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Computer Simulation of Knowledge Transfer Dynamics in a Spatial Innovation Ecosystem: Evidence from the Chengxi Sci-Tech Innovation Corridor, Hangzhou

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Abstract

Science and technology innovation corridors concentrate innovation resources, organize knowledge flows, and accelerate technology commercialization. Yet, the dynamic mechanisms linking spatial structure and knowledge transfer remain underexplored. Using the Chengxi Sci-Tech Innovation Corridor in Hangzhou as a case, this study develops a hybrid simulation framework combining Agent-Based Modeling and System Dynamics. Universities, research institutes, firms, startups, intermediary platforms, and government actors are modeled as heterogeneous agents, while System Dynamics captures macro-level feedback among policy, talent, knowledge stock, and innovation output. Scenario simulations show that knowledge transfer is jointly shaped by spatial proximity, actor heterogeneity, absorptive capacity, trust, network structure, and policy support. Combined optimization yields the strongest long-term improvement, suggesting coordinated spatial, network, and institutional interventions are crucial.

Keywords

Knowledge Transfer, Spatial Innovation Ecosystem, Innovation Corridor, Agent-Based Modeling, System Dynamics

1. Introduction

Innovation-driven development has increasingly reshaped the spatial organization of regional economies. In this process, science and technology innovation corridors have become more than linear industrial belts or physical development zones. They operate as spatially embedded innovation ecosystems in which universities, laboratories, platform enterprises, startups, public agencies and intermediary organizations interact to generate, transfer and apply knowledge. Compared with traditional science parks, innovation corridors emphasize multi-node coordination, cross-boundary connectivity and the circulation of knowledge across differentiated functional spaces.

The Chengxi Sci-Tech Innovation Corridor in Hangzhou provides a representative case for examining this transformation. The corridor links Xihu, Yuhang and Lin'an districts along an east-west innovation axis and contains major universities, research platforms, digital economy firms, incubators and policy support mechanisms. It has gradually evolved from a policy-led science and technology agglomeration zone into a metropolitan-scale innovation ecosystem. Its eastern section is closely related to university-based original knowledge creation, the central section is dominated by the digital economy and entrepreneurial platforms, and the western section is more associated with industrial application and manufacturing transformation. This differentiated spatial structure makes knowledge transfer neither uniform nor automatic.

Although existing research has generated valuable insights into innovation ecosystems, knowledge transfer and innovation corridors, several gaps remain. First, many studies of innovation ecosystems emphasize organizational collaboration or industrial upgrading, but treat spatial structure only as a descriptive background. Second, studies of knowledge transfer often focus on firms, projects or university-industry collaboration, while corridor-scale and ecosystem-scale mechanisms receive less attention. Third, empirical studies of innovation corridors often rely on static indicators, planning narratives or case interpretation, which are less effective for revealing how collaboration networks evolve and how policy interventions reshape system behavior over time.

This article addresses these gaps by constructing a hybrid simulation framework for knowledge transfer in the Chengxi Sci-Tech Innovation Corridor. The framework combines Agent-Based Modeling, which represents heterogeneous actor behavior and decentralized interaction, with System Dynamics, which captures macro-level accumulation and feedback. The study asks three questions: how do spatial proximity, actor heterogeneity and network structure influence knowledge transfer dynamics; how do trust, absorptive capacity and collaboration patterns affect transfer efficiency and innovation output; and how do different intervention scenarios reshape the long-term evolution of knowledge transfer and innovation performance?

The contribution of the article is threefold. Conceptually, it treats the innovation corridor as a spatial innovation ecosystem rather than as a simple industrial agglomeration. Methodologically, it integrates micro-level agent interaction and macro-level system feedback in a single simulation framework. Practically, it translates simulation results into planning implications for improving multi-node coordination, spatial accessibility, network bridging and policy support within a real innovation corridor.

2. Literature Review and Analytical Framework

2.1. Spatial Innovation Ecosystems and Innovation Corridors

Recent scholarship has increasingly conceptualized innovation ecosystems not merely as collections of firms but as relational systems involving heterogeneous actors, digital infrastructures, institutional arrangements, and territorial linkages that collectively shape innovation capacity [1]. Within these ecosystems, orchestrated interactions among knowledge producers, intermediaries, firms, users, and public institutions are essential for translating inputs into innovation outcomes [2]. Studies further emphasize that innovation ecosystems are adaptive and evolutionary, with performance contingent on actors' abilities to coordinate resources, respond to uncertainty, and convert interactions into technological and commercial results [3] [4].

Building upon this ecosystem perspective, innovation corridors extend the concept into spatial planning and regional development. A corridor functions as a coordination mechanism linking multiple innovation nodes, facilitating cross-place collaboration, and enabling circulation of knowledge, talent, and capital [5]. The effectiveness of such corridors is determined not only by the scale of resources they encompass but also by the internal relational structures that enable communication, collaboration, and knowledge conversion. Hence, the spatial layout of an innovation corridor actively shapes the opportunities for interaction and the efficiency of knowledge transfer [6]. Recent empirical studies highlight that corridors with dense, trust-rich, and well-networked nodes demonstrate higher innovation performance, suggesting that spatial proximity alone is insufficient without relational and institutional support [7].

2.2. Knowledge Transfer, Proximity and Absorptive Capacity

Knowledge transfer is the process through which one actor's knowledge is transmitted, interpreted, absorbed, and applied by another actor [8]. It encompasses explicit knowledge, which can be codified in patents, documents, or technical manuals, and tacit knowledge, which depends on repeated interactions, trust, and organizational learning [9]. The absorptive capacity of the receiving actor—the ability to recognize, assimilate, and exploit external knowledge—is critical in determining whether knowledge transfer produces effective innovation outcomes [10] [11].

Spatial proximity facilitates knowledge transfer by lowering interaction costs and increasing the likelihood of contact, particularly for tacit knowledge [12]. However, proximity is necessary but not sufficient: actors may be geographically close yet organizationally disconnected, or trust may be lacking to support the exchange of valuable knowledge [13] [14]. Therefore, the efficiency of knowledge transfer in spatial innovation ecosystems depends on the interplay of proximity, absorptive capacity, trust, network embeddedness, and institutional support. Weakness in any of these factors can create bottlenecks, constraining innovation despite high geographic or digital connectivity [15] [16]. Empirical studies further show that digital platforms and data-driven coordination mechanisms can amplify absorptive capacity and enable knowledge spillovers across regional innovation nodes [17] [18].

Overall, the literature suggests that innovation performance in spatially organized ecosystems is a function of both spatial and relational factors. While early studies focused heavily on geographic clustering, recent work emphasizes the importance of actor coordination, absorptive capacity, and institutional facilitation in enabling knowledge to flow effectively across nodes [19] [20]. This theoretical insight underpins the analytical framework of this study: understanding innovation corridors requires examining not only physical connectivity but also the capacity of actors and institutions to recognize, assimilate, and utilize knowledge within spatially structured networks.

2.3. Analytical Framework

This article constructs an analytical framework linking spatial structure, actor interaction, knowledge transfer and innovation output. The Chengxi Sci-Tech Innovation Corridor is conceptualized as a spatial innovation ecosystem composed of heterogeneous actors embedded in differentiated subspaces. Spatial proximity affects the probability of interaction and collaboration; actor capabilities determine whether contact can become effective knowledge exchange; trust and network ties shape the stability and continuity of collaboration; and policy support influences talent attraction, platform provision and commercialization conditions.

Within this framework, knowledge transfer follows a dynamic chain: spatial organization creates interaction opportunities; agents select partners and form collaborative ties; knowledge is exchanged and absorbed through repeated interaction; successful transfer increases the corridor's knowledge stock; and accumulated knowledge contributes to innovation output through commercialization and industrial application. Computer simulation is used because this process is nonlinear, cumulative and difficult to observe directly through static indicators alone.

3. Study Area and Data

The Chengxi Sci-Tech Innovation Corridor is one of the most important innovation spaces in Zhejiang Province. It stretches roughly 39 kilometers from east to west and covers a planned area of about 416 km^2, linking Xihu District, Yuhang District and Lin'an District into a continuous innovation belt. The approved territorial spatial plan further identifies a 14.3 km^2 core planning area around Yuncheng and Future Sci-Tech City, while also defining ecological redlines, development boundaries and connectivity targets. The corridor's spatial structure is therefore both linear and multi-nodal.

From the perspective of innovation function, the corridor can be summarized as one belt, three science cities and multiple innovation nodes. Xihu District is anchored by Zijingang Sci-Tech City and benefits from the proximity of Zhejiang University and university-related innovation circles. Yuhang District is dominated by Future Sci-Tech City and has become the strongest digital economy and platform economy node. Lin'an District is centered on Qingshan Lake Sci-Tech City, where advanced manufacturing, new materials and technology application functions are more visible. This east-central-west differentiation provides the empirical foundation for modeling spatially heterogeneous agents.

The data used in this study come from official planning documents, government work reports, district statistical bulletins, corridor-related government releases and research-informed modeling assumptions. The empirical data are organized at three levels. Corridor-level data describe the overall spatial scale, policy environment and digital economy performance. District-level data capture differences in GDP, digital economy share, R&D intensity, high-tech enterprises, technology transactions and innovation platforms. Model-level data translate these indicators into agent attributes and system parameters, such as initial knowledge stock, absorptive capacity, trust propensity, policy support intensity and network bridging capability.

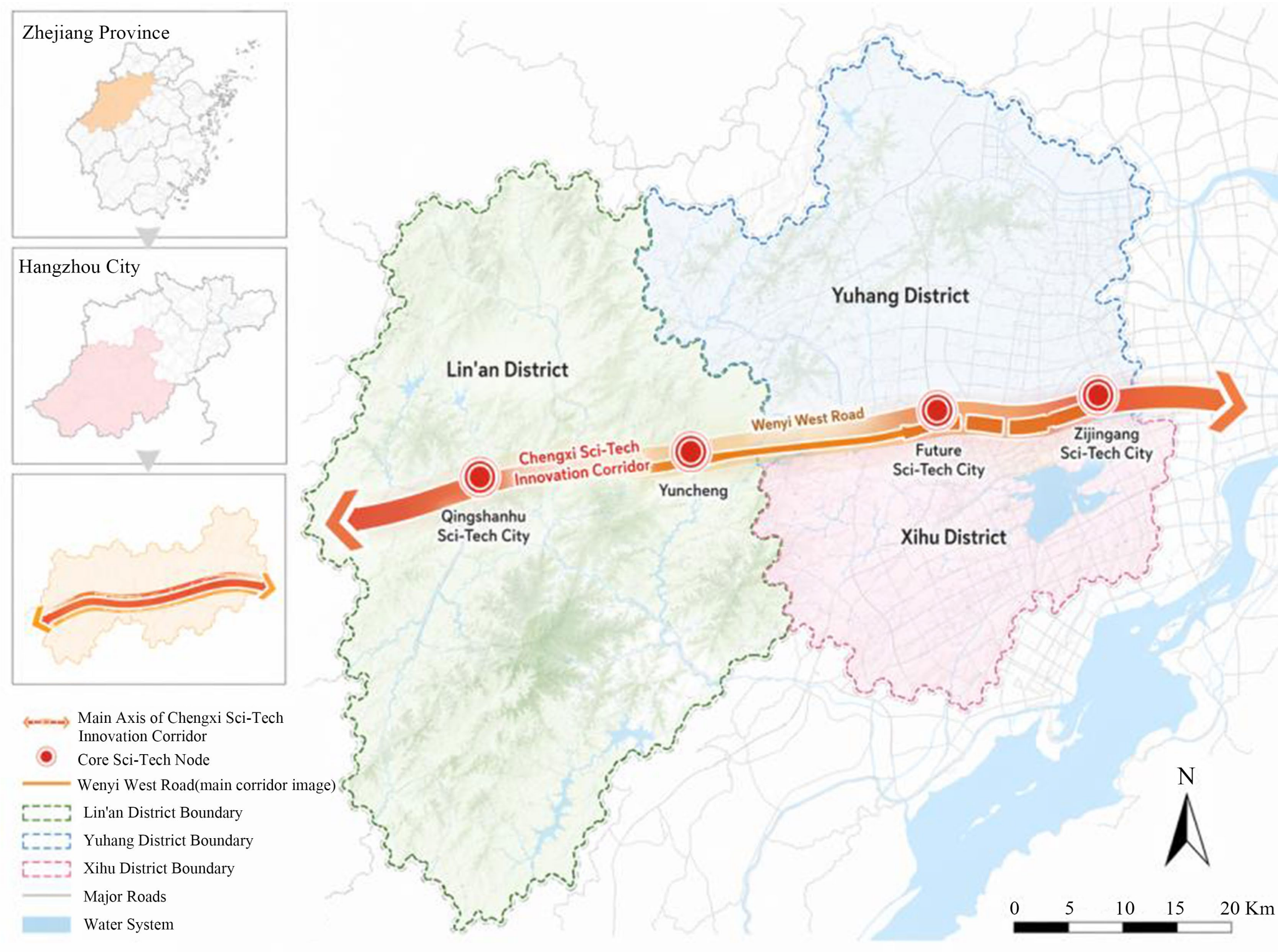
Before analyzing the dynamics of knowledge transfer within the Chengxi Sci-Tech Innovation Corridor, it is essential to understand its overall macro-level characteristics. Table 1 presents key indicators including spatial length, planned area, core planning area, ecological protection redline, urban development boundary, digital economy performance, and talent accumulation. These indicators establish the empirical foundation for setting initial parameters in the simulation model and highlight the functional and resource differences across the eastern, central, and western sections of the corridor.

Table 1. Key macro indicators of the Chengxi sci-tech innovation corridor.

Indicator	Value
Spatial length	39 km
Planned area	416 km^2
Core planning area	14.3 km^2
Ecological protection redline	22.7 km^2
Urban development boundary	193.9 km^2
Core digital economy, H1 2025	140.03 billion yuan
New high-level talents, H1 2025	5199 persons
Share of Hangzhou's new high-level talents, H1 2025	25.7%
Industrial value added, 2016	106.3 billion yuan
Industrial value added, 2025	422.36 billion yuan
AI industry revenue, 2025	252.04 billion yuan

Source: Compiled from official planning documents and government releases.

Figure 1 visually depicts the geographical location and overall spatial layout of the corridor. It shows how the innovation nodes are distributed across Xihu, Yuhang, and Lin'an districts, providing insight into how spatial proximity might influence knowledge transfer and connectivity between different segments.

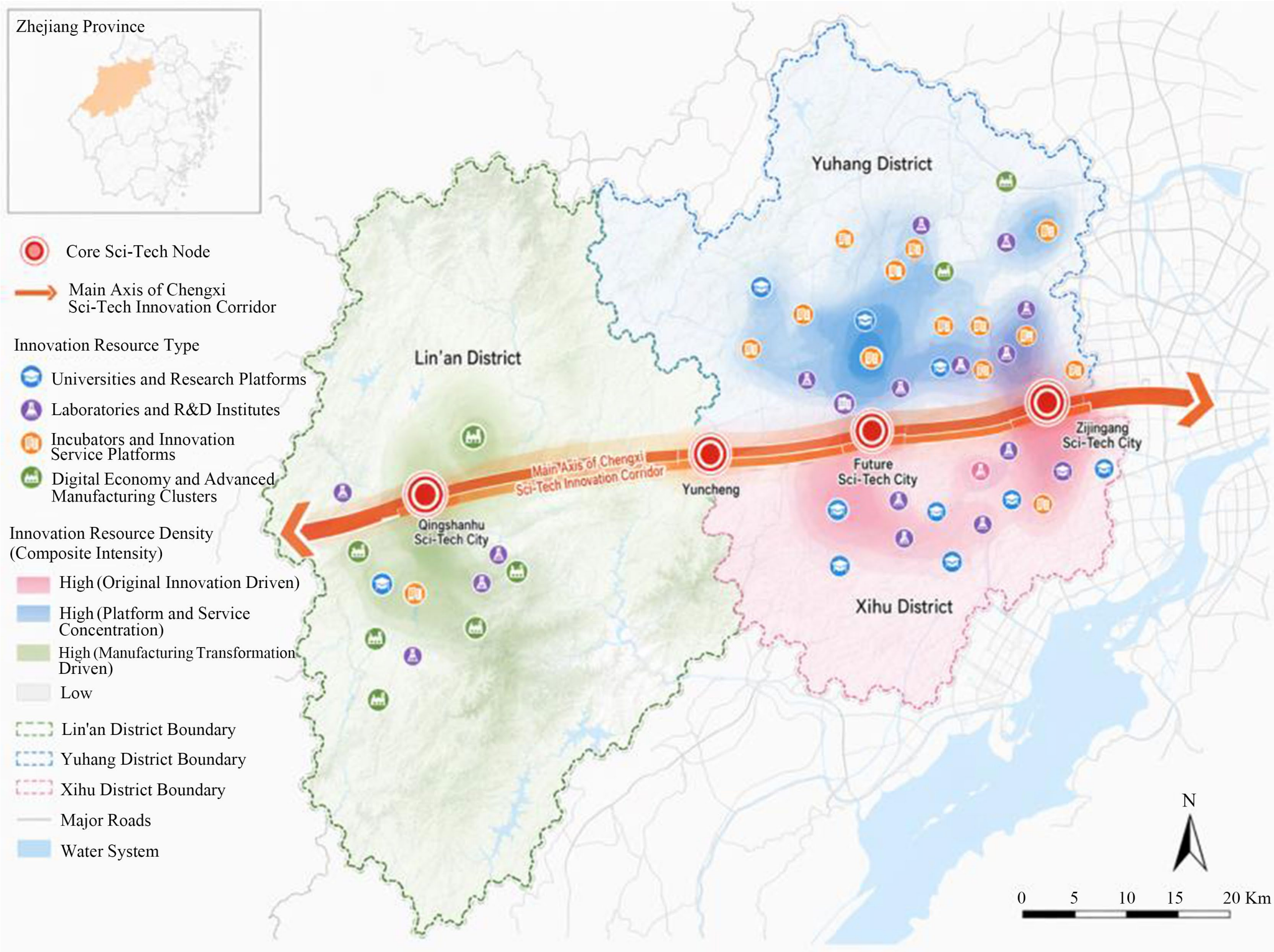


Source: Author's drawing based on the territorial spatial plan and relevant government releases.

Figure 1. Location and overall spatial structure of the Chengxi sci-tech innovation corridor.

Figure 2 presents the distribution of key innovation resources and core nodes across the corridor. By showing the locations of universities, research institutes, digital economy firms, and incubation platforms, it highlights the concentration of innovation capacity and the structural opportunities for knowledge transfer among actors.

Table 2 compares the three core districts in terms of GDP, GDP growth, digital economy output, digital economy share of GDP, R&D intensity, and the number of new national high-tech enterprises. These metrics illustrate functional complementarity across districts, supporting heterogeneous initial conditions in the simulation model.



Source: Author's drawing based on district statistical bulletins, planning documents and government materials.

Figure 2. Distribution of innovation resources and core nodes in the Chengxi sci-tech innovation corridor.

Table 2. Comparative innovation indicators of the three core districts in 2024.

District	GDP (billion yuan)	GDP growth (%)	Core digital economy (billion yuan)	Digital economy share of GDP (%)	R&D intensity (%)	New national high-tech enterprises
Xihu	233.15	4.9	71.03	30.5	4.50	226
Yuhang	335.57	6.0	229.80	68.5	4.55	578
Lin'an	73.29	5.2	9.37	12.8	N/A in bulletin	90

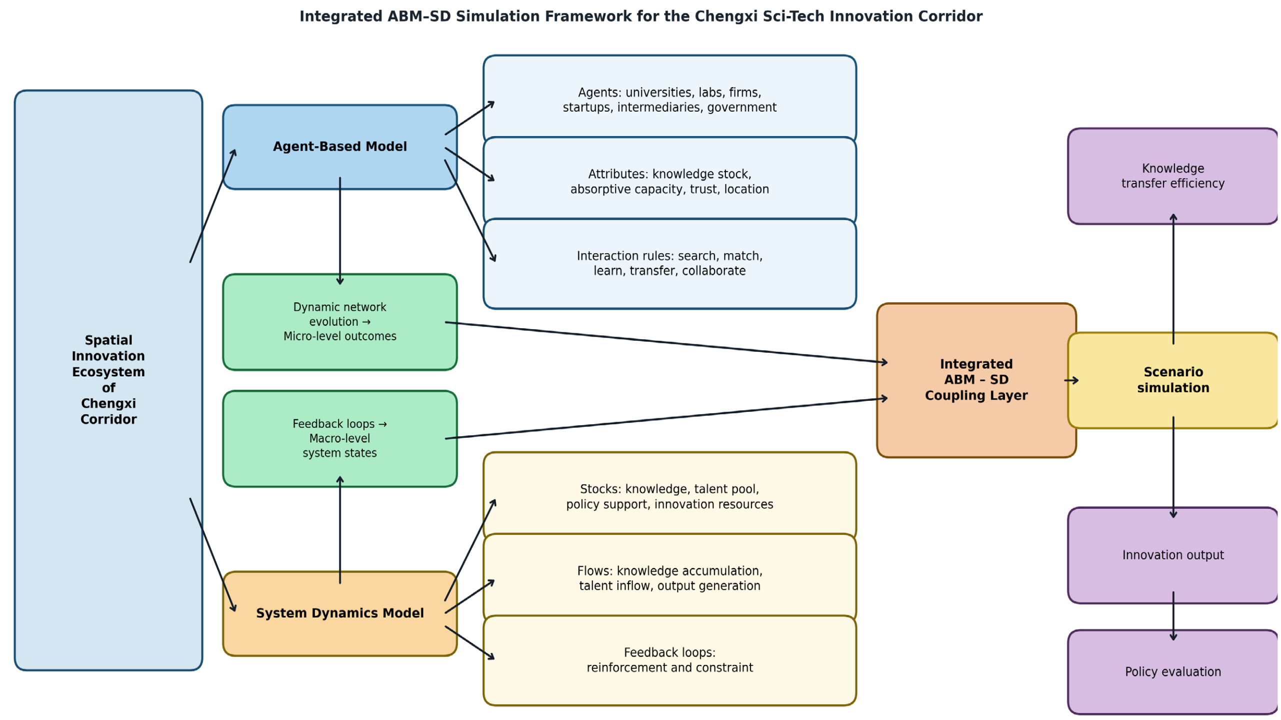
Source: Compiled from the 2024 district statistical bulletins.

The district comparison confirms that the corridor is not spatially balanced in a simple quantitative sense, but functionally complementary. Yuhang has the largest GDP and the strongest digital economy intensity, making it the central node for platform coordination, venture formation and digital industrialization. Xihu has a strong research and higher-education base, which supports original knowledge creation and technology transactions. Lin'an has a smaller overall economy but provides an important downstream space for manufacturing-oriented transformation and application. These differences justify the use of heterogeneous initial conditions in the simulation model.

4. Methodology: Hybrid ABM-SD Simulation Model

4.1. Overall Model Logic

The study adopts a hybrid model combining Agent-Based Modeling and System Dynamics. ABM is used to represent decentralized interaction among heterogeneous innovation actors, while SD is used to represent cumulative system-level feedback. This combination is appropriate because knowledge transfer in an innovation corridor emerges from both micro-level collaboration and macro-level accumulation. Individual actors search for partners, build trust, exchange knowledge and learn from one another. Over time, these micro-level actions reshape the corridor's knowledge stock, talent pool, network cohesion and innovation output.



Source: Constructed by the author.

Figure 3. Overall modeling framework of the hybrid ABM-SD simulation.

The ABM module includes six types of agents: universities, research institutes, established firms, startups, intermediary platforms and government actors. Each agent has attributes including spatial location, knowledge stock, absorptive capacity, trust propensity, collaboration willingness and network position. Interaction among agents follows a sequence of partner search, matching, collaboration, knowledge exchange, absorption and possible innovation output. The probability of successful transfer depends on spatial proximity, capability compatibility, trust, prior ties and intermediary support.

The SD module captures the macro-level evolution of policy support, talent pool, corridor knowledge stock, network cohesion and innovation output. Positive feedback occurs when higher policy support attracts talent and strengthens platforms, which then improves knowledge transfer conditions and increases innovation output. Balancing feedback may also occur because coordination cost, commercialization thresholds and absorptive limits prevent knowledge transfer from being automatically transformed into output. The hybrid model therefore connects local interactions with long-term system behavior.

Figure 3 illustrates the hybrid simulation framework combining Agent-Based Modeling (ABM) and System Dynamics (SD). The figure highlights how micro-level interactions among heterogeneous actors translate into macro-level outcomes, including knowledge stock, network cohesion, and innovation output, reflecting the dynamic feedback mechanisms of the corridor's ecosystem.

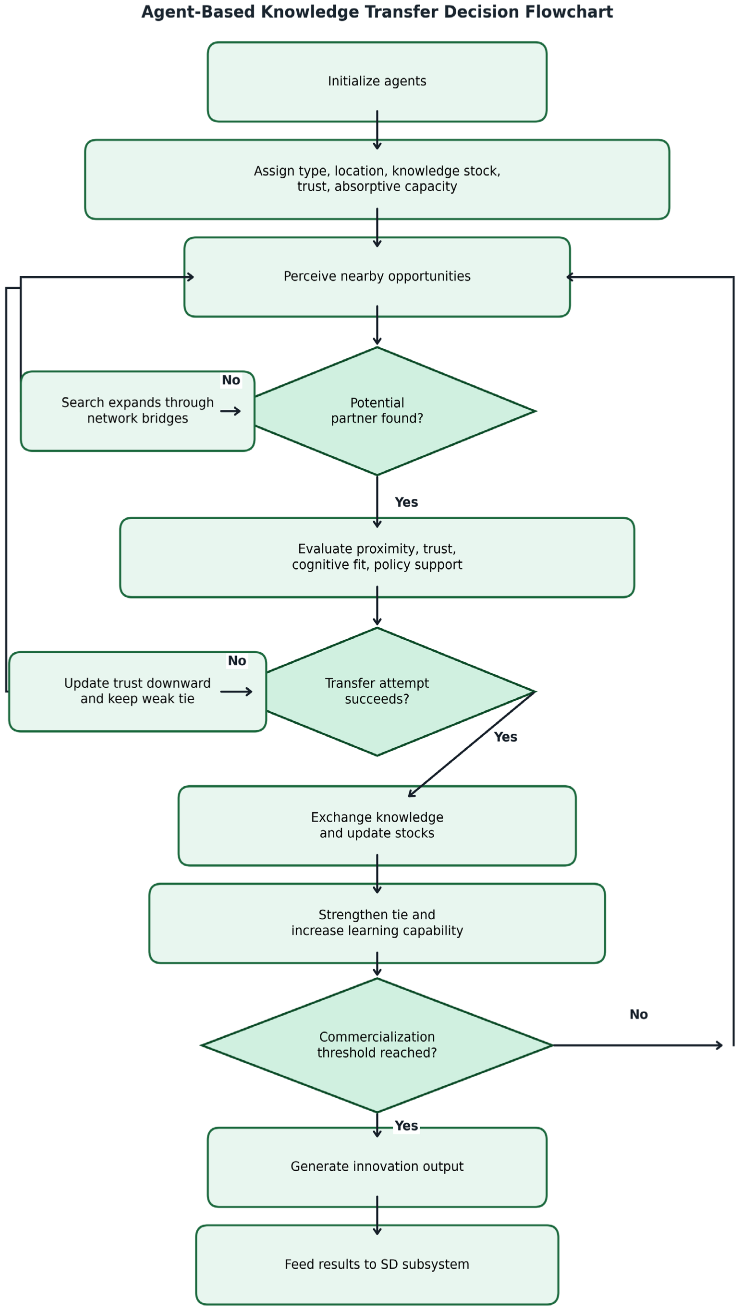
Table 3 lists the six types of agents included in the ABM module—universities, research institutes/labs, established firms, startups, intermediary institutions, and government actors—along with their functional roles, typical initial strengths, main constraints, and key model attributes. This classification clarifies agent behavior in the knowledge transfer process.

Table 3. Agent types and core attributes.

Agent type	Functional role	Typical initial strengths	Main constraints	Key model attributes
University	Original knowledge creation	High knowledge stock, high research productivity	Lower immediate commercialization	Knowledge stock, absorptive capacity, openness
Research institute/lab	Frontier research and platform output	High scientific capability, strong spillover potential	Limited market coordination	Knowledge stock, technology maturity, openness
Established firm	Knowledge recombination and scaling	Higher market access, stronger exploitation capacity	Organizational inertia	Absorptive capacity, trust, commercialization threshold
Startup	Exploration and rapid recombination	Flexibility, innovation orientation	Resource shortage, fragile networks	Risk preference, absorptive capacity, learning speed
Intermediary institution	Matching and translation	Bridge position, lower transaction costs	Limited direct output	Matching efficiency, trust amplification
Government actor	Policy coordination and support	Resource mobilization, rule-setting	Indirect rather than direct innovation	Policy intensity, platform investment

Source: Constructed by the author.

Figure 4 visualizes the logic of agent interaction and knowledge transfer in the ABM module. It shows how agents select partners, exchange knowledge, update trust, and accumulate absorptive capacity, ultimately producing innovation output when commercialization thresholds are reached.



Source: Constructed by the author.

Figure 4. Agent interaction and knowledge transfer logic in the ABM module.

4.2. Core Behavioral Rules of the ABM Module

In each simulation step, agents first search for potential partners within the corridor network. The matching probability is determined by spatial proximity, capability complementarity, trust, prior collaboration experience, and intermediary support. Once a collaborative tie is formed, knowledge transfer occurs when the sender's knowledge stock and the receiver's absorptive capacity jointly exceed a transfer threshold. Trust increases after successful repeated collaboration and decreases when collaboration fails. Absorptive capacity increases gradually through successful learning, while knowledge stock accumulates through both internal creation and external knowledge absorption. Innovation output is generated when absorbed knowledge reaches the commercialization threshold and is supported by sufficient policy, platform, and market conditions.

Table 4 outlines the core behavioral rules governing agent interactions, including partner matching, knowledge transfer, trust updating, absorptive capacity change, knowledge accumulation, and commercialization. This provides a clear mapping between real-world dynamics and their model representation.

Table 4. Behavioral rules and update mechanisms in the ABM module.

Rule	Simplified modeling logic
Partner matching	Higher proximity, trust, capability complementarity, and intermediary support increase matching probability
Knowledge transfer	Transfer succeeds when sender knowledge stock and receiver absorptive capacity exceed a threshold
Trust updating	Successful repeated collaboration increases trust; failed collaboration weakens trust
Absorptive capacity change	Successful learning gradually improves absorptive capacity
Knowledge accumulation	Knowledge stock grows through internal creation and absorbed external knowledge
Commercialization	Innovation output occurs when absorbed knowledge exceeds the commercialization threshold

Source: Constructed by the author.

4.3. Variables, Parameters and Scenarios

The variable system reflects the central proposition that knowledge transfer performance is jointly shaped by spatial proximity, actor capability, network structure and policy support. Spatial proximity is represented by relative distance, corridor segment and accessibility. Actor capability includes knowledge stock, absorptive capacity and collaboration willingness. Network variables include degree centrality, bridge position, tie strength and repeated collaboration. System outcomes include transfer efficiency, network cohesion, knowledge stock, talent pool and innovation output.

Observed district indicators are not treated as direct measurements of individual actors. Instead, they are used as empirical anchors for constructing differentiated agent attributes. For example, Xihu's research and university resources support higher initial knowledge stock for university and research agents. Yuhang's digital economy and high-tech enterprise concentration support stronger absorptive capacity and network centrality for firms and startups. Lin'an's manufacturing-oriented structure supports technology application and commercialization parameters. This conversion from statistical evidence to simulation structure makes the model empirically grounded while remaining computationally tractable.

As shown in the **Appendix**, the key simulation parameters are linked to observable corridor-level and district-level indicators, while theoretically informed assumptions are used where direct micro-level data are unavailable.

Table 5. Core variables and indicator construction.

Variable dimension	Variable	Indicator definition	Direction of expected effect	Model level
Spatial proximity	Geographic proximity	Relative distance between agents or nodes	Positive	ABM
Spatial accessibility	Corridor connectivity	Travel convenience among science cities and innovation circles	Positive	ABM/SD
Knowledge stock	Initial knowledge endowment	Research capacity, platform level, accumulated expertise	Positive	ABM
Absorptive capacity	Learning and assimilation ability	Ability to recognize, internalize, and apply external knowledge	Positive	ABM
Trust	Relational trust coefficient	Stability and willingness in repeated collaboration	Positive	ABM
Network embeddedness	Degree and bridge position	Number and strategic quality of network ties	Positive	ABM
Policy support	Public intervention intensity	Funding, incubators, concept centers, talent support, services	Positive	SD

Source: Constructed on the basis of corridor statistics, district bulletins and hybrid-modeling literature.

Table 6. Scenario setting for the simulation.

Scenario category	Scenario code	Core assumption	Main purpose
Baseline	S0	Current corridor structure and observed district heterogeneity	Benchmark comparison
Spatial proximity enhancement	S1	Reduced effective distance and improved accessibility	Test proximity effect on transfer frequency
Spatial fragmentation	S2	Increased effective distance and weaker cross-node interaction	Test sensitivity to spatial barriers
Trust enhancement	S3	Higher trust coefficient and stronger repeat collaboration	Test relational mechanism
Network bridging enhancement	S4	More bridge ties among subspaces and actor groups	Test topology mechanism
Policy strengthening	S5	Higher public support for platforms, incubation, and talent	Test macro intervention effect
Combined optimization	S6	Joint improvement in proximity, trust, and policy support	Test systemic synergy

Source: Constructed by the author.

Seven scenarios are designed for comparison. The baseline scenario represents the current corridor structure and district heterogeneity. The spatial accessibility enhancement scenario reduces effective distance and increases cross-node contact. The spatial fragmentation scenario increases access barriers and tests the negative effect of weaker connectivity. The trust enhancement scenario raises the probability that repeated collaboration produces stable ties. The network bridging scenario strengthens intermediary platforms and cross-node connectors. The policy strengthening scenario increases public support for talent, platforms and commercialization. The combined optimization scenario integrates accessibility improvement, trust enhancement, network bridging and policy support.

Table 5 details the variables used in the simulation, their indicators, expected effect directions, and mapping to the model layer (ABM or SD). This provides transparency in how empirical data informs model dynamics.

Table 6 presents the seven simulation scenarios, including baseline, spatial proximity enhancement, spatial fragmentation, trust enhancement, network bridging, policy strengthening, and combined optimization. Each scenario is associated with core assumptions and specific objectives to test the effects of spatial, relational, and institutional interventions.

4.4. Definition and Normalization of Outcome Indicators

To make the simulation outputs comparable across different dimensions, the main outcome variables are reported as normalized indices with 2025 = 100. For each indicator, the normalized value is calculated as:

$$\text{Index}_t = \left(\text{Value}_t / \text{Value}_{2025}\right) \times 100$$

Knowledge transfer efficiency refers to the proportion of successful knowledge-transfer events among potential inter-agent interactions. Network cohesion reflects the density and stability of collaborative ties among agents, especially repeated and cross-node collaborations. Knowledge stock represents the accumulated knowledge generated internally and absorbed from external partners. Innovation output is defined as a composite index reflecting patents, technology commercialization, startup growth, and industrial application performance.

Table 7 defines key outcome indicators such as knowledge transfer efficiency, network cohesion, knowledge stock, talent pool, policy support, and innovation output. Normalization ensures comparability across dimensions with 2025 = 100 as the reference.

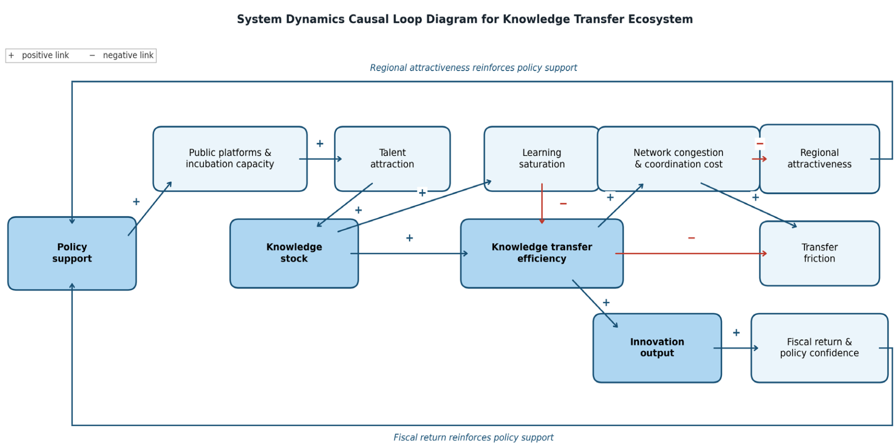
Table 7. Definition and normalization of main outcome indicators.

Indicator	Definition	Normalization rule
Knowledge transfer efficiency	Successful knowledge-transfer events relative to potential inter-agent interactions	2025 = 100
Network cohesion	Density and stability of collaborative ties, including repeated and cross-node ties	2025 = 100
Knowledge stock	Accumulated internal and externally absorbed knowledge	2025 = 100
Talent pool	Accumulated high-level innovation talent supporting knowledge absorption and commercialization	2025 = 100
Policy support	Public support intensity for platforms, incubation, talent, and commercialization	2025 = 100
Innovation output	Composite index of patents, commercialization, startup growth, and industrial application	2025 = 100

To ensure that the simulation results are consistent and reproducible, Table 8 outlines the key experimental settings used in the hybrid ABM-SD model. It specifies the simulation period, time steps, spatial units, agent types and numbers, platform, scenario settings, and output reporting conventions. These settings provide transparency for replicating the model and interpreting the results across different intervention scenarios.

Table 8. Simulation setup and reproducibility settings.

Item	Setting
Simulation period	2025-2035
Number of time steps	11 annual steps
Time step	One year per step
Spatial units	Xihu District, Yuhang District, and Lin'an District
Agent types	Universities, research institutes/labs, established firms, startups, intermediary institutions, and government actors
Number of agents	18 representative district-actor agent groups, calculated as 6 agent types × 3 corridor districts
Simulation platform	Custom Python-based simulation model
Scenario settings	Seven scenarios: S0 baseline, S1 proximity enhancement, S2 spatial fragmentation, S3 trust enhancement, S4 network bridging enhancement, S5 policy strengthening, and S6 combined optimization
Scenario runs	One calibrated simulation run for each scenario
Random seed handling	Not applicable; the reported outputs are deterministic calibrated scenario results rather than Monte Carlo averages
Output reporting	Final 2035 outcomes are normalized with 2025 = 100



Source: Constructed by the author.

Figure 5. Main feedback loops in the system dynamics module.

The model uses representative district-actor agent groups rather than firm-level population counts. Therefore, the number of modeled agents refers to functional representative groups formed by combining the six actor types with the three corridor districts.

Figure 5 illustrates the primary feedback loops in the SD module, showing how policy support, talent pool, knowledge stock, and network cohesion interact over time to produce innovation output. Positive and balancing feedback mechanisms highlight the complex interdependencies in the corridor ecosystem.

4.5. Model Calibration and Directional Validation

The baseline simulation results were compared with observed development trends of the Chengxi Sci-Tech Innovation Corridor. The purpose of this comparison is not to claim exact numerical prediction, but to examine whether the simulated baseline trajectory is directionally consistent with recent empirical changes in the corridor. The observed increase in industrial value added, the expansion of the digital economy, the inflow of high-level talent, and the differentiated innovation profiles of Xihu, Yuhang, and Lin'an all support the model assumption that the corridor has strong knowledge-circulation capacity but still faces downstream commercialization constraints.

Before interpreting the simulation outcomes, it is important to validate the baseline model against observed trends in the Chengxi Sci-Tech Innovation Corridor. Table 9 compares empirical evidence with the corresponding model implications, demonstrating that the simulation captures the directional behavior of key system components, including industrial development, digital economy growth, talent accumulation, and district heterogeneity. This validation provides confidence that the model is capable of reflecting the real-world evolution of knowledge transfer and innovation performance across the corridor.

Table 9. Directional validation of baseline simulation results against observed corridor trends.

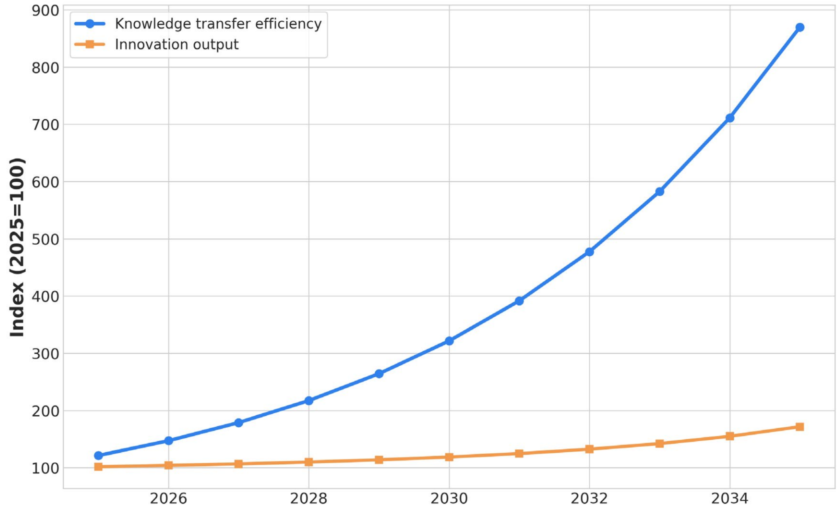
Validation dimension	Observed empirical evidence	Corresponding model implication
Industrial development	Industrial value added increased from 106.3 billion yuan in 2016 to 422.36 billion yuan in 2025	Supports the baseline assumption of cumulative innovation and commercialization growth
Digital economy foundation	Core digital economy reached 140.03 billion yuan in H1 2025	Supports high knowledge-transfer potential and strong platform-based interaction
Talent accumulation	5199 new high-level talents were added in H1 2025, accounting for 25.7% of Hangzhou's total	Supports the modeled growth of talent pool and absorptive capacity
District heterogeneity	Xihu has strong research resources, Yuhang has the highest digital-economy concentration, and Lin'an provides application-oriented industrial space	Supports differentiated initial conditions for heterogeneous agents
Baseline simulation trend	Knowledge transfer efficiency, knowledge stock, talent pool, and innovation output all increase from 2025 to 2035	Directionally consistent with observed corridor growth and functional upgrading

5. Results

5.1. Baseline Dynamics

The baseline simulation shows that the Chengxi Sci-Tech Innovation Corridor already has strong endogenous capacity for knowledge circulation. From 2025 to 2035, knowledge transfer efficiency rises substantially, network cohesion grows moderately and innovation output continues to increase. This pattern is consistent with the corridor's real-world foundation: a strong digital economy, multiple innovation platforms, high-level talent inflow and differentiated spatial functions. The result suggests that the corridor is not merely a passive container of innovation resources but already functions as a dynamic system of knowledge exchange.

However, the baseline trajectory also reveals an important structural tension. Knowledge transfer efficiency grows much faster than innovation output. This divergence is consistent with the structure of the hybrid model. In the ABM module, improved contact frequency, repeated collaboration, and stronger matching can quickly increase the number of successful knowledge-transfer events. However, in the SD module, innovation output depends not only on transferred knowledge, but also on absorptive capacity, commercialization threshold, talent accumulation, platform support, and market application conditions. Therefore, knowledge can circulate faster than it is commercialized. The baseline result suggests that the corridor's main bottleneck is not knowledge circulation itself, but the downstream conversion of transferred knowledge into patents, products, startups, and industrial output. This means that the corridor is relatively strong in generating, circulating and recombining knowledge, but the conversion of knowledge into commercialized and industrialized outcomes remains slower. Such a gap may result from organizational learning barriers, technology maturity limits, financing constraints, intellectual-property coordination and the institutional complexity of science-to-industry transformation. Therefore, planning and governance should not only promote interaction, but also strengthen commercialization channels and downstream application capacity.



Source: Simulation results.

Figure 6. Baseline scenario trajectories from 2025 to 2035.

Figure 6 illustrates the evolution of knowledge transfer efficiency, network cohesion, knowledge stock, talent pool, policy support, and innovation output under the baseline scenario. It highlights that knowledge transfer accelerates faster than commercialization and industrial output, identifying potential bottlenecks in the corridor.

Table 10 presents the final values of outcome indicators under the baseline scenario, showing the relative growth of knowledge transfer, network cohesion, innovation output, and other system measures.

Table 10. Baseline simulation outcomes in 2035 (2025 = 100).

Indicator	Baseline result
Knowledge transfer efficiency	869.80
Network cohesion	111.57
Knowledge stock	166.11
Talent pool	125.77
Policy support	120.82
Innovation output	171.68

Source: Simulation results.

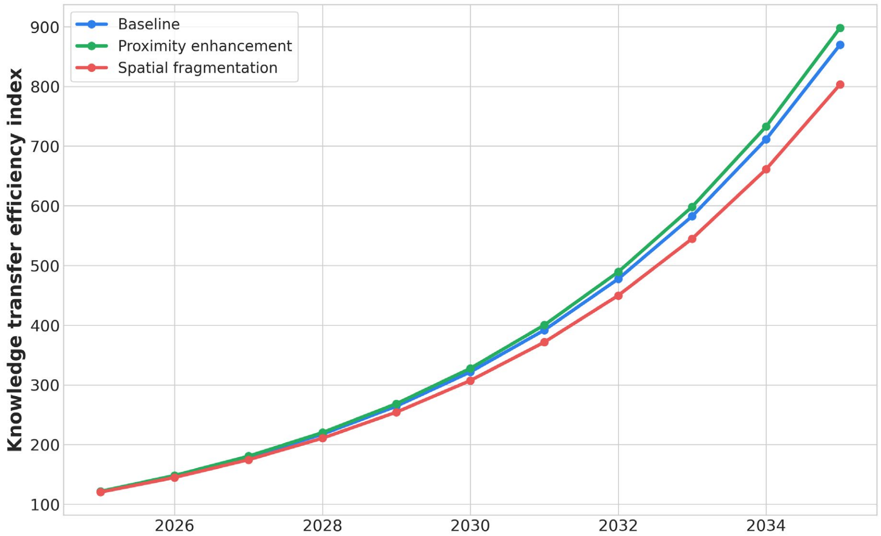
5.2. Effects of Spatial Accessibility, Trust and Network Bridging

The spatial accessibility enhancement scenario improves knowledge transfer efficiency relative to the baseline. Reduced effective distance increases the probability of contact among agents in different sections of the corridor and allows knowledge resources to circulate more frequently between Xihu, Yuhang and Lin'an. Nevertheless, the effect on innovation output is smaller than the effect on transfer efficiency. This indicates that spatial proximity can create more opportunities for exchange, but cannot by itself ensure successful absorption or commercialization. Accessibility is therefore a necessary but not sufficient condition for innovation performance.

The trust enhancement scenario produces a stronger improvement in collaboration stability and innovation output. Trust reduces transaction costs, increases willingness to share higher-value knowledge and supports repeated collaboration. In innovation ecosystems where tacit knowledge and uncertain technological projects are important, trust is especially critical because actors may hesitate to disclose valuable knowledge without reliable relationships. The simulation therefore confirms that relational quality is a key mechanism linking interaction frequency to transfer effectiveness.

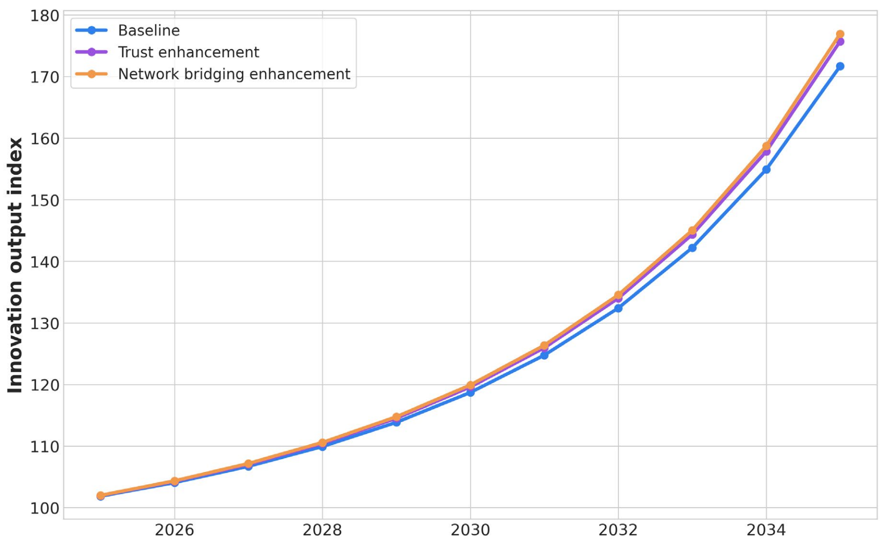
The network bridging scenario also improves performance by connecting otherwise separated nodes and actor groups. Intermediary platforms, incubators, proof-of-concept centers and technology transfer agencies play an important role in reducing structural holes. Their function is not simply administrative; they translate knowledge across organizational boundaries, match complementary actors and help weaker nodes access core resources. This result is particularly relevant for the Chengxi corridor because excessive concentration around central nodes may limit the diffusion of knowledge to peripheral or application-oriented spaces.

Figure 7 illustrates how enhancing spatial proximity affects the knowledge transfer efficiency across the corridor. The results show that reducing effective distance increases the probability of contact among agents in different districts, facilitating more frequent exchanges of knowledge. However, the figure also highlights that while spatial proximity improves transfer efficiency, its impact on ultimate innovation output is more limited, indicating that proximity alone is not sufficient to ensure successful knowledge commercialization.



Source: Simulation results.

Figure 7. Effects of spatial proximity on the knowledge transfer efficiency index.



Source: Simulation results.

Figure 8. Effects of trust enhancement and network bridging on innovation output.

Figure 8 presents the impact of relational trust and network bridging on innovation output. The figure demonstrates that increasing trust among agents reduces transaction costs and strengthens repeated collaborations, while network bridging enhances connectivity across otherwise disconnected nodes. Together, these relational mechanisms contribute to higher innovation performance, emphasizing the importance of trust and intermediary platforms in the knowledge transfer process.

5.3. Policy Strengthening and Combined Optimization

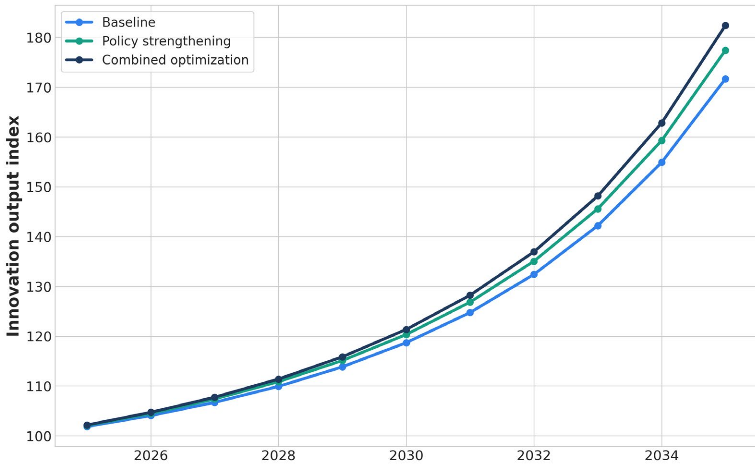
Policy strengthening improves talent accumulation, knowledge stock and innovation output. The mechanism is cumulative: stronger public support improves platforms, attracts talent, lowers collaboration barriers and increases the capacity of agents to absorb and apply knowledge. However, policy support also has limits if it is not connected with spatial and network mechanisms. Funding and services may increase resources, but without effective cross-node linkages they may reinforce existing concentration rather than produce corridor-wide diffusion.

The combined optimization scenario produces the strongest long-term improvement among all scenarios. It simultaneously improves spatial accessibility, strengthens trust, enhances bridging ties and increases policy support. This combined effect is larger than the effect of any single intervention because knowledge transfer is a system process. Accessibility increases contact opportunities, trust improves the quality of exchange, bridging expands the reach of networks and policy support strengthens the institutional environment for absorption and commercialization. The result suggests that high-quality innovation corridor development should rely on coordinated governance rather than isolated policy tools.

The final scenario comparison also shows that spatial fragmentation produces the weakest results and can reduce innovation performance by increasing effective distance, weakening collaboration frequency and limiting cross-node knowledge diffusion. This finding is important because corridor development is vulnerable to institutional segmentation, uneven infrastructure, separated platform systems and weak communication among districts. A corridor may appear continuous on a map, but if actors do not interact effectively, the innovation ecosystem remains fragmented.

Figure 9 compares the effects of policy strengthening alone versus combined optimization across spatial, relational, and institutional dimensions. The figure shows that while policy support improves talent accumulation and knowledge stock, the combined optimization scenario produces the strongest long-term effect, illustrating the synergistic benefits of coordinated interventions across multiple mechanisms.

Table 11 presents a comparative summary of all simulation scenarios in 2035, normalized to 2025 = 100. The table highlights how different interventions—ranging from baseline, spatial proximity enhancement, trust enhancement, network bridging, policy strengthening, to combined optimization—affect key outcome indicators such as knowledge transfer efficiency, network cohesion, knowledge stock, and innovation output. This comparison provides clear evidence of the relative effectiveness of each scenario, illustrating that the combined optimization scenario achieves the highest overall performance and confirming the importance of integrating spatial, relational, and policy mechanisms.



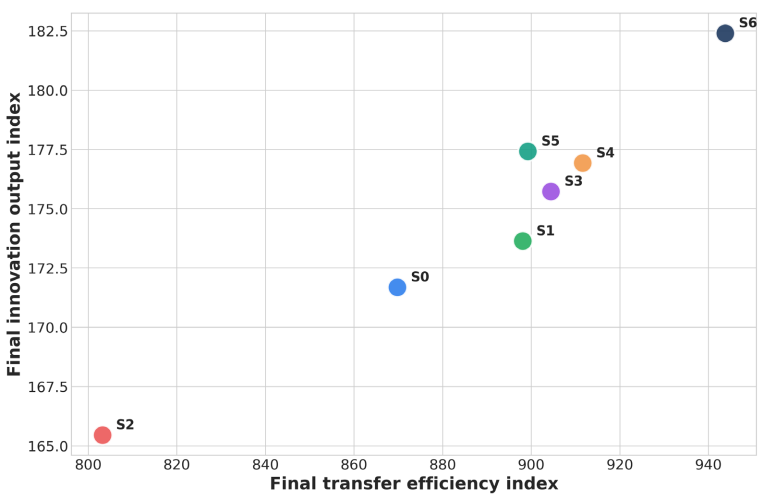
Source: Simulation results.

Figure 9. Effects of policy intervention and combined optimization on innovation output.

Table 11. Final scenario comparison in 2035 (2025 = 100).

Scenario	Transfer efficiency	Network cohesion	Knowledge stock	Innovation output
Baseline (S0)	869.80	111.57	166.11	171.68
Proximity enhancement (S1)	898.10	112.30	167.69	173.63
Spatial fragmentation (S2)	803.26	109.38	162.26	165.45
Trust enhancement (S3)	904.46	113.16	168.05	175.72
Network bridging enhancement (S4)	911.62	113.80	168.45	176.92
Policy strengthening (S5)	899.25	112.76	169.08	177.41
Combined optimization (S6)	943.80	114.84	171.60	182.39

Source: Simulation results.



Source: Simulation results.

Figure 10. Transfer efficiency and innovation output frontier across scenarios.

Figure 10 visualizes the trade-off and frontier between knowledge transfer efficiency and innovation output under all seven scenarios. The figure highlights that the combined optimization scenario (S6) achieves the highest levels in both dimensions, whereas spatial fragmentation (S2) leads to the lowest outcomes. This reinforces the conclusion that systemic coordination among proximity, trust, network bridging, and policy support is essential for maximizing innovation performance.

6. Discussion

The findings have several implications for the theory of spatial innovation ecosystems. First, they show that innovation corridor performance cannot be explained only by the concentration of high-tech firms, laboratories or policy resources. The key issue is whether these resources are connected through effective knowledge transfer chains. A corridor with abundant resources may still underperform if spatial barriers, weak trust, insufficient absorptive capacity or fragmented networks prevent knowledge from flowing across actors and nodes.

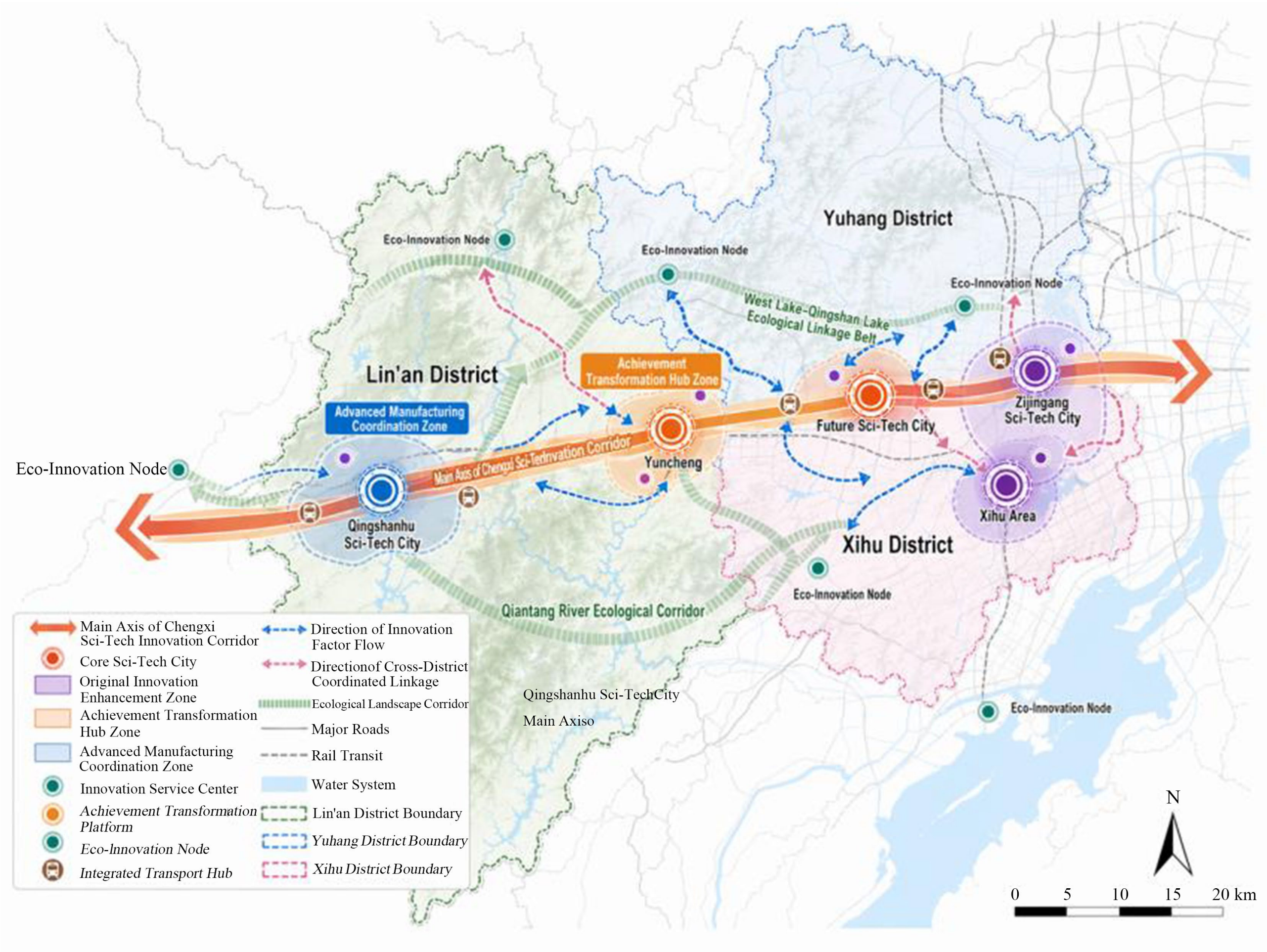
Second, the study clarifies the conditional role of spatial proximity. Proximity increases interaction opportunities and lowers communication costs, but it does not automatically produce innovation output. Knowledge must be absorbed, recombined and commercialized. Therefore, the planning of innovation corridors should move beyond physical connectivity and pay more attention to organizational connectivity, platform connectivity and institutional connectivity. This is especially important for multi-node corridors where different districts perform different innovation functions.

Third, the results support a multi-center and functionally complementary view of the Chengxi corridor. Yuhang is currently the most central digital economy and platform node, but the corridor should not develop into a monocentric system. Xihu's research and university resources, Yuhang's platform and venture ecosystem, and Lin'an's industrial application space can form a stronger knowledge transfer chain if cross-node bridging mechanisms are strengthened. In this sense, balanced development does not mean equalizing all districts, but improving the circulation and conversion of knowledge among differentiated spaces.

Finally, the hybrid ABM-SD approach demonstrates the value of simulation for planning research. Static indicators can describe where resources are located, but they cannot fully explain how knowledge flows, how collaboration networks evolve or how interventions change long-term outcomes. Simulation allows researchers and policymakers to test alternative pathways before implementation and to identify systemic bottlenecks that may not be visible in descriptive analysis.

7. Conclusions and Policy Implications

This article examined knowledge transfer dynamics in the spatial innovation ecosystem of the Chengxi Sci-Tech Innovation Corridor through a hybrid ABM-SD simulation framework. The study found that knowledge transfer is jointly shaped by spatial proximity, actor heterogeneity, absorptive capacity, trust, network structure and policy support. Under the baseline scenario, the corridor already shows strong knowledge circulation capacity, but the growth of knowledge transfer efficiency is faster than the growth of innovation output, indicating that commercialization and industrial transformation remain important bottlenecks.



Source: Author's strategic synthesis based on simulation results.

Figure 11. Spatial optimization strategy and functional enhancement of the Chengxi sci-tech innovation corridor.

The scenario analysis indicates that spatial accessibility, trust enhancement, network bridging and policy strengthening all improve system performance, but their effects differ. Accessibility mainly increases contact opportunities; trust improves collaboration quality; network bridging expands cross-node diffusion; and policy support strengthens talent and platform conditions. The combined optimization scenario produces the strongest long-term effect, confirming that innovation corridor governance should be systemic rather than single-dimensional.

Based on these findings, three policy implications can be proposed. First, the corridor should strengthen multi-node spatial organization and improve cross-node accessibility, especially links among Zijingang Sci-Tech City, Future Sci-

Tech City and Qingshan Lake Sci-Tech City. Second, intermediary platforms, incubators, proof-of-concept centers and technology transfer institutions should be strengthened as bridging actors, so that knowledge can move more effectively between universities, firms and application spaces. Third, policy support should focus not only on resource input but also on commercialization mechanisms, including intellectual-property services, pilot testing, venture financing and industry-university-research coordination.

The study has limitations. Some model parameters are derived from district-level indicators and theoretical assumptions rather than firm-level longitudinal data. Future research can improve calibration by using patent co-application networks, enterprise collaboration data, real transport accessibility measures and longitudinal innovation-output records. Despite these limitations, the article provides a useful simulation-based explanation of how spatial structure, actor interaction and institutional support jointly shape knowledge transfer in innovation corridors.

Figure 11 illustrates a strategic synthesis of spatial optimization and functional enhancement derived from the simulation results. It shows how cross-node accessibility, bridging mechanisms, and coordinated policy measures can improve knowledge flow and innovation output across the corridor, providing a visual roadmap for multi-node governance and spatial planning interventions.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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Appendix: Parameter-Data Mapping and Modeling Assumptions

To improve model transparency, the main simulation parameters were linked to observed corridor-level and district-level indicators where possible. Spatial scale and accessibility assumptions were derived from the official territorial spatial plan of the Chengxi Sci-Tech Innovation Corridor. District-level economic and innovation indicators were used to differentiate initial agent attributes across Xihu, Yuhang, and Lin'an. When direct micro-level data were unavailable, theoretically informed assumptions were adopted and kept consistent across scenarios except for the specific intervention variable being tested.

Table A1 provides a detailed mapping between simulation model parameters, their empirical anchors, and the rules used to convert observed data into model inputs. This mapping ensures transparency and allows readers to understand how district-level economic and innovation indicators were translated into initial conditions for heterogeneous agents. It clarifies the linkage between real-world evidence and simulation assumptions, thereby enhancing model credibility and reproducibility.

Table A1. Mapping between model parameters, empirical sources, and conversion rules.

Model parameter	Empirical anchor/source	Conversion rule
Initial knowledge stock	University resources, innovation platforms, R&D intensity	Higher values assigned to Xihu and research-oriented agents
Absorptive capacity	Digital economy scale, high-tech enterprise concentration	Higher values assigned to Yuhang firms and startups
Commercialization capacity	Industrial structure and application-oriented functions	Higher values assigned to Lin'an manufacturing/application agents
Spatial proximity	Corridor length, node distribution, accessibility assumptions	Effective distance used to adjust interaction probability
Policy support intensity	Government releases, talent and platform support indicators	Used as macro-level SD support variable
Network bridging capability	Intermediary platforms, incubators, proof-of-concept centers	Used to increase cross-node matching probability