사물인터넷융복합논문지 Vol. 12, No. 4, pp. 73-85, 2026 https://doi.org/10.20465/KIOTS.2026.12.4.073

Reframing Universities as Strategic Infrastructure in the AI Economy: An AIoT-Enabled Framework for Regional and National Competitiveness

Taewan Kim[1], Tae-Kook Kim[2*]
[1]Professor, College of Business Administration, University of Sharjah
[2]Professor, School of Computer and Artificial Intelligence Engineering, Pukyong National University

AI 경제에서 전략적 인프라로서 대학의 역할 재정립: 지역 및 국가 경쟁력을 위한 AIoT 기반 프레임워크

김태완[1], 김태국[2*]
[1]샤르자대학교 경영학과 교수, [2]국립부경대학교 컴퓨터·인공지능공학부 교수

Abstract Artificial intelligence (AI) is reshaping regional and national competitiveness around specialized talent, data, computing capacity, experimental environments, and governance. Existing university models emphasize education, research, commercialization, and regional engagement, but do not fully explain when university resources become shared AI infrastructure or how they generate external value. Using an integrative, concept-building literature review, this study develops a framework of the university as strategic AI infrastructure comprising five dimensions: human capital, knowledge and research, data and computing, AIoT experimentation, and coordination and governance. These dimensions create value by lowering access costs, reducing technological and organizational uncertainty, coordinating diverse actors, and generating cumulative learning through repeated experimentation. The framework shows how universities can support AI adoption, industrial upgrading, talent retention, start-up creation, public innovation, national productivity, technological sovereignty, and resilience. It also proposes an AIoT service architecture and an evaluation logic that distinguishes installed inputs from accessibility, utilization, capability development, and downstream outcomes. The study's main contribution is to shift attention from university-owned outputs to externally accessible, governed, and cumulative capabilities that enable broader participation in the AI economy.

Key Words : artificial intelligence economy, university, strategic infrastructure, AIoT, regional innovation, regional competitiveness, technological sovereignty

요 약 인공지능(AI)은 전문 인재, 데이터, 컴퓨팅 역량, 실험 환경, 거버넌스를 중심으로 지역 및 국가 경쟁력의 기반을 재편하고 있다. 기존 대학 모델은 교육, 연구, 기술사업화, 지역사회 참여를 강조해 왔으나, 대학의 자원이 어떻게 공유형 AI 인프라로 기능하며 외부 가치를 창출하는지는 충분히 설명하지 못한다. 본 연구는 통합적 문헌고찰과 개념 구축을 통해 대학을 전략적 AI 인프라로 개념화하는 분석 틀을 제시한다. 이 틀은 인적자본, 지식 및 연구, 데이터 및 컴퓨팅, AIoT 실증, 조정 및 거버넌스의 다섯 차원으로 구성된다. 이러한 인프라는 접근 비용을 낮추고, 기술적·조직적 불확실성을 완화하며, 다양한 행위자를 조정하고, 반복적 실험을 통해 누적적 학습을 촉진함으로써 가치를 창출한다. 또한 대학이 지역의 AI 도입, 산업 고도화, 인재 유지, 창업, 공공혁신뿐 아니라 국가 생산성, 기술주권, 회복탄력성에 기여할 수 있음을 설명한다. 아울러 AIoT 서비스 아키텍처와 함께 투입된 자원, 접근성, 실제 활용, 역량 개발, 후속 성과를 구분하는 평가 논리를 제안한다. 본 연구의 핵심 기여는 분석의 초점을 대학이 보유한 산출물에서 외부 행위자의 AI 경제 참여 지원으로, 접근 가능하고 체계적으로 관리되며 지속적으로 축적·발전하는 역량으로 전환한 데 있다.

주제어 : 인공지능 경제, 대학, 전략적 인프라, AIoT, 지역혁신, 지역 경쟁력, 기술주권

*교신저자 : 김태국(king@pknu.ac.kr)
접수일 2026년 08월 01일 수정일 2026년 08월 16일 심사완료일 2026년 08월 21일
www.kci.go.kr

1. Introduction

Artificial intelligence (AI) is emerging as a general-purpose technology whose economic impact extends beyond algorithms alone. Its effective utilization depends on specialized human capital, trustworthy data, computing capacity, experimental settings, domain knowledge, and governance. Accordingly, national AI-compute policy emphasizes effective access, complementary capabilities, resilience, and technological sovereignty, rather than merely the volume of installed hardware [1]. Responsible deployment further requires ongoing identification and management of risks throughout the AI life cycle [2].

These requirements are particularly evident in the context of artificial intelligence of things (AIoT). IoT architectures integrate sensing, communication, computation, and applications [3], while AI contributes capabilities such as prediction, optimization, autonomy, and decision support. Because AIoT systems function within physical environments, they must address issues including interoperability, latency, cybersecurity, safety, maintenance, user acceptance, and accountability. Recent studies demonstrate the diversity of such systems, including multisensor digital-twin integration in smart-city environments [4], AI-based home-fire detection [5], and university AI practice platforms that integrate technological and educational resources [6].

This configuration of resources generates a coordination challenge. Large firms are able to develop proprietary data and computing infrastructures, whereas small and medium-sized enterprises, start-ups, local governments, and civic organizations frequently lack the capacity to bear fixed costs or assemble all necessary capabilities. Fragmented access to equipment, data, expertise, and testing environments impedes adoption and produces a gap between technically viable demonstrations and sustained operational deployment. This gap cannot be resolved solely through hardware acquisition; access governance, technical assistance, data ownership, validation protocols, and long-term operational financing are equally critical.

Universities hold a unique combination of long-term research capability, educational authority, laboratories, campuses, public trust, and linkages with industry and government. They have been characterized as regional knowledge infrastructures [7], key actors in university-industry-government interactions [8], entrepreneurial entities that commercialize research [9], and sources of start-ups and technology transfer [10]. Perspectives on regional and engaged universities further highlight place-based problem solving [11], co-creation [12], multidextrous integration of economic and social missions [13], and ecosystem coordination by fourth-generation universities [14].

Existing studies on entrepreneurial, regional, engaged, and fourth-generation universities provide an important foundation for understanding university roles. This study extends these perspectives by shifting the focus from university-owned resources and outputs to externally accessible, reusable, and governed AI capabilities. Its distinctiveness lies in defining strategic AI infrastructure through accessibility, external enablement, cumulative investment, strategic relevance, and stable governance. The framework's conceptual validity is supported by integrating research on university roles, digital infrastructure, and AI/AIoT, while empirical validation remains a task for future research. This distinction is critical: a GPU cluster used internally constitutes an institutional resource, whereas the same infrastructure becomes regional when external users can securely access it, receive technical support, integrate computing with governed data, and translate outcomes into operational applications.

This study advances the concept of the university as strategic AI infrastructure. It addresses three research questions: (1) Under what conditions do university resources function as strategic infrastructure

www.kci.go.kr

rather than conventional institutional assets? (2) Through which mechanisms do these resources shape AIoT adoption and regional and national competitiveness? (3) How should such a model be implemented and evaluated across diverse regional contexts? The study contributes in four ways: it establishes a bounded definition with explicit criteria; identifies an AI-specific resource architecture; explains external value creation through access-cost reduction, uncertainty reduction, and coordination; and proposes a multilevel evaluation logic linking university capabilities to regional and national outcomes.

2. Theoretical Foundations and Research Gap

2.1 Evolution of University Roles

The traditional university is structured around teaching, research, and public service, with its regional impact largely indirect through graduates, publications, professional networks, and the dissemination of knowledge. The entrepreneurial university extends these functions to include patents, licensing, spin-offs, contract research, and venture formation [9,10]. Regional perspectives further expand the view by demonstrating that university roles vary according to institutional arrangements, policy contexts, and geographic conditions [11]. Engaged and co-creating universities place greater emphasis on civic involvement and collaborative problem-solving for regional challenges [12,13], while fourth-generation universities are increasingly conceptualized as coordinators of mission-driven innovation ecosystems [14].

The proposed model is cumulative rather than substitutive. Strategic AI infrastructure encompasses education, research, commercialization, and engagement, yet shifts the unit of analysis from the university's internal outputs to the enabling capacities provided to external actors. Its central concern is not merely whether a university is productive, entrepreneurial, or engaged, but whether it offers accessible and governed combinations of talent, knowledge, data, computing, experimentation, and coordination that other organizations cannot efficiently assemble independently. These distinctions are summarized in 〈Table 1〉, which compares traditional, entrepreneurial, and strategic AI infrastructure models of the university.

2.2 Infrastructure as a Relational and Strategic Construct

Infrastructure is not defined solely by physical magnitude. It becomes infrastructure through its relationship to organized practices, modes of access, and a community of users [15]. Digital

〈Table 1〉 Comparison of University Role Models

Dimension	Traditional university	Entrepreneurial university	University as strategic AI infrastructure
Core orientation	Education, research, and knowledge advancement	Research commercialization and economic value creation	Development of accessible and sustained AI capabilities for regions and nations
Primary role	Teaching and research institution	Technology-transfer and venture actor	Shared AI service and ecosystem coordination platform
Key resources	Faculty, students, curricula, and research outputs	Patents, technologies, spin-offs, and industry networks	AI talent, governed data, computing resources, AIoT testbeds, and intermediary expertise
Access and governance	Predominantly internal use under institutional governance	Selective access through commercial projects and partnerships	Transparent external access under data, security, ethical, and interoperability rules
Primary outcomes	Graduates, publications, and academic reputation	Technology transfer, start-ups, income, and employment	AI adoption, capability formation, industrial upgrading, public innovation, and resilience
Evaluation focus	Educational and research performance	Commercialization and entrepreneurial performance	Accessibility, utilization, capability development, and regional and national outcomes

www.kci.go.kr

infrastructures likewise exhibit distributed components, evolving standards, shared governance, and sustained interaction between technical systems and institutional arrangements [16]. Drawing on relational and digital-infrastructure perspectives [15,16], this study analytically derives six criteria for determining when university resources function as strategic infrastructure. Such resources should be shareable beyond organizational boundaries, enable downstream activities by other actors, require cumulative or substantial investment, exhibit public-good or coordination properties, hold strategic relevance for regional or national capabilities, and operate through stable governance and interoperability.

These criteria distinguish strategic infrastructure from ordinary university assets. A laboratory used exclusively for internal publications represents a valuable asset but does not constitute regional infrastructure. A short-term contract project may facilitate knowledge transfer but does not produce reusable infrastructure. In contrast, even a modest facility can assume an infrastructural role when open access, skilled intermediaries, standardized protocols, and connections to broader networks enable multiple organizations to develop capabilities. Infrastructure status is therefore determined by functional and relational conditions rather than by the presence of costly equipment alone.

2.3 Regional Innovation, Absorptive Capacity, and Place

Regional innovation outcomes emerge from interactions among firms, universities, public agencies, financial actors, and intermediaries, as well as from the strength of local institutions and knowledge flows [17]. University infrastructure cannot replace the absorptive capacity of firms and public organizations, defined as the prior knowledge and routines required to identify, assimilate, and apply external knowledge [18]. However, it can lower barriers through training, collaborative experimentation, data governance, and iterative problem solving.

Geographical context is important because regions encounter distinct innovation constraints. Metropolitan areas may possess talent and capital but face fragmented coordination; industrial regions may contend with legacy systems and risks in deployment; peripheral regions may lack access to computing resources, specialized personnel, and dense networks; and regions oriented toward public missions may be limited by data silos, procurement rules, and accountability requirements. Consequently, differentiated regional innovation policies are more appropriate than uniform replication strategies [19]. The role of universities within regions also varies according to institutional characteristics, partner configurations, and local expectations [20].

3. Research Approach

3.1 Review Design and Search Strategy

This study employs an integrative, concept-building literature review to construct a framework of the university as strategic AI infrastructure. This approach is suitable for synthesizing concepts across diverse theoretical and technological domains [21,22]. The review process was purposive and iterative rather than exhaustive.

Relevant literature was identified through DOI-linked publisher databases, the Korea Citation Index, and official repositories of the OECD and NIST. Searches were updated through July 2026. Search terms spanned four domains: (1) university roles, including entrepreneurial, engaged, regional, and fourth-generation universities; (2) knowledge, research, digital, and AI infrastructure; (3) AI, AIoT, living labs, digital twins, and campus or urban testbeds; and (4) regional innovation, absorptive capacity, governance, technological sovereignty, and resilience. Foundational studies were additionally identified through citation tracing.

www.kci.go.kr

3.2 Selection and Synthesis

Sources were included when they contributed to defining university roles, infrastructure characteristics, AI- or AIoT-specific resources, external value-creation mechanisms, governance requirements, regional or national outcomes, or measurable indicators. Studies that referred only generally to universities or AI without addressing infrastructure, external accessibility, governance, experimentation, or innovation outcomes were excluded.

The synthesis followed four stages. First, recurring university functions and infrastructure characteristics were identified. Second, related elements were grouped into five dimensions: human-capital infrastructure, knowledge and research infrastructure, data and computing infrastructure, AIoT experimentation infrastructure, and coordination and governance infrastructure. Third, the five dimensions were assessed against the six analytically derived infrastructure criteria presented in Section 2.2: external shareability, downstream enablement, cumulative investment, public-good or coordination properties, strategic relevance, and stable governance and interoperability. Fourth, the five dimensions were linked to three conversion mechanisms—access-cost reduction, uncertainty reduction, and coordination and translation—and situated within a broader model incorporating cumulative learning, place-based configurations, and multilevel outcomes.

The resulting framework is analytical rather than a claim of empirically verified causality. It is intended to generate measurable constructs and guide subsequent empirical research.

4. University as Strategic AI Infrastructure

4.1 Definition and Five Infrastructure Dimensions

A university functioning as strategic AI infrastructure is defined as an institution that delivers accessible, cumulative, interoperable, and governed combinations of AI-related talent, knowledge, data, computing resources, experimental settings, and coordination capacity, enabling external organizations and communities to develop, assess, or adopt AI. This construct consists of five interrelated dimensions.

Human-capital infrastructure encompasses specialized AI education, interdisciplinary AI literacy, graduate research training, and continuing education for workers and public officials. It includes not only technical specialists but also domain experts capable of defining problems, assessing data quality, interpreting model outputs, and redesigning organizational processes.

Knowledge and research infrastructure encompasses basic and applied research, interdisciplinary problem-solving, model evaluation, cybersecurity, responsible AI, and domain-specific adaptation. Its distinctive value lies in continuity: universities can sustain expertise, datasets, methodologies, and experimental knowledge over time while reconfiguring resources to address regional needs and connect ecosystem actors [23].

Data and computing infrastructure comprises shared access to GPUs or cloud resources, curated datasets, secure analytical environments, data engineering, and technical support. Its effectiveness depends not only on hardware but also on transparent allocation, identity and access management, data-use agreements, cybersecurity, and support for transitioning from prototypes to operational deployment [1].

AIoT experimentation infrastructure includes laboratories, campus living labs, digital twins, pilot systems, and connections to industrial or urban testbeds. Living-lab research views experimentation as a socio-technical process integrating users, researchers, organizations, public authorities, education, and operations [24-26]. Recent studies further illustrate multisensor digital-twin integration in smart-city environments [4] and real-time AI-based safety applications in

www.kci.go.kr

indoor settings [5].

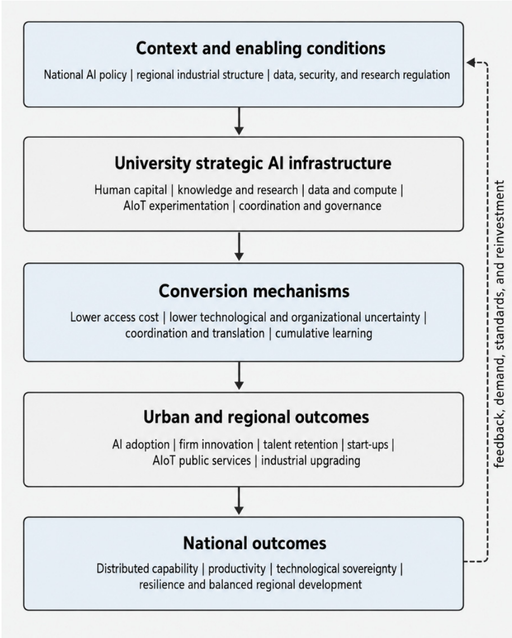
Coordination and governance infrastructure connects researchers, firms, public institutions, citizens, investors, and external knowledge networks through intermediation, data and ethical governance, standards alignment, procurement support, intellectual property arrangements, and long-term coordination. By defining who can access resources, under what conditions, and how accumulated learning is preserved, it distinguishes strategic infrastructure from a mere aggregation of assets and illustrates how institutional arrangements can reinforce technical infrastructure [27,28].

4.2 Conversion Mechanisms and Cumulative Learning

The first conversion mechanism is the reduction of access costs. Shared facilities, expertise, datasets, and training enable smaller organizations to conduct experiments without incurring the full fixed costs associated with specialized personnel, computing resources, secure data environments, and testing sites. Such cost reductions must also address transaction costs: complicated application procedures, unclear ownership, extended waiting periods, or ambiguous service responsibilities can render nominally open infrastructure effectively inaccessible.

The second mechanism involves reducing technological and organizational uncertainty. Independent assessments, pilot implementations, user feedback, and phased validation processes help determine whether an AIoT system is reliable, interoperable, safe, secure, and compatible with existing operations. This evidence mitigates the risks associated with large-scale procurement and differentiates technically promising demonstrations from sustainable operational services. Guidance from NIST further emphasizes the importance of continuous governance, mapping, measurement, and management of AI-related risks [2].

The third mechanism is coordination and translation. AI initiatives often fail because data owners, domain experts, model developers, equipment suppliers, public users, and regulators operate with differing vocabularies, incentives, and timeframes. Universities can offer neutral convening capacity, shared protocols, institutional continuity, and personnel capable of spanning organizational boundaries. Research on innovation hubs indicates that such intermediary and leadership functions can shift universities from knowledge producers to central connectors within regional ecosystems [29].



[Fig. 1] Strategic AI Infrastructure and Multilevel Competitiveness Framework

A cross-cutting dynamic mechanism is cumulative learning. Insights from one pilot project can inform standards, curricula, procurement practices, reusable data resources, safety procedures, and subsequent initiatives. Repeated external engagement can enhance university service provision, while regional demand provides universities with problems, data, funding, and employment pathways. This feedback loop differentiates infrastructure from isolated projects and highlights why sustained

www.kci.go.kr

operation is as critical as initial capital investment. As summarized in [Fig. 1], these relationships are conditioned by regional absorptive capacity, industrial demand, operating resources, regulatory environments, and talent-retention conditions.

5. Multilevel Outcomes and Competitive Effects

5.1 Regional Competitiveness

At the regional scale, strategic university infrastructure can shape competitiveness through interconnected outcomes. Education and research activities attract students, researchers, and knowledge-intensive firms. Shared access to data, computing resources, and technical assistance promotes experimentation and adoption among local firms. Start-ups and collaborative initiatives contribute to economic diversification and generate specialized employment opportunities. AIoT applications across mobility, energy, safety, healthcare, environment, logistics, and public administration can enhance public service performance and overall quality of life.

These effects are contingent. A university may produce highly skilled graduates who leave if the region lacks appropriate employment opportunities. Shared computing resources may remain underutilized if firms have limited absorptive capacity or if access procedures are overly complex. Public datasets may be unusable without adequate legal, semantic, and technical governance. Research on knowledge spillovers further indicates that university impacts vary geographically depending on regional capabilities and the presence of effective transfer intermediaries [30,31]. Regional competitiveness also has a demographic dimension. Studies of South Korea indicate that regional economic disparities and persistent socio-cultural differences are associated with geographical variation in fertility, with potential implications for the long-term sustainability of regional labor and talent bases [32,33]. Accordingly, place-based policy should align university investment with industrial demand, entrepreneurship, talent retention, procurement systems, and living conditions.

5.2 National Capability, Sovereignty, and Resilience

At the national level, networks of differentiated universities can offer distributed AI capabilities. Rather than requiring each institution to replicate costly resources, national strategies can integrate shared computing infrastructure, interoperable data environments, specialized regional testbeds, common standards, and complementary areas of expertise. This configuration enhances efficiency through specialization while strengthening resilience via redundancy and geographic dispersion.

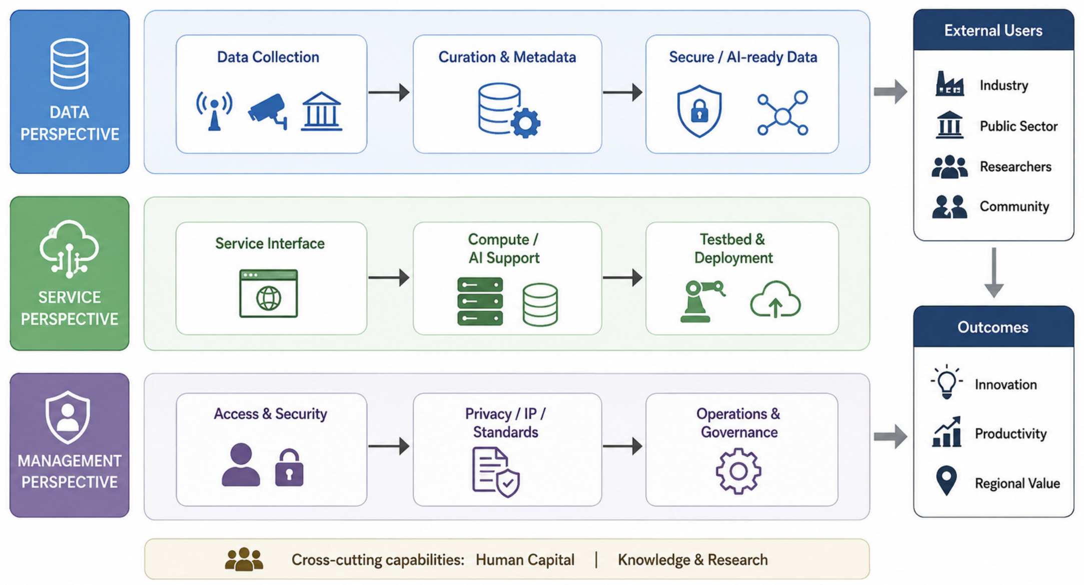
Within this framework, technological sovereignty does not imply full self-sufficiency or domestic control over every component. Instead, it entails sufficient internal capacity to understand, assess, adapt, secure, and govern critical AI systems. Universities contribute through sustained research, independent evaluation, advanced education, open methodologies, and institutional memory. Their role becomes particularly significant where reliance on external models, cloud platforms, semiconductor technologies, or data standards introduces strategic vulnerabilities.

6. AIoT Operating Architecture and Place-Based Design

6.1 From Assets to an Accessible Service System

A strategic infrastructure university requires an operational architecture rather than a collection of isolated projects. First, a clear external interface should provide a service catalogue,

www.kci.go.kr



[Fig. 2] University-Centered AIoT Service Architecture: Data, Service, and Management Perspectives

eligibility criteria, security requirements, expected timelines, and contact points. Second, shared technical services should integrate computing, data engineering, cybersecurity, model evaluation, and AIoT system integration. Third, campus-based or partner testbeds should enable staged experimentation, ranging from laboratory validation to realistic operational settings. Fourth, a governance function should oversee data rights, intellectual property, ethics, procurement, incident response, and long-term maintenance. Fifth, the university should link local services with national research networks and specialized facilities that cannot be efficiently replicated. [Fig. 2] operationalizes the five infrastructure dimensions through three complementary design perspectives—data, service, and management—within an externally accessible service architecture. Human-capital and knowledge-and-research functions cut across the service layers, while data and computing, AIoT experimentation, and coordination and governance are represented more explicitly.

Intermediary roles are critical. Faculty-led projects often conclude when funding ends, while firms may struggle to articulate problems in academic terms. Dedicated professionals such as solution architects, data stewards, testbed managers, industry coordinators, and responsible-AI specialists can ensure continuity and facilitate translation across organizational domains. Their performance should be assessed based on capability transfer, repeated utilization, and deployment quality, rather than solely on the number of interactions or agreements.

6.2 Place-Based Configurations

The same model should not be applied uniformly across all regions. The composition of infrastructure needs to reflect the primary capability gaps as well as the industrial and public objectives specific to each region. 〈Table 2〉 operationalizes the general framework into four representative configurations. While the typology is not comprehensive and regions may exhibit overlapping profiles, it helps avoid policy approaches that replicate the asset structures of leading technology clusters without addressing context-specific constraints.

www.kci.go.kr

〈Table 2〉 Place-Based Configurations of University Strategic AI Infrastructure

Regional context	Dominant bottleneck	Priority university infrastructure	Representative AIoT missions	Principal risk
Metropolitan AI hub	Fragmented actors despite abundant talent and finance	Frontier research, specialized compute, global networks, standards and orchestration	Advanced mobility, health, finance, and platform innovation	Resource concentration and weak diffusion to smaller firms or regions
Industrial city or cluster	Legacy systems, skills gaps, and deployment risk	Edge AI, industrial data spaces, digital twins, workforce reskilling, shared validation	Smart manufacturing, port logistics, energy, safety, and predictive maintenance	Pilot projects that do not integrate with operational processes
Peripheral or capacity-constrained region	Thin labor markets and limited access to compute and expertise	Remote shared compute, mobile test facilities, modular education, inter-university networks	Agriculture, fisheries, environment, disaster monitoring, and public access services	Dependence on temporary funding and continued talent out-migration
Public-mission or smart-city region	Data silos, procurement barriers, and uncertain accountability	Trusted data governance, campus-city living labs, independent evaluation, citizen participation	Mobility, safety, energy, healthcare, welfare, and urban administration	Privacy, cybersecurity, vendor lock-in, and weak public legitimacy

7. Measurement, Novelty, and Contributions

7.1 Measurement Logic

Based on the distinctions developed in the preceding sections, this study proposes a five-stage evaluation logic comprising inputs, accessibility, actual utilization, capability development, and downstream outcomes. Inputs include equipment, personnel, datasets, and experimental environments; however, the mere presence of these resources indicates only potential capacity and does not, by itself, demonstrate effective infrastructure performance. Conventional university rankings do not directly measure external accessibility or capability formation and may also reflect regional asymmetries and methodological instability [34,35]. Accessibility reflects whether resources are visible, affordable, secure, and usable for external organizations. Utilization indicators identify who engages with the resources and for what purposes. Capability indicators assess whether external users can sustain adoption with reduced reliance on university support. Outcome indicators capture firm-level adoption, productivity, entrepreneurship, talent retention, public-service effectiveness, technological autonomy, and resilience.

Evaluation also demands attention to causal inference. A high-performing region may both sustain a strong university and exhibit elevated AI adoption; correlation alone does not confirm university-driven effects. Future research should therefore employ longitudinal approaches, matched regional or organizational comparisons, project-level adoption data, network analysis, qualitative process tracing, and mixed-method designs. Infrastructure assessment should also document failure and non-use, as unsuccessful pilots can still yield important insights regarding data quality, interoperability, safety, procurement processes, or workforce preparedness. 〈Table 3〉 summarizes this five-stage evaluation logic by linking each stage to its core analytical question, illustrative indicators, and key interpretive cautions.

7.2 Novelty and Theoretical Contribution

The framework makes four contributions. First, it clarifies strategic AI infrastructure as a construct defined by external shareability, downstream enablement, cumulative investment, public-good or coordination properties, strategic relevance, and stable governance and interoperability. Second, it specifies an AIoT-oriented resource architecture integrating talent, knowledge, governed data, computing, physical experimentation, model evaluation, and operational governance. Third, it explains multilevel value creation through access-cost reduction, uncertainty reduction, coordination, and cumulative learning. Fourth, it redirects evaluation from resource ownership

www.kci.go.kr

〈Table 3〉 Evaluation Logic for Strategic AI Infrastructure

Evaluation stage	Core question	Illustrative indicators	Interpretive caution
Inputs	What resources have been installed?	Faculty and staff, GPU capacity, datasets, laboratories, test sites, operating budget	Inputs indicate potential capacity, not infrastructure performance
Accessibility	Can external actors obtain and safely use the resources?	Eligibility, access time, affordability, technical support, security and data-use rules	Formal openness may coexist with high transaction costs
Actual use	Who uses the resources, how often, and for what missions?	External GPU hours, dataset reuse, testbed users, repeat users, cross-sector projects	High volume is not necessarily high-value or inclusive use
Capability formation	Do users become more capable of independent AI adoption?	Trained employees, validated systems, data-governance maturity, repeat deployment, standards	Capability gains may appear after the funded project ends
Downstream outcomes	What regional and national effects plausibly follow?	Firm adoption and productivity, start-ups, talent retention, public-service performance, resilience	Attribution requires longitudinal, matched, network, or mixed-method designs

and internal outputs toward accessibility, utilization, capability development, and system-level performance.

7.3 Empirical Research Agenda and Falsifiability

The framework is empirically testable: its distinctiveness would be weakened if external accessibility, governance, intermediary support, and repeated use did not explain AI adoption beyond conventional indicators such as publications, patents, and start-ups. Comparative, longitudinal, network, and mixed-method studies can test construct validity, conversion mechanisms, capability formation, place-based contingencies, and national network effects, as summarized in 〈Table 4〉.

8. Policy and Management Implications

Universities should integrate education, research, digital infrastructure, campus operations, and external engagement within a unified service and governance architecture. Regional governments should align public data, procurement, and real-world test sites with university capabilities, while national policy should support specialization, interoperability, operating expenses, cybersecurity, and data stewardship. Funding and evaluation should emphasize external accessibility, actual utilization, capability transfer, and public-mission performance rather than capital investment alone.

〈Table 4〉 Empirical Research Agenda for Strategic AI Infrastructure

Validation target	Primary question	Suitable research design	Illustrative evidence
Construct validity	Is strategic AI infrastructure empirically distinct from entrepreneurial or engaged-university performance?	Comparative cases, expert content validation, scale development, and discriminant-validity tests	Accessibility, external enablement, cumulative investment, governance, and public-value scores
Conversion mechanisms	Do shared university resources reduce access costs, uncertainty, and coordination barriers?	Longitudinal project records, process tracing, mediation analysis, and matched project comparisons	Time and cost to pilot, validation failures, partner diversity, coordination time, and repeat use
Capability formation	Do external users become more capable of independent and responsible AI adoption?	Before-after assessment, matched user and non-user organizations, interviews, and maturity scoring	Internal AI staff, repeat deployment, data-governance maturity, model monitoring, and reduced support intensity
Place contingencies	How do regional industrial structure and absorptive capacity condition infrastructure effects?	Multiregional comparison, multilevel models, configurational analysis, and comparative case studies	Industrial variety, firm capabilities, talent retention, public procurement, and interorganizational networks
National networks	Do specialization and interoperability improve efficiency, sovereignty, and resilience?	Network analysis, policy comparison, scenario analysis, and infrastructure stress testing	Interregional use, redundancy, switching capacity, domestic evaluation capability, and recovery time

www.kci.go.kr

9. Boundary Conditions and Risks

The framework remains contingent on user absorptive capacity, sustained operating resources, and effective governance. Major risks include regional concentration, temporary project funding, compromised academic autonomy, privacy and cybersecurity threats, and technological obsolescence. These risks require networked access, modular design, interoperability, independent oversight, and balanced investment in technical, human, and institutional capabilities. The strategic-infrastructure role should complement rather than substitute for basic research, broad-based education, critical inquiry, and the university's public mission.

10. Conclusion

This study reconceptualizes the university as strategic infrastructure within the AI economy. The construct builds upon traditional, entrepreneurial, engaged, and fourth-generation university models by emphasizing shared human capital, knowledge, data, computing resources, AIoT experimentation, and governance. These resources function as infrastructure only when they are externally accessible, enable other actors, accumulate over time, and address capabilities that individual organizations or markets are likely to underprovide. Operationally, these capabilities can be organized through complementary data, service, and management perspectives.

Three primary mechanisms explain the generation of external value: reduced access costs, diminished technological and organizational uncertainty, and coordination among heterogeneous actors. Cumulative learning links repeated experimentation to enhanced standards, curricula, datasets, services, and institutional arrangements. Through these mechanisms, universities can facilitate regional AI adoption, industrial upgrading, talent retention, start-up creation, and public-sector innovation. When connected through national networks and aligned with place-specific demand, regional capabilities can contribute to productivity, technological sovereignty, and resilience.

The practical implication is that university AI investments should be designed as accessible, governed, interoperable, and sustainable service systems rather than as isolated assets. The research implication is to develop and validate a university strategic AI infrastructure index, examine external utilization and capability development, compare metropolitan, industrial, peripheral, and public-mission regions, and identify feedback relationships among infrastructure, regional adoption, and public investment. The value of the framework ultimately depends not on the volume of installed technology but on the enduring capabilities that universities enable beyond their institutional boundaries.

REFERENCES

[1] OECD, "A Blueprint for Building National Compute Capacity for Artificial Intelligence," OECD Digital Economy Papers, No.350, OECD Publishing, Paris, 2023.

[2] E.Tabassi, "Artificial Intelligence Risk Management Framework (AI RMF 1.0)," NIST AI 100-1, National Institute of Standards and Technology, 48 pp., 2023.

[3] J.Gubbi, R.Buyya, S.Marusic and M.Palaniswami, "Internet of Things (IoT): A Vision, Architectural Elements, and Future Directions," Future Generation Computer Systems, Vol.29, No.7, pp.1645-1660, 2013.

[4] B.H.Gu, H.K.Lam, T.K.Kim, S.Y.Ok and S.H.Lee, "Observation-Metadata-Centric Digital Twin Ontology for Heterogeneous MultiSensor Data in Smart Cities," IEEE Internet of Things Journal, Vol.13, No.9, pp.18893-18908, 2026.

[5] B.Peng and T.K.Kim, "YOLO-HF: Early Detection of Home Fires Using YOLO," IEEE Access, Vol.13, pp.79451-79466, 2025.

[6] K.H.Lee, "A Study on the Design of an IoT-Based LLM Token Resource Management and AI Practice Support Platform," Journal of Internet of Things and Convergence, Vol.12, No.2, pp.103-109, 2026.

[7] D.Charles, "Universities as Key Knowledge Infrastructures

www.kci.go.kr

in Regional Innovation Systems," Innovation: The European Journal of Social Science Research, Vol.19, No.1, pp.117-130, 2006.

[8] H.Etzkowitz and L.Leydesdorff, "The Dynamics of Innovation: From National Systems and Mode 2 to a Triple Helix of University-Industry-Government Relations," Research Policy, Vol.29, No.2, pp.109-123, 2000.

[9] H.Etzkowitz, "Research Groups as Quasi-Firms: The Invention of the Entrepreneurial University," Research Policy, Vol.32, No.1, pp.109-121, 2003.

[10] D.D.Gregorio and S.Shane, "Why Do Some Universities Generate More Start-Ups Than Others?," Research Policy, Vol.32, No.2, pp.209-227, 2003.

[11] M.Trippl, T.Sinozic and H.L.Smith, "The Role of Universities in Regional Development: Conceptual Models and Policy Institutions in the UK, Sweden and Austria," European Planning Studies, Vol.23, No.9, pp.1722-1740, 2015.

[12] G.Trencher, M.Yarime, K.B.McCormick, C.N.H.Doll and S.B.Kraines, "Beyond the Third Mission: Exploring the Emerging University Function of Co-Creation for Sustainability," Science and Public Policy, Vol.41, No.2, pp.151-179, 2014.

[13] E.Thomas, R.Pugh, D.Soetanto and S.L.Jack, "Beyond Ambidexterity: Universities and Their Changing Roles in Driving Regional Development in Challenging Times," The Journal of Technology Transfer, Vol.48, No.6, pp.2054-2073, 2023.

[14] M.L.A.M.Bogers, S.A.Poursaeidi, M.Mahdad and M.T.Norn, "Catalyzing Regional Innovation Ecosystems to Address Global Challenges: Toward the Fourth-Generation University?," Research-Technology Management, Vol.69, No.2, pp.14-22, 2026.

[15] S.L.Star and K.Ruhleder, "Steps Toward an Ecology of Infrastructure: Design and Access for Large Information Spaces," Information Systems Research, Vol.7, No.1, pp.111-134, 1996.

[16] D.Tilson, K.Lyytinen and C.Sørensen, "Research Commentary—Digital Infrastructures: The Missing IS Research Agenda," Information Systems Research, Vol.21, No.4, pp.748-759, 2010.

[17] A.Rodríguez-Pose and R.Crescenzi, "Research and Development, Spillovers, Innovation Systems, and the Genesis of Regional Growth in Europe," Regional Studies, Vol.42, No.1, pp.51-67, 2008.

[18] W.M.Cohen and D.A.Levinthal, "Absorptive Capacity: A New Perspective on Learning and Innovation," Administrative Science Quarterly, Vol.35, No.1, pp.128-152, 1990.

[19] F.Tödtling and M.Trippl, "One Size Fits All? Towards a Differentiated Regional Innovation Policy Approach," Research Policy, Vol.34, No.8, pp.1203-1219, 2005.

[20] E.Uyarra, "Conceptualizing the Regional Roles of Universities, Implications and Contradictions," European Planning Studies, Vol.18, No.8, pp.1227-1246, 2010.

[21] R.Whittemore and K.Knafl, "The Integrative Review: Updated Methodology," Journal of Advanced Nursing, Vol.52, No.5, pp.546-553, 2005.

[22] R.J.Torraco, "Writing Integrative Literature Reviews: Guidelines and Examples," Human Resource Development Review, Vol.4, No.3, pp.356-367, 2005.

[23] S.Heaton, D.S.Siegel and D.J.Teece, "Universities and Innovation Ecosystems: A Dynamic Capabilities Perspective," Industrial and Corporate Change, Vol.28, No.4, pp.921-939, 2019.

[24] M.Hossain, S.Leminen and M.Westerlund, "A Systematic Review of Living Lab Literature," Journal of Cleaner Production, Vol.213, pp.976-988, 2019.

[25] D.Shin, "A Living Lab as Socio-Technical Ecosystem: Evaluating the Korean Living Lab of Internet of Things," Government Information Quarterly, Vol.36, No.2, pp.264-275, 2019.

[26] C.Stuckrath, J.Rosales-Carreón and E.Worrell, "Conceptualisation of Campus Living Labs for the Sustainability Transition: An Integrative Literature Review," Environmental Development, Vol.54, Article 101143, 2025.

[27] K.H.Lee, "A Study on the Design and Operation of an IoT-Based AX Convergence Curriculum Model," Journal of Internet of Things and Convergence, Vol.12, No.2, pp.165-172, 2026.

[28] Y.J.Son and J.J.Youn, "Exploring Cyclic Learning Community Experiences for Building an AI Educational Welfare Governance Model," Journal of Internet of Things and Convergence, Vol.12, No.1, pp.205-212, 2026.

[29] J.Youtie and P.Shapira, "Building an Innovation Hub: A Case Study of the Transformation of University Roles in Regional Technological and Economic Development," Research Policy, Vol.37, No.8, pp.1188-1204, 2008.

[30] M.Fritsch and V.Slavtchev, "Universities and Innovation in Space," Industry and Innovation, Vol.14, No.2, pp.201-218, 2007.

[31] N.Fukugawa, "Knowledge Spillover from University Research before the National Innovation System Reform in Japan: Localisation, Mechanisms, and Intermediaries," Asian Journal of Technology Innovation, Vol.24, No.1, pp.100-122, 2016.

[32] T.Kim, K.Lee and S.Lee, "The Impact of Economic Growth and Regional Disparity on the Fertility Rate in South Korea," The Korea Spatial Planning Review, Vol.121, pp.3-21, 2024.

[33] T.Kim, D.Choi and S.Lee, "The Impacts of Socio-cultural Determinants on Fertility in South Korea," Journal of the Korean Official Statistics, Vol.29, No.2, pp.24-52, 2024.

www.kci.go.kr

[34] T.Kim and T.K.Kim, "Global Inequality in Research: A Quantitative Analysis of 1628 Institutions in THE World University Rankings 2025," IEEE Access, Vol.13, pp.161262-161278, 2025.

[35] T.Kim and T.K.Kim, "Systemic Analysis of the QS International Research Network Indicator Using Big Data: Regional Inequalities and Recommendations for Improved University Rankings," IEEE Access, Vol.13, pp.111335-111353, 2025.

김 태 완(Taewan Kim) [정회원]

- 2014년 2월 : 싱가포르국립대학교 경영전문대학원 NUS Business School(경영학 석사)
- 2024년 8월 : 서울대학교 농경제사회학부 지역정보학전공(경제학 박사)
- 2024년 8월 ~ 현재 : 아랍에미리트 샤르자대학교 경영학과 교수

〈관심분야〉
인공지능(AI), 빅데이터(big data), 대학평가, 대학전략

김 태 국(Tae-Kook Kim) [종신회원]

- 2004년 8월 : 고려대학교 전기전자전파공학부(공학사)
- 2006년 8월 : 고려대학교 메카트로닉스학과(공학석사)
- 2014년 8월 : 고려대학교 모바일솔루션학과(공학박사)
- 2016년 3월 ~ 2022년 2월 : 동명대학교 AI학부 교수
- 2022년 3월 ~ 현재 : 국립부경대학교 컴퓨터·인공지능공학부 교수

〈관심분야〉
사물인터넷(IoT), 콘텐츠 전송 네트워크(CDN), 이동성, 인공지능(AI), 빅데이터(big data), 모바일 서비스

www.kci.go.kr