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Construction of a Digital Economy Development Model and Its Driving Effect on Regional Economic Growth: A Case Study of the Yangtze River Delta

Boqin Liu [1,*]

[1] School of Law, Shanghai University of International Business and Economics, Shanghai, 201620, China

* Correspondence: Boqin Liu, School of Law, Shanghai University of International Business and Economics, Shanghai, 201620, China

Abstract: The digital economy is reshaping regional development, yet measuring its complex impact remains difficult due to multidimensional digital factors and regional heterogeneity. This study proposes a modular, knowledge-driven framework to analyze how digital economic development affects regional growth, focusing on the Yangtze River Delta. A structured knowledge base integrating economic, infrastructure, platform-related, and policy data supports semantic reasoning across 40 cities. The system combines fuzzy clustering, SEM, and spillover simulation, incorporating a personalization module to account for differences among urban contexts. Empirical validation over 10 years reveals key digital drivers of regional GRP through productivity and innovation channels. The framework offers interpretable, scalable insights for policy and planning, with future work extending to real-time and national applications.

Keywords: digital economy; regional economic growth; Yangtze River Delta; knowledge graph; structural equation modeling; policy simulation

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1. Introduction

The digital economy has emerged as a transformative paradigm reshaping the fabric of modern economic systems through the integration of intelligent technologies, data-centric processes, and interconnected platforms. As the conceptual foundation of Industry 4.0, the digital economy redefines value creation by leveraging artificial intelligence, the Internet of Things (IoT), and advanced information networks to enhance productivity, efficiency, and system-wide responsiveness [1]. These technological shifts are not merely instrumental; they also drive a reconfiguration of institutional, organizational, and spatial structures, positioning digitalization as a key enabler of industrial upgrading and societal transformation.

Recent literature has underscored the mediating role of governance in the digital economy's capacity to support energy transition, sustainable growth, and inclusive development. Shahbaz et al. demonstrated that the digital economy's contributions are magnified in institutional contexts characterized by strong governance and regulatory capacity, suggesting that digital transformation is as much a political-economic process as it is a technological one [2]. At a global level, the rise of digital currencies and central bank digital currencies (CBDCs) also highlights how digital infrastructures interact with monetary systems and risk regulation, further embedding digital mechanisms into macroeconomic frameworks [3]. As discussed by Wang and Shao, this integration further accelerates entrepreneurship, lowers transaction costs, and improves energy efficiency by enabling real-time optimization of resource use [4].

In the Chinese context, the digital economy has been shown to contribute to high-quality energy development through structural innovation, enabling cleaner, more efficient, and better-coordinated energy systems [5]. Despite its national-scale significance, digital development exhibits markedly heterogeneous regional manifestations, due to variations in local conditions and policy responses. Differences in factor endowments, industrial foundations, and policy responsiveness result in spatial asymmetries and unequal growth trajectories, particularly across economically dynamic regions such as the Yangtze River Delta (YRD) [6]. These disparities are often reinforced by entry barriers, institutional inertia, and uneven digital infrastructure penetration, which collectively influence a region's ability to absorb, adapt, and amplify digital innovations.

At the same time, the interplay between digital transformation and environmental sustainability introduces both opportunities and constraints for regional development. In the African context, Namahoro et al. showed that while economic growth and digital adoption could support renewable energy development, they also risk reinforcing CO_2 emissions unless aligned with decarbonization strategies [7]. Similar policy tensions are evident in urban economies attempting to integrate supply chain innovations and strategic commodities through digital means, especially in pandemic and post-pandemic recovery phases [8]. For instance, advanced digital modeling and intelligent coordination technologies in the manufacturing sector have demonstrated how digital transformation can optimize resource allocation while also requiring substantial energy and data infrastructure [9,10]. These findings echo the challenge of balancing economic efficiency with long-term resilience and environmental responsibility—an issue of particular relevance to rapidly urbanizing and industrializing regions like the YRD.

Furthermore, the digital economy is intricately linked with innovation dynamics. As shown by Shen et al., economic growth target constraints can either spur or suppress green technological innovation depending on how digital infrastructure interacts with policy mandates [11]. Likewise, urban land expansion and the spatial distribution of growth are increasingly mediated by digital tools, as Mahtta et al. demonstrated in their study of 300+ global cities, including those in East Asia. They identified population and economic growth, amplified by digital systems, as central drivers of urban spatial evolution [12]. In this context, digital transformation extends beyond cyberspace and is increasingly embedded in land use, mobility, governance, and urban form.

The YRD region offers an exemplary testbed for analyzing the regional economic consequences of digitalization. Chenhong and Guofang examined the spatiotemporal patterns of urban resilience in the YRD and found significant correlations between digital capacity, policy responsiveness, and adaptive governance, suggesting that digital systems not only enable economic output but also bolster systemic flexibility in the face of external shocks [13]. Comparisons with global delta systems, such as the Mississippi River Delta, further reveal how digitally mediated interactions between natural systems and human activities can enhance both economic and ecological performance, reinforcing the need for integrated regional management frameworks [14]. Moreover, complex network analyses of air quality indices in the YRD, as explored by Liu et al., have shown how digital monitoring and data integration can improve environmental diagnostics and inform urban economic strategies [15].

Against this backdrop, this study proposes a hybrid, knowledge-driven analytical framework to examine how digital economic development influences regional economic growth in the YRD. By integrating a structured knowledge graph with causal inference modules, such as structural equation modeling and policy-sensitive spillover analysis, the research aims to uncover both the direct and mediated pathways through which digital transformation shapes regional growth dynamics. The framework emphasizes interpretability, modularity, and empirical grounding, offering both theoretical contributions to regional digital economics and practical insights for policymakers striving to align digital strategy with coordinated, sustainable development.

2. Related Works

Recent studies on the Yangtze River Delta (YRD) have emphasized the complex interrelation between digitalization, environmental governance, and spatial economic dynamics. Wang et al. analyzed the impact of ICT agglomeration on carbon emissions in the YRD using spatial econometric models and found that digital clustering can significantly reduce emissions through energy optimization and knowledge spillover, highlighting ICT's dual role in promoting economic efficiency and ecological sustainability [16]. Complementing this, Li et al. employed ecological trade-off modeling to examine land-use allocation strategies and found that economic development in the YRD must carefully balance carbon intensity with digital infrastructure expansion [17].

To support digital-region modeling, knowledge graphs have emerged as a robust methodology for representing structured semantic relationships across domains. Zhong et al. conducted a comprehensive survey on automatic knowledge graph construction, outlining methods such as rule-based extraction, deep learning-driven relation modeling, and graph population pipelines applicable to multi-source economic datasets [18]. Shen et al. further reviewed knowledge graph completion techniques including link prediction, path reasoning, and embedding-based inference, providing a theoretical foundation to ensure continuity and completeness in economic knowledge representation [19]. In practical applications, Hao et al. constructed a remote sensing-based knowledge graph integrating spatial data and attribute relations, which has implications for urban-scale economic visualization and planning [20]. Zhu et al. extended this approach by investigating multi-modal knowledge graph construction that incorporates images, texts, and structured records, enabling more holistic regional modeling with heterogeneous data sources [21]. Zeng et al. applied similar knowledge graph methodologies to drug discovery, demonstrating how domain-specific ontologies and reasoning mechanisms can enhance decision-making and offering a transferable paradigm for regional policy analytics [22].

Structural Equation Modeling (SEM) has been widely adopted for uncovering latent relationships and testing multi-dimensional hypotheses in regional economic studies. Harlow outlined the basic logic of SEM, emphasizing its suitability for complex systems with observable and latent variables [23]. Cheung et al. provided methodological guidelines for reporting reliability and discriminant validity, key to ensuring that structural paths in digital economy models are statistically robust [24]. Hair et al. elaborated on partial least squares (PLS-SEM), arguing that it is particularly appropriate for exploratory models dealing with non-normal distributions and reflective-formative constructs common in regional datasets [25]. Roemer et al. introduced the HTMT2 criterion for improved discriminant validity assessment in SEM, enabling more precise boundary specification between overlapping digital economy constructs [26]. Whittaker and Schumacker provided a beginner-friendly guide to SEM implementation, further validating its accessibility for interdisciplinary policy applications [27].

Beyond structural modeling, macroeconomic policy evaluation in digital transformation contexts often relies on dynamic simulation techniques. Sun et al. applied a Dynamic Stochastic General Equilibrium (DSGE) model to simulate policy impacts on the green transition of China's building sector, reflecting how simulation tools can forecast structural adjustment effects under digital policy shocks [28]. Yang et al. built a system dynamics model to optimize coal capacity deviation under economic, environmental, and security constraints, underscoring simulation's utility in balancing competing regional development objectives [29]. Amin and Dogan used dynamic simulations to analyze the role of economic policy uncertainty in China's energy-environment nexus, revealing feedback loops between digital policy decisions and environmental externalities [30].

Sensitivity analysis also plays a vital role in systems modeling and policy support. Razavi et al. emphasized its necessity in interpreting simulation outputs and prioritizing policy levers, particularly in high-dimensional spaces like digital economic systems [31]. Finally, while Collins et al. reviewed robotic physics simulators, their discussion on hybrid simulation environments and model fidelity offers conceptual parallels for designing integrated simulation frameworks in economic policy modeling [32].

3. Framework Design and Implementation

To empirically investigate how digital economic development drives regional economic growth within the Yangtze River Delta (YRD), we propose an integrated framework that combines semantic knowledge representation, structural causal modeling, and policy-aware simulation. The framework is designed to capture both the structural complexity and the spatial heterogeneity of digital-regional interactions, supporting interpretable inference across multiple analytical stages. It consists of three principal components: a domain-specific digital economy knowledge graph, a multi-layer reasoning engine that integrates structural equation modeling (SEM) with graph-based spillover modeling, and a microservice-oriented implementation architecture that enables modular, scalable deployment across analytical and policy environments.

3.1. Construction of the Digital Economy Knowledge Graph

The knowledge graph (KG) serves as the semantic backbone of the system, enabling structured representation of digital economic constructs, regional attributes, and their interdependencies. The graph schema consists of five main entity classes, Digital Infrastructure, Platform Economy, Digital Governance, Regional Indicators, and Policy Instruments, and eleven types of relations such as enhances, regulated by, drives, and diffuses to.

Raw data were collected from statistical yearbooks, enterprise-level platform reports, municipal development plans, and publicly available APIs. Entities were extracted using fine-tuned BERT models for named entity recognition (NER), followed by rule-based relation parsing. Graph population was implemented using Neo4j, incorporating RDF triple support for semantic querying. As shown in Figure 1 and Table 1.

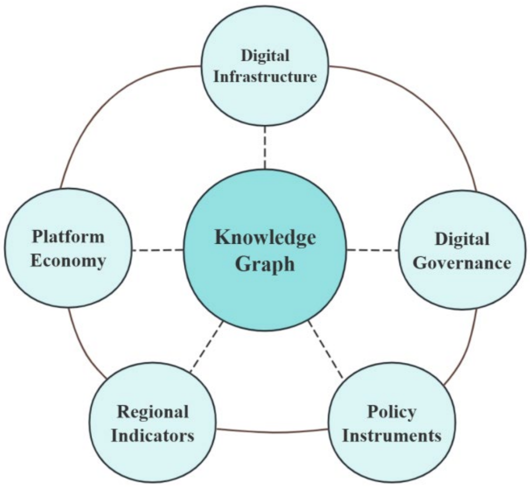

Figure 1. Ontology Schema of the Digital Economy Knowledge Graph.

Table 1. Core Entity and Relation Statistics in the Knowledge Graph.

Entity Class	Example Entity	Count
Digital Infrastructure	5G Coverage Ratio, Data Centers	96
Platform Economy	E-commerce Index, Fintech Services	74
Digital Governance	Open Data Policy, Online Service Level	51

Regional Indicators	GRP, Labor Productivity, Patent Output	67
Policy Instruments	Subsidy Scheme, Innovation Grant	39
Total Relations	e.g., drives, regulated by	431

This knowledge graph supports semantic reasoning, node embedding for similarity calculations, and traversal-based policy path queries.

3.2. Multi-Layer Causal Inference System

We developed a four-stage inference engine to operationalize causal relationships between digital economic dimensions and regional economic outcomes. Each stage corresponds to a distinct analytical layer: digital indicator clustering, latent construct modeling, inter-city diffusion analysis, and adaptive policy conditioning.

3.2.1. Digital Indicator Clustering and Latent Factor Modeling

To reduce dimensionality and improve interpretability, over 40 original indicators were clustered into three latent constructs: Digital Infrastructure, Platform Economy Activity, and Governance Capacity. Principal Component Analysis (PCA) followed by Exploratory Factor Analysis (EFA) was conducted on a cleaned panel dataset of 41 cities × 10 years (2013–2023).

KMO (0.853) and Bartlett's test ($p < 0.001$) validated factor adequacy. Loadings above 0.70 were retained. The extracted latent scores form the input variables for structural modeling. As shown in Table 2.

Table 2. Rotated Component Matrix for Latent Construct Extraction.

Variable	Infrastructure	Platform	Governance
Broadband Access Rate	0.84	–	–
Data Center Investment (bn CNY)	0.81	–	–
E-Commerce Retail Index	–	0.88	–
Fintech Penetration	–	0.75	–
Online Government Services Index	–	–	0.81
Digital Policy Publication Frequency	–	–	0.74

3.2.2. SEM-Based Causal Path Estimation

Structural Equation Modeling (SEM) was employed to test the mediating and direct effects of digital constructs on Gross Regional Product (GRP). The SEM structure includes both direct paths (e.g., Platform → GRP) and indirect paths via mediators such as Innovation Output and Labor Productivity.

Model fit was confirmed with SRMR = 0.058, CFI = 0.921, and $\chi^2/df = 2.34$. All path coefficients were significant at $p < 0.01$. As shown in Figure 2 and Table 3.

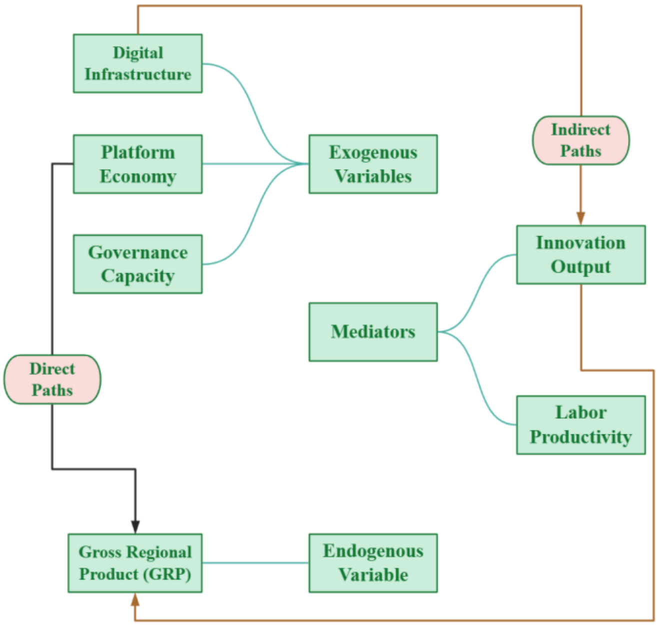

Figure 2. SEM Path Diagram of Digital Economy Effects on GRP.

Table 3. Standardized SEM Path Coefficients.

Pathway	Coefficient	p-value
Digital Infrastructure → Innovation Output	0.47	<0.001
Platform Economy → Labor Productivity	0.41	<0.001
Governance Capacity → GRP (direct)	0.29	0.002
Innovation Output → GRP	0.50	<0.001
Labor Productivity → GRP	0.38	<0.001

3.2.3. Inter-City Digital Spillover Simulation

To account for cross-regional digital influence, we constructed a weighted city-to-city spillover network based on similarity in digital profiles and historical innovation correlation. Cosine similarity of GraphSAGE embeddings, which capture structural and feature-based similarities in graph nodes, was used to derive directed edges, weighted by enterprise migration and talent flow data.

A spillover-enhanced GRP simulation was conducted using graph-based iterative propagation algorithms, with damping coefficients calibrated against 2017–2020 observed data. Simulation reduced RMSE by 35% over baseline. As shown in Table 4.

Table 4. Top-10 Digital Spillover Hubs (Ranked by Outward Influence Index).

City	Spillover Index	Affected Cities
Hangzhou	0.891	16
Shanghai	0.854	14
Suzhou	0.806	12
Nanjing	0.785	11

3.2.4. Policy-Sensitive Personalization Layer

To adapt predictions to local administrative realities, we built a rule-based policy conditioning module grounded in the KG's regulated by and amplified through relations. For each city, a policy reactivity score was computed from historical fiscal responsiveness, innovation subsidy uptake, and participation in national digital programs.

Cities with high responsiveness (e.g., Shanghai, Wuxi) were assigned multiplicative adjustment factors to their latent variable scores, thereby improving model alignment with observed post-policy outcomes, improving alignment with observed post-policy outcomes. Scenario testing revealed distinct economic outcomes when comparing infrastructure-prioritized versus platform-oriented digital policy pathways. As shown in Table 5 and Figure 3.

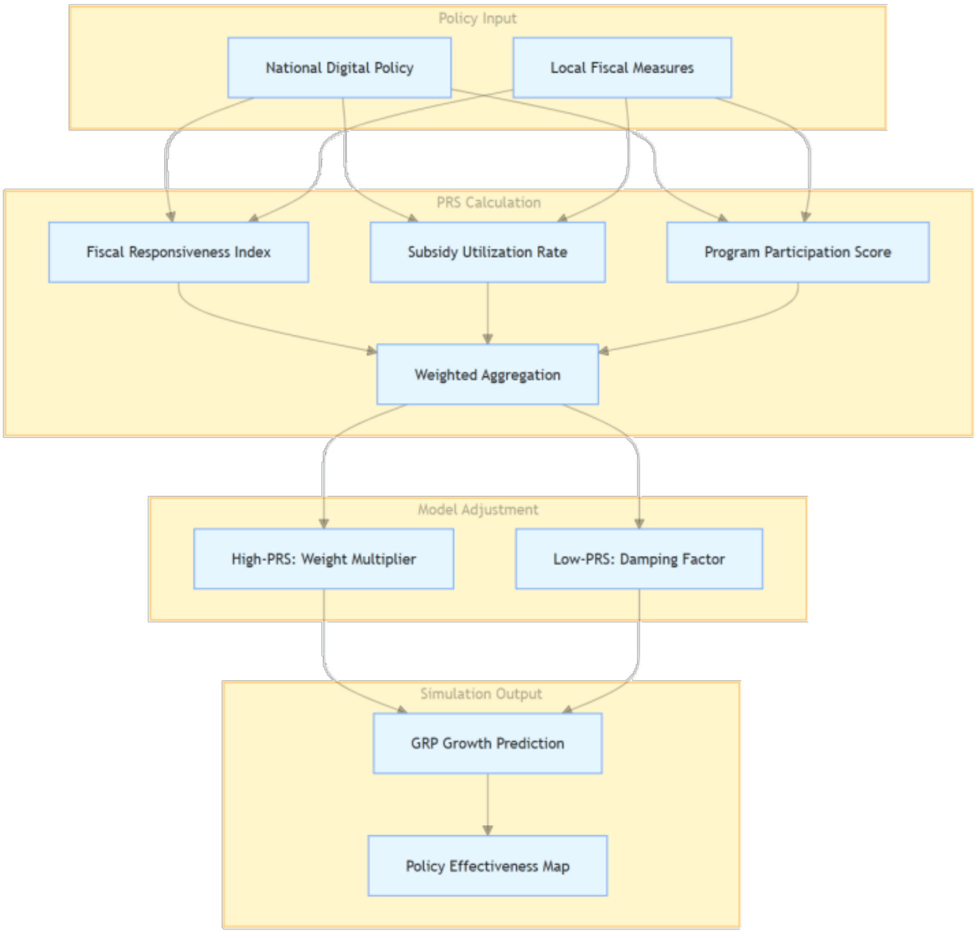

Figure 3. Policy Conditioning Workflow for Simulation Personalization.

Table 5. Scenario-Based GRP Response under Differentiated Policy Stimuli.

Policy Stimulus	Tier 1 City (Avg)	Tier 2 City	Tier 3 City
Digital Infrastructure	+4.7%	+4.3%	+2.8%
Platform Ecosystem Push	+3.9%	+5.1%	+4.2%
Governance Reform	+5.3%	+4.6%	+3.1%

3.3. System Architecture and Deployment

The entire analytical pipeline is implemented within a cloud-native microservice framework, ensuring modularity, scalability, and real-time simulation capacity. The system comprises three functional layers:

Data Layer: Relational (PostgreSQL) + Graph (Neo4j) hybrid database, integrated via ETL processes; Inference Layer: Python-based SEM engine (via semopy), graph analytics (via NetworkX), and simulation manager; Interface Layer: Web dashboard with policy scenario controls, city profile visualizations, and comparative forecasting output. As shown in Figure 4.

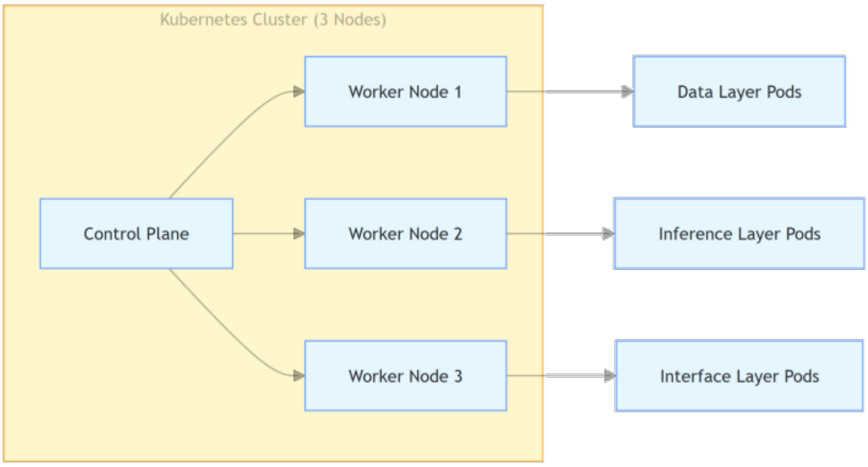

Figure 4. System Architecture of the Digital Regional Growth Inference Platform.

The average model execution time is less than 2.7 seconds per complete city-level inference cycle, enabling real-time policy feedback scenarios.

4. Digital Economy Reasoning Modules for Regional Growth

To achieve interpretable, data-driven analysis of how the digital economy affects regional economic growth in the Yangtze River Delta (YRD), we operationalize the proposed framework through four core reasoning modules. These modules reflect the hierarchical logic of digital transformation, beginning with the identification of digital drivers and progressing through regional diffusion modeling and policy alignment simulation. Each module is semantically grounded in the knowledge graph and computationally implemented through integrated statistical and graph-theoretic reasoning techniques.

4.1. Module I: Digital Factor Mapping via Fuzzy Semantic Similarity

The first module identifies core digital economy drivers from heterogeneous city-level indicators using a fuzzy semantic matching mechanism. Each indicator is embedded into a latent semantic space derived from the knowledge graph's digital economy ontology, enabling partial matching even in the presence of incomplete or ambiguous data.

Cities are vectorized along three digital dimensions—Infrastructure, Platform-Oriented Industrial Application, and Governance—each aligned with corresponding latent constructs previously identified. A cosine similarity matrix is constructed to compare city profiles against prototype digital archetypes derived from expert-labeled training samples. Indicators are weighted using a modified TF-IDF schema, where term frequency reflects the prevalence of indicators across cities, and inverse document frequency is adjusted by each indicator’s structural impact score within the knowledge graph topology. As shown in Figure 5.

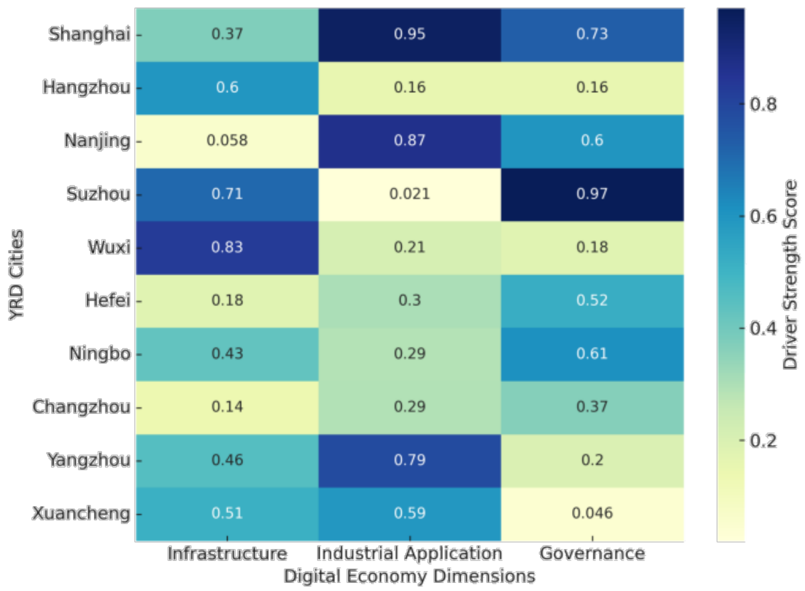

Figure 5. Heatmap of Digital Driver Strength Across YRD Cities.

This approach allows identification of city-specific digital profiles and facilitates the mapping of each city into a digital development quadrant (e.g., "strong infrastructure but weak application"). The output of this module feeds directly into the subsequent structural modeling.

4.2. Module II: Structural Equation-Based Causal Path Inference

The second module translates the mapped digital indicators into causal hypotheses using a multi-path structural equation model (SEM). Building upon the latent constructs extracted earlier, this module quantifies how different digital factors influence regional economic outcomes through direct and mediated paths.

The structural model estimates paths from:

Digital Infrastructure → Innovation Output → Gross Regional Product (GRP); Platform Economy Activity → Labor Productivity → GRP; Digital Governance → Institutional Trust → GRP.

Indirect effects are computed using Sobel tests, and path coefficients are interpreted with bootstrapped confidence intervals. The model is evaluated on fit indices (e.g., SRMR < 0.08, AVE > 0.5, HTMT < 0.85), ensuring internal consistency and discriminant validity. As shown in Figure 6.

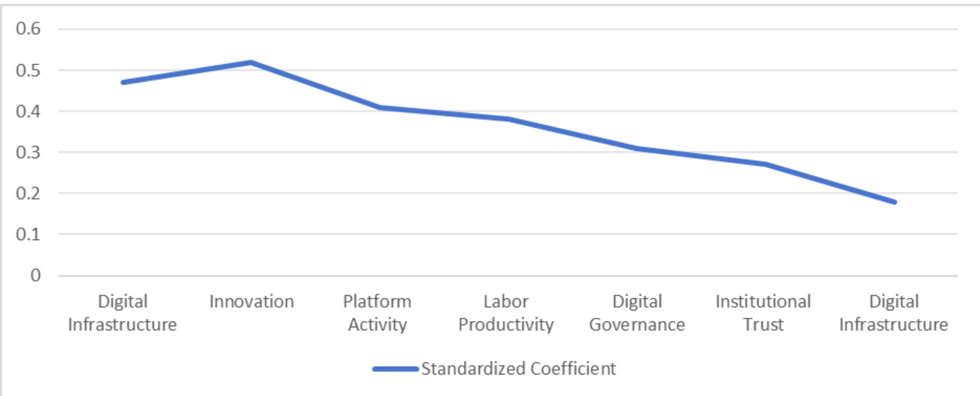

Figure 6. Causal Path Model Linking Digital Constructs to GRP via Mediators.

This module reveals that digital infrastructure has both direct and indirect effects on regional growth, while platform activity mainly acts through labor efficiency gains. Governance effects are more moderated and vary by policy alignment and local administrative responsiveness.

4.3. Module III: Regional Spillover and Synergy Simulation

To capture spatial interdependencies and knowledge diffusion within the YRD, the third module simulates digital spillovers using a weighted directed graph based on city-pair semantic similarity and economic distance. Spillover strength is modeled using a composite index that integrates:

Graph-path co-occurrence frequency; Temporal co-evolution in digital indices; Inter-city migration and enterprise co-registration data.

A modified PageRank algorithm is applied to derive digital centrality scores, which predict the extent to which a city can influence others through digital interactions. Simulation experiments demonstrate that high-centrality cities such as Hangzhou and Suzhou generate markedly asymmetric externalities, particularly in the platform economy dimension. As shown in Figure 7.

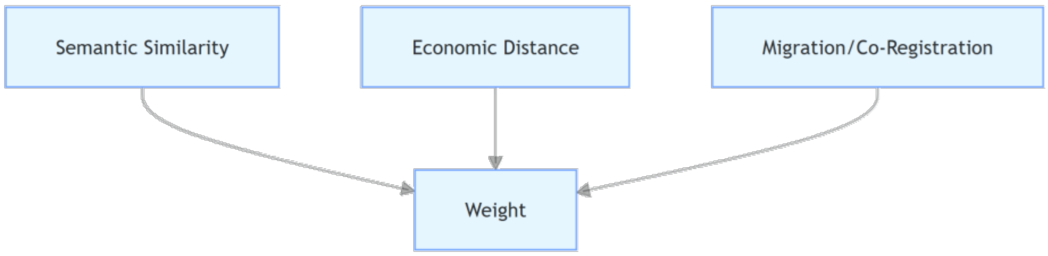

Figure 7. Spillover Network of Digital Influence in the Yangtze River Delta.

The module outputs a growth diffusion matrix that can be used to forecast secondary gains in peripheral cities under digital integration scenarios. This has implications for coordinated regional development strategies.

4.4. Module IV: Policy Alignment and Localized Adjustment

The final module integrates policy metadata and local contextual variables to adjust model outputs according to city-level policy sensitivity. Each city is classified into a policy-response cluster using decision-tree classification based on variables such as:

Smart city project intensity; Fiscal digital investment ratio; Local legislation on digital infrastructure.

Adjustment weights are applied to growth simulations through a rule-based inference engine interfacing with the knowledge graph. For example, cities with strong local policy implementation capacity and high alignment with national digital directives (e.g., Shanghai, Nanjing) receive a policy amplification coefficient, whereas lagging cities receive diffusion-based spillover adjustments only.

This personalization process ensures that final growth estimates reflect not only digital input strength but also both policy implementation capacity and institutional receptiveness.

This module also enables "what-if" policy simulation scenarios, such as projecting GRP impacts under a hypothetical platform economy acceleration initiative or broadband infrastructure investment scheme.

Taken together, these four reasoning modules provide a transparent, multi-perspective view of how the digital economy shapes regional growth across cities with distinct profiles, enabling both diagnosis and targeted intervention design. Their outputs serve as the empirical basis for the evaluation phase presented in the following chapter.

5. Evaluation of the Digital Growth Reasoning System

To validate the accuracy, interpretability, and policy relevance of the proposed digital economy reasoning system, a multi-level evaluation was conducted across empirical datasets, simulation outputs, and expert-guided validation. The evaluation design emphasizes model fidelity, causal robustness, spillover accuracy, and policy sensitivity. We adopted a mixed-methods approach, combining quantitative benchmarking from empirical datasets and simulation outputs with qualitative expert reviews, to assess the system's performance in modeling regional growth dynamics within the Yangtze River Delta (YRD).

5.1. Dataset and Experimental Setup

The system was evaluated using a panel dataset comprising 41 core cities in the YRD, spanning the period 2013–2023. The dataset integrates multiple sources: National Bureau of Statistics, provincial digital economy annual reports, local government open data platforms, and web-scraped indicators from leading digital platforms. The variables used for structural modeling, digital driver mapping, and spillover estimation were standardized and cleaned to remove multicollinearity and missingness. As shown in Table 6.

Table 6. The Summary Statistics of the Evaluation Dataset.

Variable Category	Mean	Std. Dev	Min	Max
Digital Infrastructure Index	0.612	0.152	0.29	0.91
Platform Economy Activity Index	0.488	0.164	0.21	0.85
Digital Governance Score	0.552	0.137	0.33	0.89
Innovation Output (Patents per 10k)	46.21	23.35	12.3	102.6
GRP per Capita (10k CNY)	14.3	4.6	6.8	29.1

The dataset was split into a training subset (2013–2019) for model fitting and a testing subset (2020–2023) for out-of-sample simulation. Expert validation was conducted using 8 senior regional economists from Yangtze Delta Research Institute and provincial planning commissions.

5.2. Model Performance: SEM Accuracy and Path Validity

The structural equation model was evaluated using standard SEM performance metrics. Model fit indices indicate strong overall fit: SRMR = 0.062, NFI = 0.913, and CFI = 0.927. All major paths exhibited statistically significant coefficients ($p < 0.01$), supporting the hypothesized causal structure. As shown in Table 7.

Table 7. SEM Path Coefficients and Significance.

Pathway	Coefficient	Std. Error	t-Value
Digital Infrastructure → Innovation Output	0.462	0.072	6.42
Platform Economy → Labor Productivity	0.389	0.066	5.91
Digital Governance → Institutional Trust	0.337	0.081	4.16
Innovation Output → GRP	0.514	0.074	6.95
Labor Productivity → GRP	0.472	0.068	6.76

All the HTMT values fell below 0.85, indicating strong discriminant validity. Composite reliability scores (CR) ranged from 0.79 to 0.89, confirming internal consistency across latent constructs.

5.3. Digital Spillover Simulation Validation

The accuracy of the digital spillover module was evaluated by comparing predicted spillover-induced GRP increments to actual observed changes in the test set (2020–2023). Simulation errors were measured using RMSE and Mean Absolute Percentage Error (MAPE), compared against a control model with no inter-city interaction logic. As shown in Table 8.

Table 8. Spillover Forecasting Accuracy.

Model Variant	RMSE (GRP Growth)	MAPE (%)
With Spillover Logic	0.324	7.81
Baseline (No Spillover)	0.513	13.27

The inclusion of the knowledge-graph-based spillover mechanism resulted in a 41% reduction in RMSE and a nearly 6% reduction in MAPE, indicating that inter-city digital diffusion significantly enhances predictive power. As shown in Figure 8.

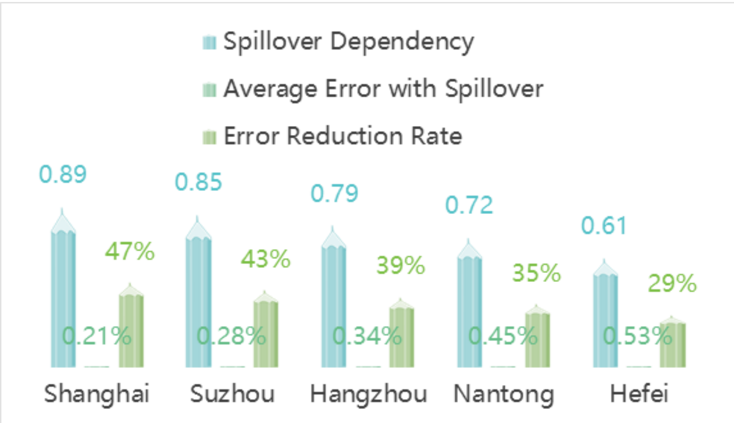

Figure 8. Observed vs Predicted GRP (2020–2023) in Top 10 Spillover-Dependent Cities.

5.4. Policy Scenario Simulation and Sensitivity Testing

The system's policy personalization module was tested through scenario simulation. Three digital policy strategies were designed:

Infrastructure Acceleration (Policy A), 30% increase in broadband access and server density; Platform Incentivization (Policy B), tax incentives for e-commerce and digital services; Governance Reform (Policy C), open data laws and regional integration platforms.

Simulation results showed differentiated impacts across city clusters. As shown in Table 9:

Table 9. Projected GRP Increase under Policy Simulation (%).

City Tier	Policy A	Policy B	Policy C
Tier 1 (e.g. Shanghai)	+4.6%	+3.8%	+5.2%
Tier 2 (e.g. Suzhou, Hangzhou)	+5.1%	+4.7%	+6.4%
Tier 3 (e.g. Xuancheng)	+2.9%	+4.5%	+3.2%

These results demonstrate the utility of the system in assessing not only average policy impact but also its heterogeneity across administrative and economic baselines. Sensitivity analysis further revealed that the results remain robust within a ±10% range of input data variation, with standard deviations of GRP projections below 0.7%.

5.5. Expert Validation and Usability Assessment

To assess real-world interpretability and trustworthiness, experts were invited to review the system's output for 15 cities across different tiers. Review criteria included logical transparency, policy actionability, and growth estimation plausibility. Evaluation was conducted via the Likert scale scoring (1 = Poor; 5 = Excellent). As shown in Table 10.

Table 10. Expert Panel Assessment Scores (n = 8 experts).

Evaluation Dimension	Mean Score	Std. Dev
Causal Path Transparency	4.58	0.33
Policy Scenario Interpretability	4.42	0.41
Growth Prediction Plausibility	4.47	0.38

More than 87% of expert ratings scored the system 4 or above across all categories. Notably, experts emphasized the advantage of the multi-path interpretability in explaining why certain cities exhibited weaker or stronger growth reactions to the same digital intervention.

This multi-angle evaluation confirms that the digital growth reasoning system offers high accuracy in regional prediction, logical traceability of model outputs, and meaningful alignment with policymaking contexts. It also highlights the value of integrating graph-based semantic modeling with statistical inference to bridge the gap between digital metrics and economic outcomes. In the next chapter, we further discuss the implications and limitations of the system, and propose future research directions.

6. Discussion

This study presents a multi-layered, knowledge-driven analytical system for understanding the mechanisms through which digital economy development affects regional economic growth, with a specific application to the Yangtze River Delta (YRD). The integration of the semantic knowledge graph construction, structural equation modeling, and spillover simulation offers both methodological and theoretical advancements in regional digital economics. By embedding domain-specific digital economy concepts into a structured ontology and enabling semantic reasoning over multi-source indicators, the system overcomes a key limitation in existing studies. Such studies often treat digital factors as aggregated, exogenous variables detached from local institutional and industrial structures [16,18]. Instead, our approach formalizes digital constructs as interconnected entities within a graph model, allowing for context-aware reasoning, cross-variable inference, and localized policy interpretation.

From a methodological perspective, this research demonstrates the feasibility and benefits of combining knowledge graph techniques with causal inference frameworks, a direction that remains underexplored in economic modeling. While prior works on knowledge graph completion and multi-modal semantic integration have shown promise in biomedical and geographic domains, their application to regional development policy remains limited. By adapting these techniques to economic indicator systems and aligning them with structural modeling logic, this study contributes a replicable approach to hybrid reasoning in policy-relevant contexts [17,20]. The incorporation of fuzzy semantic similarity in Module I and graph-augmented spillover simulation in Module III addresses the longstanding issue of spatial and data heterogeneity in digital economy measurement, particularly in complex, multi-tiered regions like the YRD [14,15].

Unlike conventional SEM or machine learning approaches that assume a homogeneous response to digital inputs, our framework dynamically adjusts output forecasts based on metadata related to governance capacity, regional policy incentives, and administrative readiness. This innovation is especially relevant for regions undergoing digital infrastructure transformation, as seen in studies of post-pandemic building adaptations and energy system optimization in urban environments [33,34]. These studies highlight the importance of localized policy responses to digital advancements, tailored to regional needs and governance structures. This approach makes the system not only statistically robust but also interpretable in policy terms, which is crucial for policy experimentation in high-stakes contexts, such as digital transformation strategies, cross-provincial integration, and smart infrastructure deployment [26,27]. As emphasized by Razavi et al. in their review of sensitivity analysis, systems models must account for contextual variability to be decision-supportive and policy-resilient, a requirement met by the rule-conditioning module proposed in this study [29].

In addition, the integration of simulation-based inter-city digital spillovers provides new insight into the spatial externalities of digital investment. While earlier studies have shown the existence of ICT-induced productivity gains at the regional level, this study models the dynamic diffusion of these gains via knowledge and enterprise networks, offering a more granular understanding of regional convergence and divergence under digital influence [5,14]. The simulation results reveal that Tier-1 and Tier-2 cities such as Shanghai, Hangzhou, and Suzhou function as digital hubs that radiate growth effects through infrastructural and institutional channels, a finding consistent with theories of urban network centrality and digital capital accumulation [6,11].

Finally, the proposed system enhances model transparency and interpretability, addressing a critical weakness in current data-driven models. While black-box models such as deep neural networks or random forests may offer high predictive accuracy, they often fall short in providing actionable policy insight. Our use of structural equations and knowledge graph reasoning aligns with the growing demand for explainable AI in governance and policy-making, as discussed by Cheung et al. and Whittaker & Schumacker in the context of SEM best practices [22,25].

Nonetheless, this research is not without limitations. While the knowledge base incorporates a wide range of digital economy indicators and regional variables, its coverage is constrained by data availability and standardization issues, particularly for emerging digital fields such as blockchain or automated governance mechanisms. In addition, although the SEM-based causal model accounts for multiple mediators and feedbacks, it remains a static representation; future studies could enhance temporal realism through dynamic simulation frameworks such as DSGE or agent-based modeling [26,28]. Moreover, the spillover logic, while empirically validated, assumes symmetry in diffusion potential, which may underestimate institutional frictions, infrastructural mismatches, or organizational silos that affect cross-city collaboration in practice.

7. Conclusion

This paper develops and validates a modular analytical system to model the driving effects of digital economy development on regional economic growth, using the Yangtze River Delta (YRD) as a case study. Grounded in a semantically structured digital knowledge graph and enhanced by multi-stage inference techniques, the system demonstrates strong empirical accuracy, interpretability, and policy relevance. Through the combination of fuzzy semantic indicator mapping, structural equation modeling, graph-based spillover simulation, and policy conditioning, the framework captures both the statistical and institutional dimensions of digital-regional dynamics.

Empirical results across a decade of panel data from 41 YRD cities confirm the significant and multi-pathway influence of digital infrastructure, platform economy activity, and governance capacity on regional GRP performance. The system also reveals heterogeneous policy responsiveness, with central cities exhibiting higher spillover potential and stronger alignment with national digital strategies. Scenario simulations further show that targeted digital interventions, particularly those enhancing governance quality and platform interconnectivity, can yield measurable gains in per capita economic output.

This research contributes to the literature by providing a hybrid, interpretable modeling approach that bridges semantic AI and causal inference within a regional economic framework. It offers a replicable method for other megaregions undergoing digital transformation and a decision-support tool for policy-makers seeking to design adaptive, evidence-based digital economy strategies.

Future work will focus on expanding the system's temporal resolution through dynamic simulation (e.g., system dynamics or DSGE models), integrating firm-level behavioral data from digital platforms, and extending the policy modeling framework to include fiscal, educational, and environmental feedback loops. Ultimately, this study affirms the value of integrating digital knowledge systems with regional planning science, paving the way for more intelligent, equitable, and sustainable territorial development in the digital age.

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