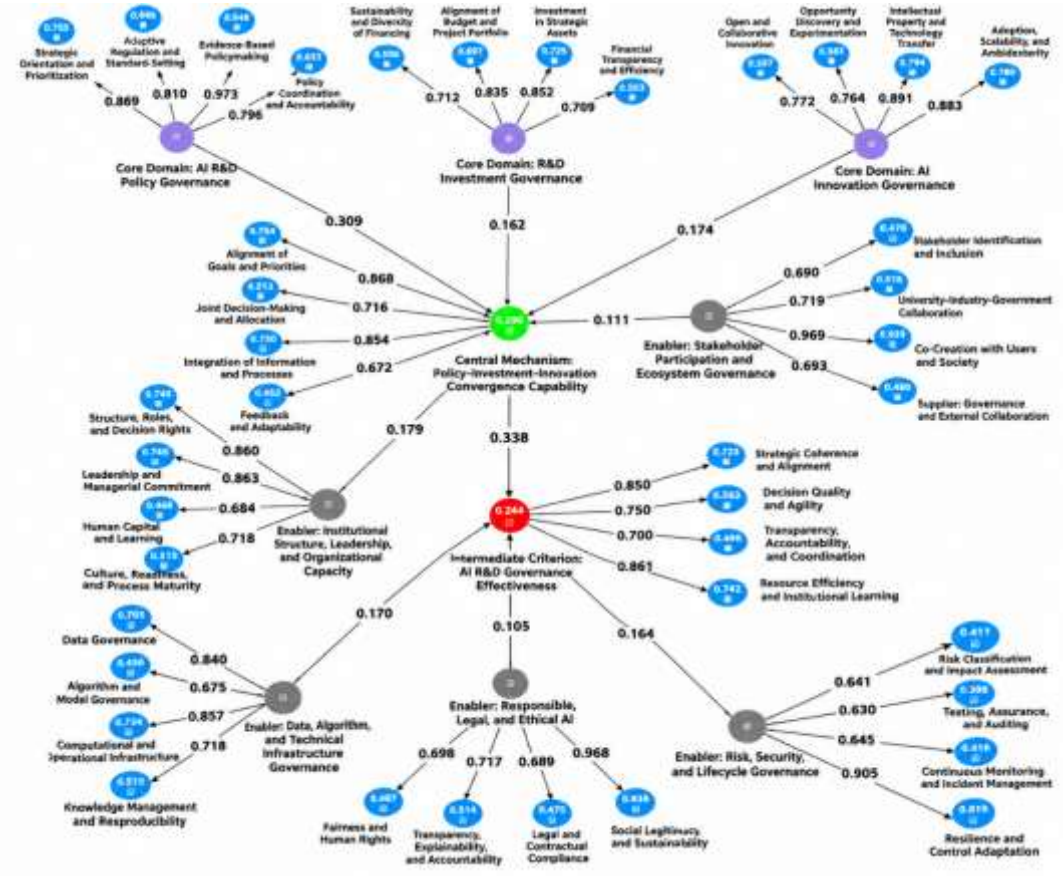


Figure 1. Conceptual model of the study with path coefficients and factor loadings

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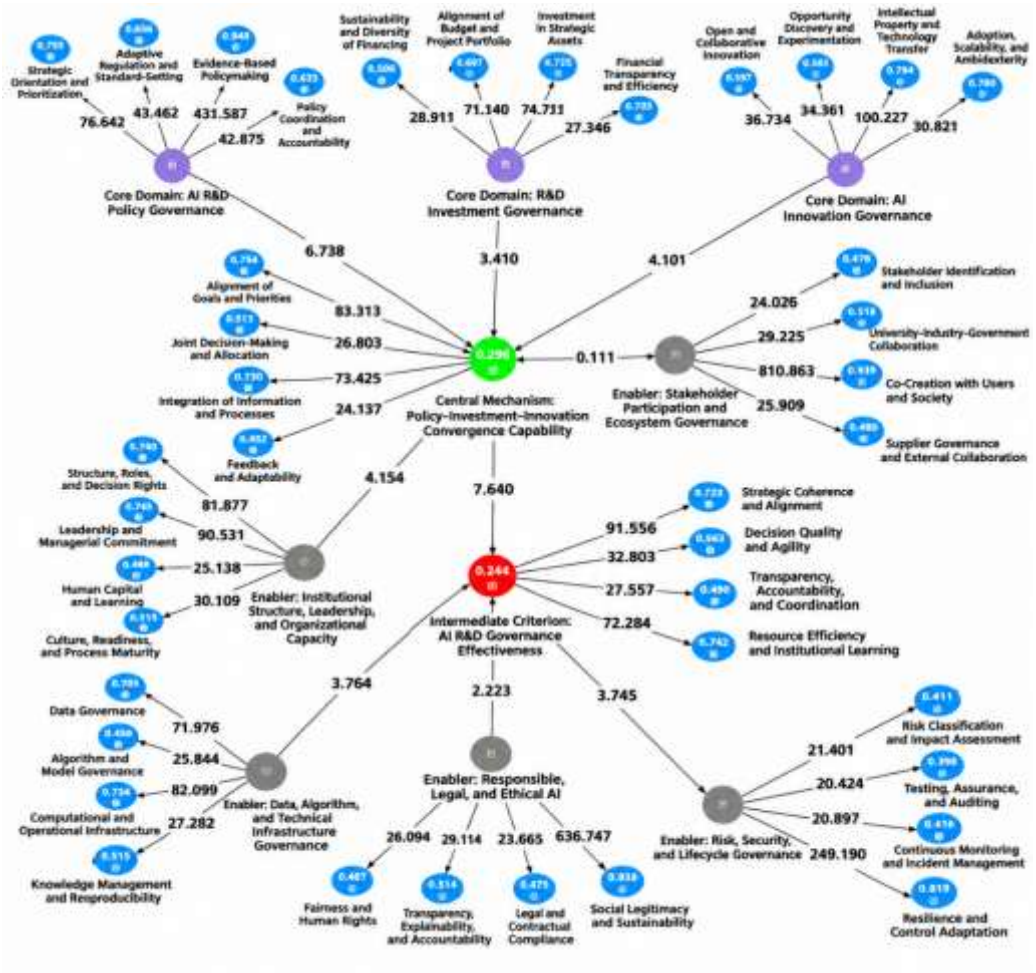


Figure 2. Conceptual model of the study with *t*-statistic values

Table 5. Results of Direct Path Tests

No.	Path	Path Coefficient	Standard Deviation	*t* Statistic	*p* Value	Result
1	Core domain of AI innovation governance → Central mechanism of policy–investment–innovation convergence capability	0.174	0.042	4.101	< .001	Supported
2	Institutional structure, leadership, and organizational capacity enabler → Central mechanism of policy–investment–innovation convergence capability	0.179	0.043	4.154	< .001	Supported
3	Stakeholder participation and ecosystem governance enabler → Central mechanism of policy–investment–innovation convergence capability	0.111	0.043	2.562	.010	Supported
4	Core domain of AI R&D policy governance → Central mechanism of policy–investment–innovation convergence capability	0.309	0.046	6.738	< .001	Supported
5	Core domain of R&D investment governance → Central mechanism of policy–investment–innovation convergence capability	0.162	0.047	3.410	.001	Supported
6	Central mechanism of policy–investment–innovation convergence capability → Intermediate criterion of AI R&D governance effectiveness	0.338	0.044	7.640	< .001	Supported
7	Risk, security, and lifecycle governance enabler → Intermediate criterion of AI R&D governance effectiveness	0.164	0.044	3.745	< .001	Supported
8	Data, algorithm, and technical infrastructure governance enabler → Intermediate criterion of AI R&D governance effectiveness	0.170	0.045	3.764	< .001	Supported
9	Responsible, legal, and ethical AI enabler → Intermediate criterion of AI R&D governance effectiveness	0.105	0.047	2.223	.026	Supported

To assess the explanatory power of the structural model, the coefficient of determination (R^2) and adjusted coefficient of determination were examined. The coefficient of determination represents the proportion of variance in the endogenous constructs explained by the predictor variables in the model. In general, R^2 values of 0.25, 0.50, and 0.75 can be interpreted as indicating weak, moderate, and substantial explanatory power, respectively.

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Table 6. Indicators of Explanatory Power and Predictive Relevance of the Model Constructs

Construct	R^2	Q^2
Testing, assurance, and auditing	0.396	0.280
Strategic coherence and alignment	0.723	0.444
Legal and contractual compliance	0.474	0.340
Feedback and adaptability	0.451	0.301
Resource efficiency and institutional learning	0.741	0.489
Resilience and control adaptation	0.818	0.528
Joint decision-making and allocation	0.512	0.333
Adaptive regulation and standard-setting	0.655	0.422
Strategic orientation and prioritization	0.754	0.000
Algorithm and model governance	0.454	0.000
Supplier governance and external collaboration	0.478	0.000
Data governance	0.705	0.000
Leadership and managerial commitment	0.745	0.000
Computational and operational infrastructure	0.733	0.506
Structure, roles, and decision rights	0.739	0.301
Central mechanism of policy–investment–innovation convergence capability	0.287	0.319
Human capital and learning	0.466	0.416
Investment in strategic assets	0.725	0.512
Evidence-based policymaking	0.947	0.481
Financial transparency and efficiency	0.502	0.491
Transparency, explainability, and accountability	0.513	0.207
Transparency, accountability, and coordination	0.488	0.283
Stakeholder identification and inclusion	0.474	0.492
Risk classification and impact assessment	0.410	0.655
Fairness and human rights	0.485	0.355
Culture, readiness, and process maturity	0.514	0.344
Intellectual property and technology transfer	0.793	0.359
Knowledge management and reproducibility	0.514	0.358
Social legitimacy and sustainability	0.938	0.277
Intermediate criterion of AI R&D governance effectiveness	0.236	0.318
Open and collaborative innovation	0.582	0.359
Co-creation with users and society	0.939	0.526
Policy coordination and accountability	0.632	0.355
Alignment of goals and priorities	0.753	0.583
Alignment of budget and project portfolio	0.505	0.171
University–industry–government collaboration	0.516	0.405
Sustainability and diversity of financing	0.696	0.000
Continuous monitoring and incident management	0.415	0.000
Adoption, scalability, and ambidexterity	0.779	0.000
Opportunity discovery and experimentation	0.596	0.622
Decision quality and agility	0.562	0.440
Integration of information and processes	0.729	0.567

The results showed that the reported R^2 values for the endogenous variables ranged from 0.244 to 0.948. The R^2 values for convergence capability and governance effectiveness were 0.296 and 0.244, respectively; therefore, the antecedents included in the model explained 29.6% and 24.4% of the variance in these two principal constructs, respectively. In addition, the Q^2 values of the endogenous constructs ranged from 0.171 to 0.655, and their positive values support the predictive relevance of the model in the assessment conducted. Regarding overall model fit, the SRMR value was 0.070 and the NFI value was 0.914, which, according to commonly accepted thresholds, indicate an acceptable level of fit. In addition, the goodness-of-fit (GoF) index was calculated as 0.649.

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4. Discussion and Conclusion

The findings of the present study provide empirical support for a multidimensional model of artificial intelligence research and development governance in which policy governance, investment governance, innovation governance, institutional capacity, stakeholder participation, data and technical infrastructure governance, responsible AI, and risk and lifecycle governance interact through the central mechanism of policy–investment–innovation convergence capability. The structural model showed that all nine hypothesized direct relationships were positive and statistically significant. Among the antecedents of convergence capability, AI R&D policy governance had the strongest effect with a path coefficient of 0.309, followed by institutional structure, leadership, and organizational capacity with a coefficient of 0.179, AI innovation governance with 0.174, R&D investment governance with 0.162, and stakeholder participation and ecosystem governance with 0.111. Convergence capability itself had the strongest direct effect on AI R&D governance effectiveness, with a path coefficient of 0.338. In addition, data, algorithm, and technical infrastructure governance showed a positive effect of 0.170 on governance effectiveness, risk, security, and lifecycle governance had an effect of 0.164, and responsible, legal, and ethical AI had an effect of 0.105. These results collectively indicate that effective AI R&D governance is not produced by a single governance domain, but rather by the integration of strategic direction, resource allocation, innovation processes, technical infrastructure, risk controls, and organizational coordination.

The strongest antecedent of convergence capability was AI R&D policy governance. This result suggests that convergence among policy, investment, and innovation is primarily shaped by the clarity of strategic orientation, evidence-based policymaking, adaptive regulation, prioritization, and policy accountability. In practical terms, the finding implies that investment and innovation activities are unlikely to converge effectively unless policy priorities are explicit, measurable, and institutionally embedded. This result is consistent with research showing that AI policy development increasingly relies on coordinated combinations of policy objectives, implementation instruments, and institutional arrangements rather than isolated interventions (Alinaghian et al., 2021). It also aligns with the policy-mix perspective, in which coherence among objectives and instruments is regarded as necessary for effective technological and sustainability transitions (Rogge & Reichardt, 2016). The result is further supported by the mission-oriented innovation literature, which emphasizes that direction-setting is a prerequisite for aligning public investment and innovation activity with strategic missions (Mazzucato, 2018; McLaren & Kattel, 2025). In the context of AI governance, this finding indicates that policy governance operates as the main source of directionality through which organizational priorities are translated into investment portfolios and innovation programs.

The importance of policy governance is also consistent with national and public-sector AI governance research. Studies examining AI policy strategies across countries indicate that the development of AI capabilities requires coordinated interventions in R&D, human resources, data, infrastructure, standards, financing, and innovation ecosystems (van Noordt et al., 2025). Similarly, research on AI governance in Iran has highlighted the growing role of coordinated policy frameworks, strategic documents, and ecosystem-oriented interventions in developing national AI capacities (Aghayari & Karimmian, 2024; Safdari Ranjbar et al., 2023). The National Artificial Intelligence Document of the Islamic Republic of Iran also reflects the need for institutional coordination across technological, scientific, financial, and regulatory domains (Supreme Council of the Cultural, 2024). Therefore, the relatively larger effect of policy governance in the present model is theoretically plausible because policy determines both the direction and the criteria according to which financial, technical, and innovation decisions can be aligned.

Institutional structure, leadership, and organizational capacity also had a positive and significant effect on convergence capability. This finding indicates that convergence is not simply a result of formal policies; it depends on organizational arrangements that assign decision rights, clarify responsibilities, support leadership involvement, develop human capital, and institutionalize learning. This result is consistent with organizational AI governance research that emphasizes governance as a system of structures, processes, and relational mechanisms through which AI-related responsibilities are allocated and controlled (Mäntymäki et al., 2022). It is also in line with findings that many organizations still lack clearly defined AI governance roles, which can weaken accountability and coordination (Frimpong & Botchey, 2026). The result supports the argument that responsible AI governance should be treated as an organizational capability rather than only as a compliance

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framework, because organizational routines, managerial commitment, and institutionalized learning determine whether governance principles are translated into practice (Haque, 2026). Thus, the significant effect of this construct confirms that convergence requires organizational capacity to connect strategic decisions with operational execution.

The positive effect of AI innovation governance on convergence capability further indicates that mechanisms for experimentation, opportunity discovery, open innovation, intellectual property management, technology transfer, scalability, and ambidexterity contribute to stronger integration between policy and investment. This finding is important because AI R&D is inherently iterative and uncertain. Policy priorities and investment decisions need continuous feedback from experimentation and technological learning. The result is consistent with the transformation of innovation policy from linear R&D models toward system-oriented and transformative approaches that emphasize experimentation, collaboration, directionality, and institutional change (Schot & Steinmueller, 2018). It also corresponds with the mission-oriented perspective, in which innovation activities are expected to contribute to broader strategic objectives rather than remain disconnected technological projects (Mazzucato, 2018). At the same time, AI innovation creates both value-creating and value-destroying effects, making governance of experimentation and scaling particularly important (Mancuso et al., 2025). The positive coefficient found in this study therefore suggests that innovation governance strengthens convergence when experimentation and scaling are connected to policy goals and resource decisions.

R&D investment governance also exerted a significant positive effect on convergence capability. This result indicates that alignment of budgets with strategic priorities, diversification of financing, investment in strategic technological assets, and financial transparency are important for translating policy goals into innovation activity. The finding is consistent with the increasing recognition that AI development requires substantial and heterogeneous forms of investment, including computational infrastructure, data preparation, human expertise, secure platforms, and operational capabilities (Fonteneau et al., 2025). The result also supports mission-oriented innovation research, which emphasizes that financial resources must be strategically directed rather than distributed independently of policy missions (Mazzucato, 2018; McLaren & Kattel, 2025). In this sense, investment governance can be interpreted as the operational bridge between strategic priorities and actual research and innovation portfolios. The significant coefficient confirms that convergence requires not only common policy objectives, but also financing mechanisms that reinforce these objectives.

Stakeholder participation and ecosystem governance had the smallest, although still significant, effect on convergence capability. This finding suggests that engagement with universities, industry, government, users, suppliers, and other ecosystem actors contributes to convergence, but its influence may be more indirect or contingent than internal policy and organizational mechanisms. The result is consistent with the innovation-system literature, which emphasizes that AI development depends on interactions among multiple actors rather than isolated organizational activity (Schot & Steinmueller, 2018). It also aligns with studies of Iran's AI innovation ecosystem that highlight collaboration among public agencies, universities, firms, startups, and financing institutions as necessary for developing AI capabilities (Safdari Ranjbar et al., 2023). Moreover, the emphasis on inclusive AI development in international policy discourse suggests that stakeholder participation is essential for ensuring that AI development responds to broader economic and social needs (United Nations Conference on & Development, 2025). The smaller coefficient may reflect the fact that ecosystem participation only improves convergence when internal governance structures are sufficiently mature to incorporate external knowledge and coordinate cross-organizational interests.

The most important structural finding of the study was the positive effect of policy–investment–innovation convergence capability on AI R&D governance effectiveness. With a coefficient of 0.338, this relationship was stronger than the other direct predictors of governance effectiveness. This result supports the central argument of the study that convergence capability is not merely an auxiliary coordination mechanism, but a core organizational capability through which policy priorities, resource allocation, and innovation activities are transformed into coherent governance outcomes. This interpretation is consistent with the organizational AI governance literature, which increasingly conceptualizes governance as an integrated system of structures, decision processes, responsibilities, and controls (Berente et al., 2021; Mäntymäki et al., 2022). It is also consistent with systematic reviews showing that AI governance remains fragmented when ethical, technical, managerial, and strategic mechanisms are treated separately (Bashir & Ravi, 2025; Batool et al., 2025; Birkstedt et al., 2023). The present

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findings extend this literature by suggesting that the organizational capability to integrate policy, investment, and innovation may be one mechanism through which fragmentation is reduced.

The effect of convergence capability on governance effectiveness can also be explained through the policy-mix and mission-oriented innovation perspectives. Policy-mix theory emphasizes that policy consistency, coherence, and credibility are central to effective governance of complex technological transitions (Rogge & Reichardt, 2016). Mission-oriented innovation research similarly emphasizes that institutions must connect strategic direction, investment portfolios, experimentation, and learning processes (Mazzucato, 2018; McLaren & Kattel, 2025). The present results suggest that these theoretical ideas can also be applied at the organizational level of AI R&D governance. When policy priorities are translated into investment criteria and innovation portfolios, and when project outcomes are subsequently fed back into policy and resource-allocation decisions, governance becomes more coherent, responsive, and adaptive. This helps explain why convergence capability had the largest coefficient among the direct predictors of governance effectiveness.

Data, algorithm, and technical infrastructure governance had a significant positive relationship with governance effectiveness. This result demonstrates that strategic convergence must be complemented by technically robust governance arrangements. Data ownership, quality, provenance, model documentation, validation, secure infrastructure, interoperability, MLOps, and knowledge reproducibility directly affect the reliability and governability of AI R&D processes. This result is consistent with the broader literature emphasizing that organizational AI governance must include technical and data-related control mechanisms rather than being limited to managerial or ethical principles (Berente et al., 2021; Birkstedt et al., 2023). It is particularly aligned with research emphasizing the embedding of ethical and governance principles throughout the data lifecycle, from collection and preparation to model deployment and monitoring (Huang et al., 2026). Public-sector implementation research also shows that AI governance becomes effective only when high-level principles are translated into operational and technical routines (De Almeida & dos Santos Junior, 2025). Thus, technical infrastructure governance appears to be an essential condition for converting governance intentions into reproducible and controllable AI practices.

Risk, security, and lifecycle governance also showed a significant positive effect on governance effectiveness. This finding indicates that AI R&D governance is strengthened when organizations systematically classify risks, conduct impact assessments, test models, monitor performance and data drift, manage incidents, and establish resilience and recovery mechanisms. The result strongly corresponds with risk-based AI governance approaches. The NIST AI Risk Management Framework emphasizes continuous governance, mapping, measurement, and management of risks across the AI lifecycle (Tabassi, 2023). Wirtz et al. similarly propose a risk- and guideline-based integrative governance framework in which AI risks are addressed through coordinated organizational and regulatory mechanisms (Wirtz et al., 2022). The present finding reinforces the view that governance effectiveness depends not merely on ex ante approval but on continuous lifecycle oversight. This is particularly important in AI because models, datasets, operational environments, and risk profiles may change after deployment.

Responsible, legal, and ethical AI also had a positive and statistically significant relationship with governance effectiveness, although its coefficient was smaller than those of convergence capability, technical governance, and risk governance. This result indicates that fairness, human rights, transparency, explainability, accountability, contractual compliance, social legitimacy, and sustainability remain meaningful determinants of governance effectiveness. The finding is compatible with the OECD's emphasis on trustworthy AI principles, including human-centered values, transparency, robustness, security, and accountability (Oecd, 2024). It is also aligned with responsible AI governance research, which argues that ethical principles must be operationalized through organizational mechanisms and decision processes rather than treated as abstract commitments (Haque, 2026; Papagiannidis et al., 2025). The relatively smaller coefficient may suggest that responsible AI principles influence governance effectiveness most strongly when they are embedded within institutional, technical, and risk-management processes. In other words, ethical principles become more effective when they are translated into operational governance capabilities.

The measurement model also supported the reliability and convergent validity of the constructs, with Cronbach's alpha and composite reliability values generally above accepted thresholds and AVE values exceeding 0.50. This finding indicates that the qualitative themes identified in the exploratory phase were successfully transformed into empirically distinguishable

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measurement dimensions. The use of a mixed-methods design therefore appears to have been particularly valuable in the present study because the qualitative phase captured the organizational and contextual dimensions of AI R&D governance, while the quantitative phase tested the structural relationships among those dimensions. This approach responds to the broader literature's call for more empirically grounded AI governance research, particularly research capable of moving beyond conceptual frameworks toward organizational implementation (Batool et al., 2025; Birkstedt et al., 2023). The high inter-coder agreement observed in the qualitative phase also strengthens confidence that the extracted themes represented relatively stable conceptual categories rather than idiosyncratic interpretations.

The explanatory and predictive indices further suggest that the proposed model captures a meaningful, although not exhaustive, portion of governance effectiveness and convergence capability. The model explained 29.6% of the variance in convergence capability and 24.4% of the variance in governance effectiveness according to the reported results, while positive Q^2 values supported predictive relevance. These findings are reasonable given the complexity of AI R&D governance, which is influenced by technological, institutional, political, organizational, and environmental factors. The acceptable SRMR and NFI values also support the overall adequacy of the model. From a theoretical perspective, the results indicate that AI R&D governance should not be conceptualized as a single-layer control system. Rather, it appears to function as a nested governance architecture in which core domains, organizational enablers, technical controls, risk mechanisms, and convergence capabilities jointly contribute to governance effectiveness.

Overall, the findings reinforce the transition in AI governance research from principle-based governance toward capability-based and implementation-oriented governance. Early discussions often emphasized ethical principles and regulatory requirements, while more recent research increasingly focuses on organizational structures, implementation mechanisms, lifecycle controls, governance maturity, and operational capabilities (Alrasbi & Ariaratnam, 2026; De Almeida & dos Santos Junior, 2025; Haque, 2026). The present study contributes to this development by identifying convergence capability as a central mechanism connecting policy governance, investment governance, and innovation governance. This contribution is also relevant to the emerging maturity perspective, in which effective AI governance is associated with progressively institutionalized structures, roles, processes, controls, and learning mechanisms (Alrasbi & Ariaratnam, 2026). The model therefore provides an integrative explanation of how AI R&D governance can move from fragmented arrangements toward a coordinated and adaptive organizational system.

The study has several limitations that should be considered when interpreting the findings. First, the quantitative phase was conducted within the context of the Information and Communication Technology Research Institute and related organizations, which may limit the generalizability of the findings to private firms, universities, other public research institutes, or organizations operating in different institutional environments. Second, the cross-sectional design captures perceptions at one point in time and therefore cannot fully reveal how governance capabilities, institutional maturity, or convergence mechanisms evolve over time. Third, the questionnaire was developed on the basis of qualitative findings from 14 experts, and although multiple procedures were used to strengthen trustworthiness and measurement quality, the resulting constructs may still reflect characteristics of the specific organizational and national context. Fourth, the use of self-reported data may introduce common method bias and perceptual bias. Fifth, some of the model's endogenous constructs displayed moderate levels of explained variance, suggesting that additional organizational, environmental, technological, and regulatory variables may contribute to governance effectiveness.

Future research should test the proposed model in different organizational and national contexts and compare whether the relative importance of the identified governance dimensions changes across public research institutions, universities, technology companies, startups, and regulatory bodies. Longitudinal studies could examine how convergence capability develops over time and whether improvements in governance maturity produce measurable changes in innovation outcomes, risk performance, or public value. Future studies could also examine mediating and moderating mechanisms, such as organizational maturity, technological uncertainty, environmental dynamism, leadership style, regulatory intensity, or organizational size. Comparative studies across sectors and countries could provide stronger evidence regarding the external validity of the model. Researchers may also extend the model by incorporating objective indicators of R&D performance, commercialization, innovation speed, research quality, budget efficiency, risk incidents, or technology readiness rather than relying exclusively on perceptual measures.

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For practice, research institutes and organizations engaged in AI development should establish an integrated governance architecture rather than allowing policy, budgeting, innovation, data, ethics, and risk functions to operate independently. Senior management should create joint decision structures that connect strategic priorities with budget allocation and project portfolio decisions, supported by shared dashboards and traceable decision processes. Organizations should periodically review whether funding patterns correspond to declared AI priorities and whether innovation projects generate feedback for policy revision. Clear ownership should be established for data, models, projects, risks, and outcomes, while technical governance should include model documentation, data-quality controls, reproducibility, secure infrastructure, lifecycle monitoring, and incident management. Responsible AI requirements should be translated into operational criteria for project approval, testing, contracting, deployment, and review. Finally, governance maturity should be assessed periodically so that weaknesses in leadership, coordination, technical infrastructure, stakeholder participation, risk controls, and organizational learning can be identified and systematically improved.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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References

Aghayari, P., & Karimmian, Z. (2024). Governance and artificial intelligence: A scientometric account of two intertwined stories. *Science and Technology Policy*, *17*(4), 1-17. https://doi.org/10.22034/jstp.2025.11814.1837

Alinaghian, A., Safdari Ranjbar, M., & Mohammadi, M. (2021). Policy goals and instruments for artificial intelligence development: An exploration of policy programs in selected countries. *Rahyaft*, *31*(3), 95-122. https://doi.org/10.22034/rahyaft.2022.10940.1280

Alrasbi, O., & Ariaratnam, S. T. (2026). The Organizational Transformation of Artificial Intelligence in Smart Cities: An Urban Artificial Intelligence Governance Maturity Model. *Urban Science*, *10*(1), 63. https://doi.org/10.3390/urbansci10010063

Bashir, H., & Ravi, M. J. (2025). A systematic review of strategic artificial intelligence governance frameworks and mechanisms in studies from 2017 to 2025. *Cyberspace and Social Media Studies*, *2*(3), 9-54. https://doi.org/10.22083/cssms.2025.538964.1067

Batool, A., Zowghi, D., & Bano, M. (2025). AI governance: a systematic literature review. *Ai and Ethics*, *5*(3), 3265-3279. https://doi.org/10.1007/s43681-024-00653-w

Berente, N., Gu, B., Recker, J., & Santhanam, R. (2021). Managing artificial intelligence. *MIS quarterly*, *45*(3), 1433-1450. https://doi.org/10.25300/MISQ/2021/16274

Birkstedt, T., Minkkinen, M., Tandon, A., & Mäntymäki, M. (2023). AI governance: themes, knowledge gaps and future agendas. *Internet Research*, *33*(7), 133-167. https://doi.org/10.1108/INTR-01-2022-0042

De Almeida, P. G. R., & dos Santos Junior, C. D. (2025). Artificial intelligence governance: Understanding how public organizations implement it. *Government Information Quarterly*, *42*(1), 102003. https://doi.org/10.1016/j.giq.2024.102003

Fonteneau, F., Mollins, J., Marchi, S., Russo, L., Gentaz, A., Daoud, M., & André, A. A. (2025). *Advancing the measurement of investments in artificial intelligence*. https://doi.org/10.1787/13e0da2f-en

Frimpong, V., & Botchey, O. K. (2026). Where are the AI governance roles? An early-stage empirical mapping of presence, absence, and structure in organisational AI oversight. *Businesses*, *6*(2), 18. https://doi.org/10.3390/businesses6020018

Haque, A. (2026). Responsible AI governance as an organisational capability: A theory-building integrative review for sustainable organisations. *Sustainability*, *18*(20), 10501. https://doi.org/10.3390/su182010501

Huang, X., Kou, T., & Zhou, Q. (2026). Embedding AI ethics in the data lifecycle: A framework for enterprise AI governance. *Technology in Society*, *86*, 103261. https://doi.org/10.1016/j.techsoc.2026.103261

Mancuso, I., Petruzzelli, A. M., Panniello, U., & Vaia, G. (2025). The bright and dark sides of AI innovation for sustainable development: Understanding the paradoxical tension between value creation and value destruction. *Technovation*, *143*, 103232.

Mäntymäki, M., Minkkinen, M., Birkstedt, T., & Viljanen, M. (2022). Defining organizational AI governance. *Ai and Ethics*, *2*(4), 603-609.

Mazzucato, M. (2018). Mission-oriented innovation policies: challenges and opportunities. *Industrial and Corporate Change*, *27*(5), 803-815.

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McLaren, J., & Kattel, R. (2025). Policy capacities for mission-oriented innovation policy: A case study of UKRI and the industrial strategy challenge fund. *Technological Forecasting and Social Change*, *214*, 124049. https://doi.org/10.1016/j.techfore.2025.124049
Oecd. (2024). *Revised recommendation of the Council on artificial intelligence*.
Papagiannidis, E., Mikalef, P., & Conboy, K. (2025). Responsible artificial intelligence governance: A review and research framework. *The Journal of Strategic Information Systems*, *34*(2), 101885. https://doi.org/10.1016/j.jsis.2024.101885
Rogge, K. S., & Reichardt, K. (2016). Policy mixes for sustainability transitions: An extended concept and framework for analysis. *Research Policy*, *45*(8), 1620-1635.
Safdari Ranjbar, M., Alinaghian, A., & Ghaderi, F. (2023). An examination of policies for developing the artificial intelligence innovation ecosystem in Iran. *Innovation Economy Ecosystem Studies*, *3*(3), 99-120. https://doi.org/10.22111/innoeco.2022.43535.1036
Schot, J., & Steinmueller, W. E. (2018). Three frames for innovation policy: R&D, systems of innovation and transformative change. *Research Policy*, *47*(9), 1554-1567.
Soleimanzadeh, S., Eslami, M., Mousavi Shafaee, M., & Golmohammadi, V. (2024). Artificial intelligence governance in the digital age: An analysis of U.S. strategies and approaches. *Foreign Relations Quarterly*, *16*(2), 193-224.
Supreme Council of the Cultural, R. (2024). *National Artificial Intelligence Document of the Islamic Republic of Iran*.
Tabassi, E. (2023). *Artificial Intelligence Risk Management Framework (AI RMF 1.0)*. https://doi.org/10.6028/NIST.AI.100-1
United Nations Conference on, T., & Development. (2025). *Technology and innovation report 2025: Inclusive artificial intelligence for development*.
van Noordt, C., Medaglia, R., & Tangi, L. (2025). Policy initiatives for Artificial Intelligence-enabled government: An analysis of national strategies in Europe. *Public Policy and Administration*, *40*(2), 215-253. https://doi.org/10.1177/09520767231198411
Wirtz, B. W., Weyerer, J. C., & Kehl, I. (2022). Governance of artificial intelligence: A risk and guideline-based integrative framework. *Government Information Quarterly*, *39*(4), 101685.

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