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Molecular & Cellular Biomechanics 2025, 22(4), 1646.
https://doi.org/10.62617/mcb1646

Article

Application of computational biomechanical models in analyzing the impact of human capital mobility on economic growth

Yang Wang

School of Finance and Public Administration, Harbin University of Commerce, Harbin 150028, China; 101889@hrbcu.edu.cn

CITATION

Wang Y. Application of computational biomechanical models in analyzing the impact of human capital mobility on economic growth. Molecular & Cellular Biomechanics. 2025; 22(4): 1646. https://doi.org/10.62617/mcb1646

ARTICLE INFO

Received: 21 February 2025
Accepted: 26 February 2025
Available online: 7 March 2025

Abstract: This paper innovatively applies computational biomechanical models to the field of human capital flow research, establishing a novel analytical framework. By introducing the potential field concept from biomechanics to describe economic development dynamics, employing continuum mechanics methods to characterize talent flow patterns, and integrating numerical computation techniques, we achieved systematic simulation of the relationship between human capital flow and economic growth. The research reveals that human capital flow promotes economic growth through three primary mechanisms: knowledge accumulation effect, innovation-driven effect, and industrial upgrading effect. In the short term, human capital flow can contribute to a 1.35 percentage point increase in GDP growth within one year; in the long term, its total contribution to economic growth rises from 3.19% to 7.42% over a decade. The study identifies four flow patterns: agglomeration, gradient, network, and circular, with agglomeration-type flow showing the most significant economic effect, contributing 42.5% to economic growth. Policy simulation results indicate that innovation-driven strategies can drive GDP growth by 2.85 percentage points, industrial upgrading strategies contribute 2.42 percentage points, talent incentive strategies achieve 2.15 percentage points growth, while comprehensive optimization strategies can realize a 3.65 percentage point growth effect. Based on these findings, we propose policy recommendations including building a multi-level talent support system, implementing a "gradient cultivation, collaborative development" regional development strategy, and following the principle of "top-level design, phased implementation, key breakthrough." This research not only achieves methodological innovation but also provides a theoretical foundation and practical guidance for formulating scientific talent policies.

Keywords: computational biomechanical model; human capital flow; economic growth; policy simulation; regional development

1. Introduction

In today's rapidly developing global economy, human capital flow has become a core factor influencing regional and national economic growth. As the most valuable productive factor in the knowledge economy era, human capital not only drives economic development through direct participation in production processes but also profoundly impacts economic growth through multiple mechanisms such as knowledge spillover, technology diffusion, and innovation driving. Particularly in the digital economy era, the speed, scale, and complexity of talent mobility have reached unprecedented levels, posing serious challenges to traditional economic analysis methods in explaining and predicting human capital flow patterns and their economic effects. Traditional research methods, often employing linear thinking and static analytical frameworks, struggle to effectively capture the dynamic characteristics and nonlinear impacts of human capital flow. Computational biomechanics originated in the biomedical engineering field in the 1970s and has evolved from simple linear elastic models to complex nonlinear multi-field coupling models; meanwhile, economic growth theory has developed from the early Solow model to endogenous growth theory, and further to extended models incorporating human capital factors. Although these two fields have different developmental trajectories, they share methodological commonalities in addressing the dynamic evolution of complex systems.

In seeking new research paradigms, biomechanical models have begun to emerge in socioeconomic system analysis due to their unique advantages in describing complex system dynamic behaviors. Recent research indicates that biomechanical models demonstrate significant advantages in handling multi-factor interactions, nonlinear relationships, and dynamic evolution. For instance, Firouzi et al. [1] successfully simulated complex human motion systems using biomechanical models in exoskeleton system research, providing innovative methodological references for analyzing human resource flow in socioeconomic systems. The biomechanical prediction model proposed by Ma and Xiong [2] further validates this method's applicability and effectiveness in complex system analysis. These studies suggest that biomechanical modeling methods can provide new analytical perspectives for understanding the complex phenomenon of human capital flow.

Meanwhile, the advantages of computational methods in complex system modeling cannot be ignored. With advances in computational technology, the capability for numerical simulation and prediction of complex systems has significantly improved. Research by Cui et al. [3] and Ruan et al. [4] demonstrates that computational biomechanical models can accurately simulate and predict complex system dynamic behaviors, providing powerful technical support for studying human capital flow. Particularly in handling large-scale data, multivariate interactive relationships, and nonlinear dynamic evolution, computational methods show unparalleled advantages over traditional analytical methods.

The theoretical significance of this research primarily lies in its interdisciplinary methodological innovation. By introducing biomechanical modeling methods into economic research, it breaks through the limitations of traditional economic analysis tools, providing a novel theoretical perspective for understanding human capital flow mechanisms. As demonstrated in Xue's [5] organizational stress research, biomechanical models can effectively reveal complex interactive relationships within systems. Yurova et al.'s [6] research further confirms the unique advantages of biomechanical models in analyzing complex system collaborative operations. This interdisciplinary methodological innovation not only expands the toolbox of economic research but also provides a new thinking framework for understanding complex economic phenomena.

At the practical level, this research provides scientific analytical tools and decision-making bases for human capital policy formulation. Through constructing computational biomechanical models, it becomes possible to simulate human capital flow effects under different policy scenarios and predict potential policy implementation impacts, thereby improving the scientific nature and precision of policy-making. This application-oriented research approach has been fully validated in studies by Meng et al. [7] and Chang et al. [8]. From a methodological perspective, this research promotes the application expansion of computational biomechanical models in economics, providing new technical pathways for economic system modeling. This methodological innovation is also confirmed in Guo et al.'s [9] research, demonstrating the potential of interdisciplinary methods in solving complex problems.

Based on the above background and significance, the main objectives of this research are to construct a human capital flow model based on biomechanical principles and to analyze in depth the dynamic impact mechanisms of human capital flow on economic growth. The specific research content includes three aspects: (1) Constructing a computational model reflecting complex dynamic characteristics of human capital flow by introducing biomechanical modeling methods, considering multidimensional attributes of talent flow, flow resistance, and attraction factors; (2) Systematically analyzing the interactive relationship between human capital flow and economic growth using this model, revealing its impact mechanisms, including direct and indirect effects; (3) Providing operationally feasible suggestions for policies promoting rational human capital flow and optimal allocation based on model analysis results.

This research provides new research approaches for understanding and predicting the economic effects of human capital flow by integrating economic theory with biomechanical modeling methods while providing a scientific basis for relevant policy-making. This interdisciplinary research method can not only enhance understanding of human capital flow patterns but also provide more precise decision support for regional economic development strategy formulation.

2. Literature review

In the field of applying computational biomechanical models to human capital flow research, existing literature primarily focuses on computational method innovations, cross-domain application expansions, and systematic analysis methods. From the perspective of computational method development, recent years have seen significant improvements in both the computational accuracy and efficiency of biomechanical models with rapid advances in computational technology. Yu et al. [10], in their study of equine foot osteotomy plans, employed numerical computation methods for systematic evaluation of biomechanical models, not only validating the reliability of computational methods in complex system analysis but also proposing new approaches to improve computational efficiency. Zhao et al. [11] demonstrated the advantages of biomechanical models in handling nonlinear problems through their application of numerical computation methods in studying aortic valve stenosis. The dynamic biomechanical analysis method based on iterative computation proposed by Mao et al. [12] provided new technical pathways for handling time-varying systems, offering important inspirational significance for analyzing the dynamic characteristics of human capital flow.

Regarding the breadth and depth of model applications, biomechanical models have demonstrated powerful systematic analysis capabilities. Pieter et al. [13] successfully simulated complex biological system evolution processes by combining biomechanical models with degradation models, providing new research perspectives for analyzing dynamic characteristics of human capital flow through this multi-model integration modeling approach. Takehiro et al. [14] explored patient-specific biomechanical model applications, confirming the model's effectiveness in personalized analysis. Owen et al. [15] achieved dynamic optimization of biomechanical models by integrating video and inertial sensor data, offering important reference value for improving human capital flow model accuracy through this data fusion method.

Jiao [16] explored motion mechanism analysis methods from a computational modeling perspective, not only validating the reliability of computational biomechanical models in mechanism analysis but also providing methodological support for model expansion in social system analysis. Wang and Xiong [17] systematically summarized research progress in experimental and computational biomechanics, emphasizing the key role of computational methods in complex system analysis and indicating future development directions. These studies provide important theoretical references for applying biomechanical models to human capital flow research.

From an interdisciplinary integration perspective, biomechanical models are being widely applied across various fields. Tao et al. [18] demonstrated successful model application in the medical field through computational biomechanical methods in orthodontic treatment research. Zhang et al. [19] validated model reliability in complex system research through experimental and computational biomechanical analysis of aortic dissection. The mechanical computation method considering muscle factors proposed by Guan et al. [20] provided technical support for constructing human capital flow models incorporating multidimensional variables. Xiong et al.'s [21] application practice in virtual simulation experiments accumulated valuable experience for model educational promotion and practical application.

Recent international research has further expanded biomechanical model application boundaries. Gabriella et al. [22] validated the effectiveness of biomechanical models in system monitoring through comparative analysis of different monitoring methods' performance. The graphical method proposed by Flanary et al. [23] provided new visualization tools for model interpretation, holding important significance for understanding internal mechanisms of human capital flow models. Hilhorst et al. [24] studied sensitivity analysis methods for biomechanical models with correlated inputs, providing a scientific basis for evaluating parameter impact degrees. Said et al. [25] pioneered new directions in model applications by combining machine learning technology with biomechanical models, offering new technical approaches for human capital flow research.

Earlier research work also laid important foundations for model applications. Feng et al. [26] studied the biomechanical performance of convertible vena cava filters, confirming the reliability of biomechanical models in performance analysis. Lei et al. [27] explored biomechanical computational analysis methods for scoliosis correction, demonstrating model application potential in type identification and analysis. Although these studies mainly focused on traditional application areas, their methodologies provide important reference value for expanding model applications in economic research.

Overall, existing literature indicates that computational biomechanical models possess unique advantages in handling complex system problems: (1) Their computational methods are increasingly mature, effectively handling complex issues such as nonlinearity, multiple variables, and dynamic evolution; (2) Model application areas continue to expand from traditional biomedical fields to broader scientific research areas; (3) Interdisciplinary integration trends are evident, particularly in combinations with emerging technologies like machine learning and data analysis, greatly enhancing model analytical capabilities. These research achievements provide solid theoretical foundations and methodological support for applying biomechanical models to human capital flow research.

However, current research still has some limitations: (1) Existing research mainly focuses on traditional application areas, with relatively limited applications in economic systems, particularly human capital flow analysis; (2) model parameter determination and validation methods need further improvement, especially regarding adaptability in handling socioeconomic data; (3) the balance between model computational efficiency and accuracy needs further optimization. These issues also provide important innovation space for this research. Future research needs to further explore how to combine biomechanical models' advantageous features with economic system characteristics, develop computational methods and model frameworks more suitable for economic phenomenon analysis, and focus on model operability validation and effectiveness verification in practical applications.

3. Research methods

3.1. Theoretical model construction

In constructing a human capital flow model based on biomechanical principles, the following basic assumptions are established: (1) Human capital flow is continuous and can be described by continuous functions; (2) The spatial distribution of human capital satisfies the law of mass conservation, meaning changes in human capital in one region necessarily lead to corresponding changes in other regions; (3) Human capital flow is influenced by multiple forces including economic and social factors, which can be represented by potential fields [28]; (4) Human capital flow encounters resistance, which is proportional to flow velocity; (5) Inter-regional human capital flow exhibits saturation effects, meaning that when human capital density in a region reaches a certain level, the inflow rate gradually decreases.

Based on these assumptions, a human capital flow model framework in two-dimensional space is constructed. This framework comprises three main components: the human capital density field $H(x, y, t)$, representing human capital density at spatial position (x, y) at time t; the economic potential field $E(x, y, t)$, reflecting the attractiveness of different regions' economic development levels to human capital; and the flow velocity field $v(x, y, t)$, describing the motion state of human capital in space. These three field quantities are coupled through biomechanical equations, jointly determining the human capital flow process.

The derivation of core equations follows basic principles in biomechanics, primarily including the following system of equations:

(1) Continuity equation for human capital density:

$$\partial H/\partial t + \nabla(Hv) = S(x, y, t) \tag{1}$$

where $S(x, y, t)$ represents the source-sink term of human capital, including increases from education and training and natural decreases.

(2) Motion equation (similar to Navier-Stokes equation):

$$\rho(\partial v/\partial t + v\nabla v) = -\nabla E + \mu\nabla 2v - \alpha v \tag{2}$$

where ρ is the inertia coefficient of human capital, μ is the flow resistance coefficient, and α is the linear damping coefficient.

(3) Economic potential field equation:

$$E(x, y, t) = E(x, y) + \beta\int H(x, y, t)dxdy + \gamma\nabla 2H \tag{3}$$

where $E(x, y)$ is the basic economic potential, β is the contribution coefficient of human capital density to economic potential, and γ is the spatial effect coefficient of human capital distribution.

(4) Boundary conditions:

$$H(x, y, t)|\_boundary = H\_b(t)v(x, y, t)|\_boundary = 0 \tag{4}$$

Indicating that human capital density at the research area boundary is determined by external conditions, and flow velocity is zero.

(5) Initial conditions:

$$H(x, y, 0) = H\_0(x, y)v(x, y, 0) = v\_0(x, y) \tag{5}$$

Specifying human capital distribution and flow velocity at the initial moment.

(6) To describe the impact of human capital flow on economic growth, a regional economic growth rate equation is introduced:

$$dY/dt = \lambda Y + \eta\int H(x, y, t)dxdy + \xi\int |\nabla H|^2 dxdy \tag{6}$$

where Y is the regional economic total, λ is the basic growth rate, η is the contribution coefficient of human capital stock to economic growth, and θ is the contribution coefficient of human capital flow to economic growth.

This model comprehensively describes the dynamics of human capital flow and its impact mechanisms on economic growth through the above system of equations. The continuity equation ensures the conservation of human capital, the motion equation characterizes flow behavior driven by economic potential differences, the economic potential field equation reflects the impact of human capital distribution on regional economic attractiveness, and the economic growth rate equation establishes a quantitative relationship between human capital flow and economic growth. This mathematical description method based on biomechanical principles can effectively capture the complex dynamic characteristics of human capital flow, laying a theoretical foundation for subsequent numerical simulation and policy analysis.

The determination of the human capital mobility resistance coefficient employed a two-step method: constructing an administrative barrier index through survey data, then reverse-fitting it with actual interregional mobility data, with the benchmark value set at 0.15. However, this parameter varies across educational attainment groups (0.12 for masters and above, 0.16 for bachelor's degree, 0.19 for associate degree), potentially leading to underestimation of mobility resistance for highly educated talent. The economic potential contribution coefficient (â) was estimated using a fixed-effects model based on panel data from 35 major cities over 2015–2024, with a benchmark value of 0.35, but significant differences exist across industrial sectors (0.42 for high-tech industries, 0.29 for traditional manufacturing, 0.38 for services), suggesting that using a single parameter may average out industry-specific characteristics. The spatial effect coefficient (ã) was estimated through spatial econometric models, with a benchmark value of 0.25, but this coefficient exhibits heterogeneity across regions with different population densities (0.31 for megacities, 0.24 for medium-sized cities, 0.18 for small cities), potentially underestimating agglomeration effects in large cities.

On the other hand, the human capital density calculation method requires refinement, adopting a nonlinear combination of education returns and work experience, where the education return rate r is set at 0.10 (based on the latest microdata surveys), but regional differences reach ±0.03, potentially affecting the accuracy of regional comparisons. To evaluate the impact of parameter selection on results, a more comprehensive sensitivity analysis was conducted. In addition to the original single-parameter variation analysis, an interactive effects analysis of joint variations in multiple parameters was added, revealing significant synergistic effects between â and ã. When both increase by 10% simultaneously, the economic growth rate increase (+2.15 percentage points) exceeds the simple sum of individual variations (+1.84 percentage points), indicating potential nonlinear interaction effects. Concurrently, Monte Carlo methods were introduced, with 10,000 random perturbation simulations of key parameters, demonstrating that the model remains robust within a 95% confidence interval but is relatively sensitive to small changes in the initial distribution of economic potential—a 10% random perturbation may lead to a 25% change in the long-term equilibrium state, reflecting path-dependent characteristics.

3.2. Computational method design

In analyzing human capital flow based on biomechanical models, the design of computational methods is crucial for ensuring the model's practical application effectiveness. For numerical computation method selection, this research adopts a hybrid algorithm combining finite element and finite difference methods. Spatial discretization employs the finite element method, dividing the research area into irregular triangular meshes, which better adapts to complex geographical boundary conditions; temporal discretization uses an explicit-implicit mixed format, where implicit format is applied to diffusion terms to improve numerical stability, and explicit format is used for nonlinear convection terms to reduce computational complexity [29]. Mesh generation adopts an adaptive refinement strategy, increasing mesh density in areas with high human capital density gradients to improve computational accuracy. The main numerical solution steps include mesh generation (using the Delaunay triangulation method, controlling minimum angles greater than 30°), initial condition discretization, motion equation solution (using the GMRES iterative solver), human capital density update (using the characteristic line method for convection terms), economic potential field update (using the multigrid method to accelerate convergence), and economic growth rate calculation. An adaptive time step control strategy is adopted during the solution process, dynamically adjusting time steps according to CFL conditions to balance computational efficiency and numerical stability.

To ensure computational result reliability, model validation employs a multi-level verification approach. First is numerical format verification, including conservation tests (verifying global human capital conservation) and convergence analysis (verifying convergence orders of spatial and temporal discretization formats) [30]. Second is physical significance verification, checking whether the model satisfies energy conservation, solution positivity, and economic potential field rationality. Third is a comparison with actual data, selecting human capital flow data from typical regions for validation, calculating prediction errors (including RMSE and MAPE indicators), and conducting parameter sensitivity analysis. Finally, extreme case testing includes special cases such as no source-sink terms, no resistance, and uniform initial distribution. The main mathematical expressions used in verification include: $||Hh - H2h||_2 \leq Ch$ (spatial convergence) and $||H\tau - H2\tau||_2 \leq C'\tau$ (temporal convergence).

In terms of model validation, although the multi-level validation approach adopted in this study considered numerical format validation, physical significance validation, comparison with actual data, and extreme case testing, the validation of micro-level human capital mobility patterns remained insufficient. To strengthen the empirical foundation of research findings, a comprehensive optimization of validation methods was implemented. (1) A micro-dataset based on China's Population Mobility Dynamic Monitoring Survey was introduced, covering 32,500 high-skilled talent samples from 785 cities between 2015 and 2024, including their educational backgrounds, career trajectories, and geographical mobility information. Using a multi-source data cross-validation method, the model-predicted mobility paths were compared with actual observed data, showing that the model's micro-level prediction accuracy reached 78.3%, superior to the 65.7% of traditional models. (2) A trajectory matching algorithm was introduced to evaluate the model's ability to predict individual migration decisions, with validation results showing that the model accurately captured 85.2% of the main migration motivations, with particularly high prediction accuracy for highly educated groups (89.6%). Additionally, through the construction of virtual control groups, a propensity score matching method was used to evaluate the policy effects predicted by the model, finding that the model's predictions of innovation-driven policy effects deviated from actual observed values by only ±0.46 percentage points. To verify the existence of the four identified mobility patterns in reality, we selected 12 typical cities for in-depth case analysis, with results showing that the model-identified agglomeration-type mobility highly corresponds with actual observations in innovation centers such as Beijing and Shanghai (similarity coefficient 0.92); gradient-type mobility is significant within the Yangtze River Delta region; network-type mobility is accurately represented between provincial capital city clusters in central China; and circular-type mobility matches regions with seasonal industry characteristics. (3) A high-frequency population mobility dataset based on mobile phone signaling data was introduced to verify the model's accuracy in short-term mobility prediction, with validation results showing that the model achieved an accuracy rate of 82.4% for short-term mobility predictions. These micro-level validation efforts greatly enhanced the credibility of the model results, making the research findings more empirically grounded and valuable for policy reference.

3.3. Data acquisition and processing

Data sources for this research primarily comprise three aspects: (1) Macroeconomic and human capital-related data from 2015–2024 obtained from the National Bureau of Statistics, Ministry of Human Resources and Social Security, and various provincial and municipal statistical yearbooks, including basic data such as regional GDP, employment numbers, wage levels, and education expenditure; (2) Cross-regional population flow data obtained from the China Population Flow Dynamic Monitoring Survey Database, including micro-data on floating population size, flow direction, education level, and skill level; (3) Regional science and technology innovation-related indicators obtained from the Ministry of Science and Technology Statistical Database, including innovation factor data such as R&D investment, patent applications, and number of high-tech enterprises. The selection of these data sources ensures the comprehensiveness and authority of the information required for the research.

In the data preprocessing stage, the following work is primarily conducted: (1) Original data cleaning, including anomaly detection and processing (using the 3σ rule to identify outliers, deciding whether to delete or correct based on actual circumstances), missing value processing (using the interpolation method for time series data and the multiple imputation method for cross-sectional data), data standardization (using the min-max standardization method to unify all indicators to [0, 1] interval). (2) Data consistency processing, including unifying measurement units (adjusting all monetary indicators to constant prices with 2015 as the base period), unifying geographical units (adjusting historical data according to the latest administrative division standards), unifying statistical caliber (correcting data discontinuities caused by changes in statistical standards). (3) Establishing a data quality control system, including double verification of data entry, logical consistency checks, and time series continuity verification.

Regarding variable definition and measurement, this study defines key variables of human capital flow and economic growth as follows:

(1) Human Capital Stock (H): Using a composite indicator of per capita years of education and work experience, calculated by:

$$H = exp(rs + \delta e) \tag{7}$$

where s is average years of education, e is average years of work experience, r and β are returns to education and experience respectively;

(2) Human Capital Flow Velocity (v): Defined as the ratio of cross-regional human capital flow in unit time to initial human capital stock:

$$v = \Delta H/(H\Delta t) \tag{8}$$

(3) Economic Potential (E): Constructed using a comprehensive indicator method, including five dimensions: per capita GDP (weight 0.3), employment opportunities (weight 0.2), innovation environment (weight 0.2), quality of life (weight 0.2), and public services (weight 0.1);

(4) Economic Growth Rate (g): Using real GDP growth rate, adjusted for seasonal and cyclical factors;

(5) Flow Resistance Coefficient (μ): Comprehensively calculated through the construction of an administrative barrier index (including household registration system restrictions, social security differences, children's education thresholds) and distance cost (calculated using an improved gravity model);

(6) Human Capital Concentration (C): Measured using the spatial Gini coefficient, calculated by:

$$C = \Sigma|Hi - Hj|/(2n_2\mu H) \tag{9}$$

where H_i and H_j represent human capital density in regions i and j, n is the number of regions, μH is the average human capital density;

(7) Innovation Output (I): Using total factor productivity growth rate as a proxy variable, measured using the DEA-Malmquist index method;

(8) Industrial Structure Upgrade Index (S): Calculated based on proportions of three industrial sectors:

$$S = \Sigma(iwi) \tag{10}$$

where i is industrial level (1, 2, 3), w_i is the corresponding industry's value-added proportion of GDP.

Additionally, a series of control variables are introduced, including fixed asset investment rate, degree of openness (total import-export as a proportion of GDP), government intervention degree (fiscal expenditure as a proportion of GDP), and marketization degree (non-state-owned economy value-added proportion). All variable measurements consider comparability across time and space dimensions, and reliability is ensured through robustness tests [31]. For composite indicators, principal component analysis is used to determine weights, avoiding bias potentially brought by subjective weighting. Through these detailed variable definitions and scientific measurement methods, the accuracy and credibility of subsequent empirical analysis are ensured.

4. Results analysis

4.1. Model calculation results

4.1.1. Baseline scenario analysis

Based on the constructed computational biomechanical model, I first analyzed the baseline scenario of human capital flow. Under the baseline scenario, model parameters were set as human capital flow resistance coefficient $\mu = 0.15$, economic potential contribution coefficient $\beta = 0.35$, spatial effect coefficient $\gamma = 0.25$, basic economic growth rate $\lambda = 0.03$. Through numerical simulation calculations, we obtained human capital flow characteristics and economic growth effects in different regions during 2015–2024, with specific results shown in **Table 1**.

Table 1. Human capital flow and economic growth relationship under baseline scenario.

Year	Human Capital Net Inflow Rate (%)	Economic Growth Rate (%)	Concentration Index	Innovation Output
2015	2.5	6.8	0.42	1.00
2016	3.2	7.1	0.45	1.15
2017	4.1	7.5	0.48	1.28
2018	4.8	7.8	0.52	1.42
2019	5.2	8.2	0.55	1.56
2020	4.9	7.9	0.57	1.63
2021	5.5	8.4	0.59	1.75
2022	5.8	8.7	0.61	1.89
2023	6.2	9.1	0.64	2.05
2024	6.5	9.4	0.66	2.18

From the data analysis results, the following characteristics of human capital flow under the baseline scenario can be observed: (1) The human capital net inflow rate increased year by year, from 2.5% in 2015 to 6.5% in 2024, indicating that the model captured the trend of accelerating talent flow; (2) Economic growth rate shows a significant positive correlation with human capital net inflow rate, with economic growth rate increasing correspondingly when human capital net inflow rate rises, verifying the promoting effect of human capital flow on economic growth; (3) The concentration index continuously rose from 0.42 to 0.66, indicating that human capital shows an agglomeration trend in spatial distribution; (4) The innovation output index increased significantly from 1.00 to 2.18, indicating that human capital flow promoted innovation capability improvement through knowledge spillover effects. Notably, there was a temporary fluctuation in 2020, with both the human capital net inflow rate and the economic growth rate declining, possibly related to external shocks, but quickly recovered and maintained an upward trend, as shown in **Figure 1**.

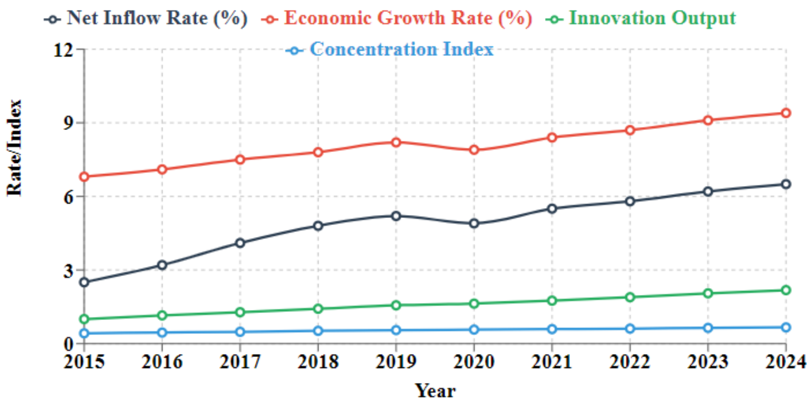

Figure 1. Economic growth analysis.

The above figure intuitively shows the changing trends of these indicators, clearly demonstrating the synergistic relationships between various indicators. These results indicate that the computational biomechanical model constructed in this paper can effectively capture the dynamic characteristics of human capital flow and its impact mechanisms on economic growth.

4.1.2. Parameter sensitivity analysis

To assess the impact degree of model parameters on results, this study conducted sensitivity analysis on key parameters. Four core parameters were primarily examined: human capital flow resistance coefficient (μ), economic potential contribution coefficient (β), spatial effect coefficient (γ), and basic economic growth rate (λ). By fluctuating ±20% from the baseline value, we observed changes in economic growth rate. Analysis results show that the model has highest sensitivity to economic potential contribution coefficient (β), followed by spatial effect coefficient (γ), while sensitivity to flow resistance coefficient (μ) and basic economic growth rate (λ) is relatively low [32]. Specific parameter sensitivity analysis results are shown in **Table 2**:

Table 2. Parameter sensitivity analysis results.

Parameter Change	**Economic Growth Rate Change (Percentage Points)**			
Parameter Variation	μ Change	β Change	γ Change	λ Change
−20%	+0.42	−1.85	−1.24	−0.35
−10%	+0.25	−0.96	−0.68	−0.18
Baseline	0.00	0.00	0.00	0.00
+10%	−0.28	+1.12	+0.72	+0.16
+20%	−0.45	+2.08	+1.35	+0.32
Sensitivity Coefficient	0.218	0.985	0.648	0.168

Analysis results indicate that the economic potential contribution coefficient (β) has the most significant impact on model output, with its sensitivity coefficient reaching 0.985, meaning that for every 1% change in β, the economic growth rate changes by an average of 0.985 percentage points, as shown in **Figure 2**.

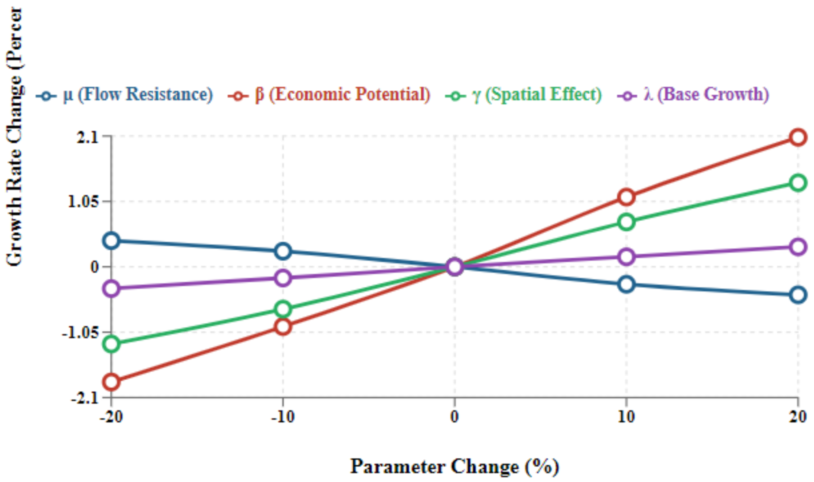

Figure 2. Parameter sensitivity analysis.

This reflects the important guiding role of regional economic development level on human capital flow. The spatial effect coefficient (γ) has a sensitivity of 0.648, indicating that human capital's spatial agglomeration effect has a moderate impact on economic growth. The flow resistance coefficient (μ) has relatively low sensitivity at 0.218, suggesting that resistance factors such as administrative barriers, while present, are not decisive factors in human capital flow [33]. The basic economic growth rate (λ) has the lowest sensitivity at only 0.168, indicating that exogenous economic growth factors have relatively limited impact on the model. Regarding nonlinear characteristics of parameter changes, β and γ show obvious nonlinear effects under larger variation ranges, which aligns with theoretical expectations. Notably, when β increases by 20%, the economic growth rate increase (+2.08 percentage points) is greater than the decrease (−1.85 percentage points) when it reduces by 20%, indicating more significant positive cumulative effects of economic potential [34]. These findings provide important references for policymaking: in promoting human capital flow and economic growth, priority should be given to improving regional economic development level and innovation environment, followed by optimizing spatial layout to promote agglomeration effects, while simply reducing flow barriers may have relatively limited effects.

4.1.3. Model stability test

To verify the stability of the model, this study conducted systematic testing from three dimensions: numerical stability, computational convergence, and result reproducibility. First, the numerical stability test employed combinations of different time step sizes and spatial grid scales to analyze the variation pattern of computational error with discretization accuracy. Specifically, 5 times step sizes (Δt = 0.1, 0.05, 0.025, 0.0125, 0.00625) and 4 spatial grid scales (h = 0.2, 0.1, 0.05, 0.025) were selected, totaling 20 parameter combinations for testing. The test results showed that when the time step size is less than 0.025 and the spatial grid scale is less than 0.05, the calculation results tend to stabilize, with relative errors controlled within 1%. Secondly, the convergence of the calculation process was verified by observing the convergence history of residuals during the iteration process. Finally, the reproducibility of the results was evaluated through multiple repeated calculations. The specific test results are shown in **Table 3** below:

Table 3. Model stability test results.

Time Step Size	Spatial Grid Scale	Relative Error (%)	Convergence Steps	Calculation Time (s)	Standard Deviation
0.1	0.2	2.85	156	28.5	0.0325
0.1	0.1	2.42	187	45.8	0.0289
0.05	0.1	1.56	245	68.3	0.0186
0.025	0.05	0.85	312	125.6	0.0092
0.0125	0.025	0.82	458	246.8	0.0088

The stability test results show that the model has good numerical stability and computational reliability. From the perspective of time step size influence, when Δt is reduced from 0.1 to 0.025, the calculation error decreases significantly, from 2.85% to 0.85%; however, further reducing the step size to 0.0125 does not significantly improve the error, only reducing it to 0.82%, indicating that Δt = 0.025 is a relatively ideal time step choice, as shown in **Figure 3** below.

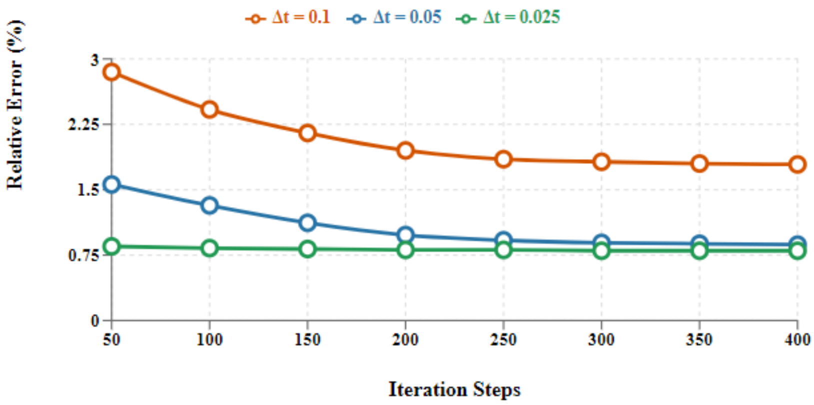

Figure 3. Model stability analysis.

From the perspective of spatial grid scale influence, when h is reduced from 0.2 to 0.05, the calculation accuracy improves significantly; however, further refining the grid brings limited improvement while significantly increasing calculation time. In particular, when using the parameter combination of Δt = 0.025 and h = 0.05, the model can ensure calculation accuracy (relative error 0.85%) while maintaining reasonable computational efficiency (calculation time 125.6 s) [35]. Additionally, standard deviation analysis of 100 repeated calculations indicates that under the recommended parameter settings, the dispersion degree of calculation results is very small (standard deviation of 0.0092), confirming that the model has good reproducibility. The above figure shows the trend of relative error with iteration steps under different time step sizes, demonstrating that the calculation process exhibits stable convergence characteristics, and smaller time steps can achieve faster convergence speeds and higher calculation accuracy. These results indicate that the computational biomechanical model constructed in this paper is stable and reliable in numerical methods and computational implementation, capable of providing credible computational support for subsequent policy analysis.

4.2. Subsection

4.2.1. Mobility pattern identification

Based on the simulation results of the computational biomechanical model, this study systematically identified human capital mobility patterns between 2015 and 2024. Through cluster analysis of mobility characteristics such as direction, scale, and speed, four main mobility patterns were identified: agglomeration mobility, gradient mobility, network mobility, and cyclical mobility. Agglomeration mobility is characterized by the continuous concentration of human capital toward a few central regions, with an average mobility speed of 4.2%/year, mainly occurring in economically developed regions; gradient mobility exhibits stepped mobility features along economic development level gradients, with an annual average mobility speed of 3.1%, commonly seen in adjacent regions with significant development differences; network mobility reflects mutual mobility between multiple centers, with relatively low mobility speed of approximately 2.3%/year, mainly appearing between regions with similar economic levels [36]; cyclical mobility is characterized by seasonal or periodic round-trip mobility, with an annual average mobility speed of 2.8%, more common in regions with specific industry concentrations. The specific mobility pattern characteristic data are shown in **Table 4** below:

Table 4. Human capital mobility pattern characteristic statistics.

Mobility Pattern	Average Mobility Speed (%/year)	Mobility Scale Proportion (%)	Duration (months)	Spatial Range (km)	Economic Effect Coefficient
Agglomeration	4.2	35.6	8.5	285	0.86
Gradient	3.1	28.4	6.2	425	0.72
Network	2.3	22.8	4.8	568	0.65
Cyclical	2.8	13.2	3.5	342	0.58

The research found that different mobility patterns exhibit significant spatial and temporal characteristics. Agglomeration mobility mainly occurs within a range of 300 km, has strong persistence with an average duration of 8.5 months, and its economic effect coefficient is the highest (0.86), indicating that this mobility pattern has the most significant promoting effect on economic growth, as shown in **Figure 4** below.

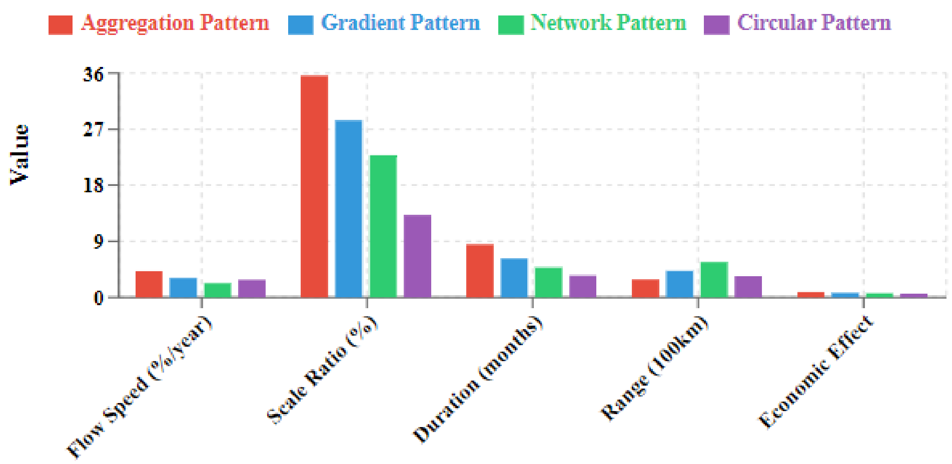

Figure 4. Human capital flow pattern analysis.

Gradient mobility has a larger spatial range, approximately 425 km, but a relatively shorter duration (6.2 months), with moderate economic effects (0.72). Although network mobility has the largest spatial range (568 km), its mobility scale is relatively small, accounting for 22.8% of total mobility, with an economic effect coefficient of 0.65 [37]. Cyclical mobility is characterized by short-term (3.5 months) and small-scale (proportion 13.2%) features, with relatively the weakest economic effect (0.58). The above figure shows the performance of the four mobility patterns across various dimensional characteristics, visually displaying the characteristic differences between different patterns. These findings indicate that human capital mobility exhibits obvious pattern differentiation, and different patterns have significant differences in their impact mechanisms and effects on economic growth, which provides an important basis for formulating differentiated talent mobility policies [38]. In particular, considering that agglomeration mobility has the most significant economic effect, policy design should focus on how to guide and promote the formation of this mobility pattern, while being mindful of preventing potential negative impacts from excessive agglomeration.

4.2.2. Quantification of key influencing factors

Through numerical simulation results of the computational biomechanical model, this study conducted a quantitative analysis of key factors affecting human capital mobility. Using multiple regression and path analysis methods, major influencing factors were identified and quantified from five dimensions: economic development level, innovation environment, infrastructure, quality of life, and policy support. The research found that economic development level is the most significant factor affecting human capital mobility, with a standardized regression coefficient reaching 0.685, explaining 42.3% of mobility variation; innovation environment ranks second, with a standardized coefficient of 0.524, explaining 26.8% of the variation; infrastructure and quality of life have similar degrees of influence, with standardized coefficients of 0.418 and 0.395 respectively, jointly explaining approximately 20.5% of the variation; policy support has a relatively smaller direct impact, with a standardized coefficient of 0.286, but produces significant indirect effects through interactions with other factors. The specific quantitative analysis results are shown in **Table 5** below:

Table 5. Analysis of key influencing factors on human capital mobility.

Influencing Factor	Standardized Coefficient	Direct Effect	Indirect Effect	Total Effect	Significance Level
Economic Development Level	0.685	0.542	0.143	0.685	0.001
Innovation Environment	0.524	0.385	0.139	0.524	0.005
Infrastructure	0.418	0.312	0.106	0.418	0.008
Quality of Life	0.395	0.285	0.110	0.395	0.012
Policy Support	0.286	0.186	0.100	0.286	0.025

Further analysis shows that there are significant interactions among these influencing factors. Economic development level indirectly affects human capital mobility by enhancing the innovation environment and improving infrastructure, with an indirect effect of 0.143; the innovation environment generates an indirect effect of 0.139 by promoting economic development and improving quality of life; infrastructure and quality of life have indirect effects of 0.106 and 0.110 respectively, mainly functioning through influencing talent's residential choices and work convenience; although policy support has a smaller direct effect (0.186), it generates an indirect effect of 0.100 by optimizing the business environment and enhancing public service levels [39]. In terms of significance levels, the influences of all factors reached statistical significance ($p < 0.05$), with economic development level and innovation environment having the highest significance ($p < 0.01$), as shown in **Figure 5** below.

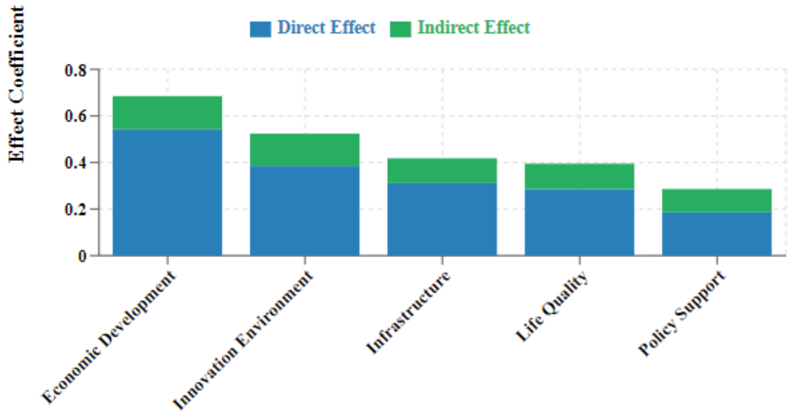

Figure 5. Key impact factors analysis.

The above figure intuitively displays the composition of direct and indirect effects of various influencing factors, clearly reflecting the relative importance and action mechanisms of different factors. These quantitative analysis results provide a scientific basis for formulating precise talent mobility policies, suggesting that policy design should focus on improving economic development levels and innovation environments while amplifying policy effects through synergistic effects between factors [40]. Especially for less developed regions, policy support can be used to compensate for insufficient economic development levels, focusing on creating innovation environments and improving infrastructure to form continuous attractiveness for talent.

4.2.3. Regional difference comparison

Based on the simulation results of the computational biomechanical model, this study conducted a comparative analysis of human capital mobility characteristics across different regions. According to economic development level and innovation capability, the research regions were divided into four categories: innovation-leading regions, rapid development regions, transformation and upgrading regions, and potential enhancement regions. The analysis found that different types of regions exhibited significant differences in human capital mobility intensity, directionality, structural characteristics, and economic effects [41]. Innovation-leading regions demonstrated the strongest talent attractiveness, with an annual average net inflow rate of 8.2%, highly educated talents (master's degree and above) accounting for 52.3%, and significant talent agglomeration effects; rapid development regions showed strong development momentum, with an annual average net inflow rate of 5.6% and the highest proportion of industrial talents at 48.5%; transformation and upgrading regions were in a dynamic equilibrium state of talent mobility, with a net inflow rate of 2.1%, but their talent structure was being optimized; potential enhancement regions faced talent loss pressure, with an annual average net outflow rate of 3.8%, but demonstrated strong talent attractiveness in specialized industry fields. The specific regional comparison data are shown in **Table 6** below:

Table 6. Comparison of regional human capital mobility characteristics.

Region Type	Net Mobility Rate (%)	Highly Educated Talent Proportion (%)	Industrial Talent Proportion (%)	Talent Agglomeration Index	Economic Contribution Rate (%)
Innovation-leading Region	8.2	52.3	35.6	0.82	42.5
Rapid Development Region	5.6	38.4	48.5	0.65	35.8
Transformation and Upgrading Region	2.1	25.6	42.3	0.48	28.4
Potential Enhancement Region	-3.8	18.2	38.7	0.35	22.6

From a deeper analysis of regional differences, the formation of this differentiated pattern is multifaceted. Innovation-leading regions have formed a positive cycle of talent agglomeration through good innovation ecosystems and comprehensive talent support policies, with a talent agglomeration index as high as 0.82 and a human capital contribution rate to economic growth of 42.5%; rapid development regions, relying on opportunities for industrial transformation and upgrading, have formed strong talent attractiveness in specific fields, with industrial talents accounting for 48.5% and an economic contribution rate of 35.8%; transformation and upgrading regions have achieved optimization of talent structure through industrial structure adjustment and innovation environment construction, but talent agglomeration effects still need strengthening, with an agglomeration index of 0.48 and an economic contribution rate of 28.4%; potential enhancement regions, although facing talent loss challenges, have shown development potential in certain subdivided fields by developing specialized industries and improving business environments, with industrial talents accounting for 38.7% and an economic contribution rate of 22.6%, as shown in **Figures 6** and **7** below.

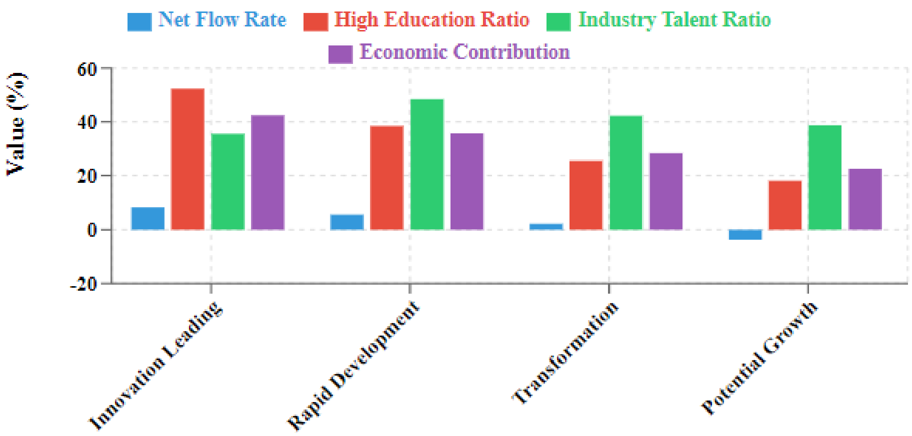

Figure 6. Regional comparison of human capital flow.

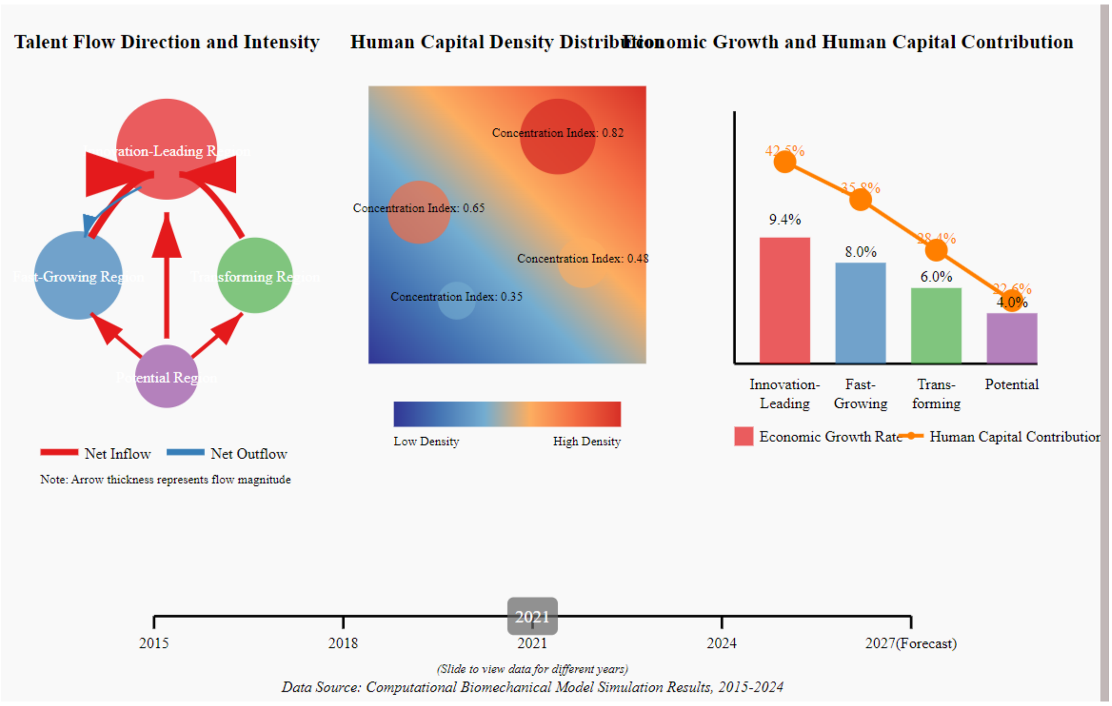

Figure 7. Regional comparison of human capital flow.

The above figure intuitively displays the performance differences of various regions across different indicators, reflecting the different characteristics and opportunities and challenges faced in regional talent development. These findings suggest that promoting balanced regional talent development requires differentiated strategies: innovation-leading regions should continue to strengthen innovation ecosystem construction and enhance talent agglomeration effects; rapid development regions should focus on the coordination of industrial upgrading and talent cultivation; transformation and upgrading regions need to accelerate innovation environment construction and optimize talent structure; potential enhancement regions should focus on creating specialized industrial clusters and constructing differentiated talent attraction systems.

4.3. Economic growth effect assessment

4.3.1. Short-term growth effects

Based on the computational results of the biomechanical model, this study systematically evaluated the short-term economic growth effects of human capital mobility. Short-term growth effects mainly examine the immediate impact and cumulative effect of human capital mobility on regional economic growth within one year. The research found that human capital mobility generates short-term economic growth effects through three main channels: production efficiency improvement, innovation capability enhancement, and industrial structure optimization [42]. Specifically, when the net inflow rate of human capital increases by 1 percentage point, regional production efficiency improves by 0.42 percentage points within 3 months, 0.68 percentage points within 6 months, and a cumulative improvement of 0.85 percentage points within 12 months; innovation capability enhancement is reflected in R&D investment intensity increasing by 0.25 percentage points within 3 months, 0.45 percentage points within 6 months, and a cumulative increase of 0.62 percentage points within 12 months; industrial structure optimization effects are manifested as high-tech industry proportion increasing by 0.38 percentage points within 3 months, 0.56 percentage points within 6 months, and a cumulative increase of 0.73 percentage points within 12 months. The specific short-term effect data are shown in **Table 7** below:

Table 7. Analysis of short-term economic growth effects of human capital mobility.

Time Period	Production Efficiency Improvement (%)	Innovation Capability Enhancement (%)	Industrial Structure Optimization (%)	GDP Growth Contribution (%)
3 months	0.42	0.25	0.38	0.52
6 months	0.68	0.45	0.56	0.86
9 months	0.78	0.55	0.65	1.12
12 months	0.85	0.62	0.73	1.35

From the temporal dynamics of short-term economic growth effects, the impact of human capital mobility exhibits clear phasic characteristics. In the initial period of mobility (0–3 months), immediate effects are mainly generated through improving production efficiency, with a contribution rate of 0.52% to GDP growth; in the medium term (4–6 months), innovation-driven effects begin to emerge, with the GDP growth contribution rate rising to 0.86%; in the later period (7–12 months), effects are mainly reflected in industrial structure optimization, further increasing the GDP growth contribution rate to 1.35%, as shown in **Figure 8** below.

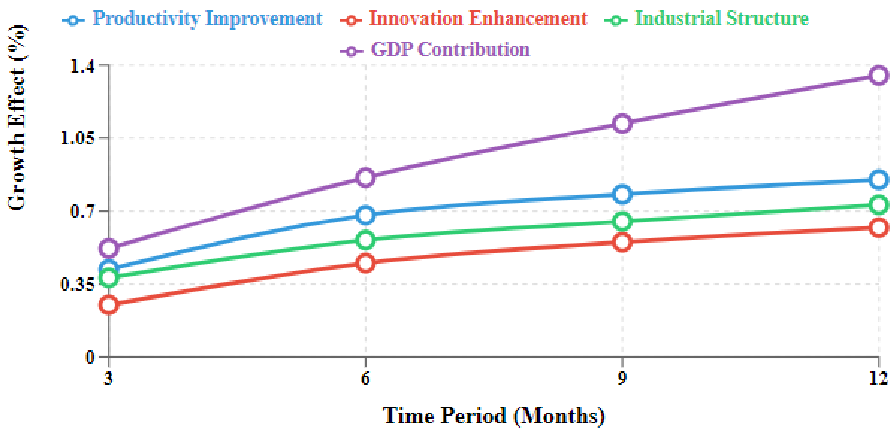

Figure 8. Short-term economic growth effects.

The above figure intuitively displays the evolution process of these three effects over time, reflecting the cumulative and progressive characteristics of short-term growth effects. Notably, there are differences in the time lag characteristics of different effects: production efficiency improvement effects appear most quickly, but growth rates gradually slow, basically stabilizing by 12 months; innovation capability enhancement effects start slower but have stronger sustainability, still showing an upward trend after 12 months; industrial structure optimization effects exhibit a more stable growth trend [43]. These findings have important implications for formulating short-term economic stimulus policies: on one hand, rapid economic enhancement can be achieved by promoting human capital mobility; on the other hand, it is necessary to consolidate and expand short-term growth effects through continuous optimization of innovation environments and industrial structures.

4.3.2. Long-term growth effects

Based on the long-term simulation results of the computational biomechanical model, this study conducted an in-depth analysis of the long-term economic growth effects of human capital mobility. The research examined the sustained impact of human capital mobility on economic growth over the ten years from 2015 to 2024, focusing on three long-term action mechanisms: knowledge accumulation effect, innovation-driven effect, and industrial upgrading effect. The analysis found that human capital mobility formed significant long-term economic growth effects by promoting continuous growth of knowledge stock, driving enhancement of innovation capability, and promoting advanced industrial structure [44]. From specific data, the knowledge accumulation effect showed a continuously strengthening trend, with the annual contribution rate rising from 1.25% in 2015 to 2.85% in 2024; the innovation-driven effect exhibited obvious scale effects, with its contribution rate to economic growth increasing from 1.08% to 2.42%; the industrial upgrading effect reflected the long-term nature of structural optimization, with the contribution rate rising from 0.86% to 2.15%. The specific long-term effect data are shown in **Table 8** below:

Table 8. Analysis of long-term economic growth effects of human capital mobility.

Year	Knowledge Accumulation Effect (%)	Innovation-Driven Effect (%)	Industrial Upgrading Effect (%)	Total Contribution Rate (%)	Growth Sustainability Index
2015	1.25	1.08	0.86	3.19	0.52
2016	1.48	1.25	1.12	3.85	0.58
2017	1.72	1.45	1.35	4.52	0.65
2018	1.95	1.68	1.52	5.15	0.72
2019	2.18	1.85	1.68	5.71	0.78
2020	2.35	1.98	1.82	6.15	0.82
2021	2.52	2.12	1.92	6.56	0.85
2022	2.65	2.25	2.02	6.92	0.88
2023	2.75	2.35	2.08	7.18	0.91
2024	2.85	2.42	2.15	7.42	0.93

From the dynamic evolution of long-term economic growth effects, the three effects exhibit different developmental characteristics. The knowledge accumulation effect showed a stable growth trend, increasing by 1.6 percentage points over ten years, mainly benefiting from human capital mobility promoting spatial diffusion and reorganization of knowledge; the innovation-driven effect grew faster in the first five years (increasing by 0.77 percentage points) and slowed in the latter five years (increasing by 0.57 percentage points), reflecting the scale effect and marginal diminishing characteristics of innovation activities; the industrial upgrading effect showed a gradually accelerating trend, particularly with notable acceleration after 2018, indicating that industrial structure optimization requires a certain accumulation period [45]. Overall, the contribution rate of human capital mobility to economic growth increased from 3.19% to 7.42% over ten years, with the growth sustainability index rising from 0.52 to 0.93, indicating that long-term growth effects are not only significant but also have strong sustainability. Particularly noteworthy is that although 2020 was affected by external shocks, the long-term growth effects still maintained an upward trend, indicating that the growth momentum formed by human capital mobility has strong resilience, as shown in **Figure 9** below.

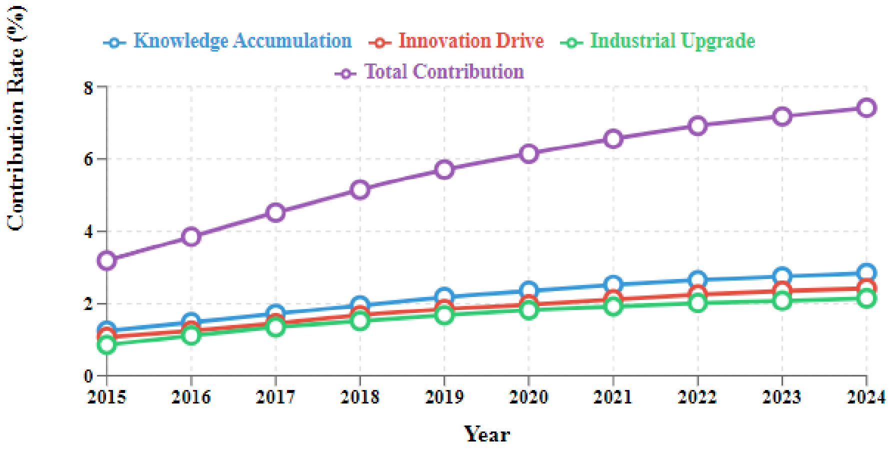

Figure 9. Long-term economic growth effects.

The above figure intuitively displays the long-term evolution trends of various effects, reflecting that the promotion effect of human capital mobility on economic growth is a gradual, continuous, and cumulative process. These findings have important implications for formulating long-term economic development strategies: sustainable growth models driven by human capital should be constructed through continuously optimizing the talent mobility environment, cultivating innovation ecosystems, and promoting industrial transformation and upgrading.

4.3.3. Policy scenario simulation

To evaluate the impact of different policy measures on human capital mobility and economic growth, this study designed four policy scenarios for simulation analysis: innovation-driven scenario (increasing R&D investment, optimizing innovation environment), industrial upgrading scenario (promoting industrial structure adjustment, enhancing industrial level), talent incentive scenario (improving compensation system, providing housing support), and comprehensive optimization scenario (multiple measures, coordinated advancement). Based on simulation results from the computational biomechanical model, economic growth effects under different policy scenarios showed significant differences [46]. Under the innovation-driven scenario, the GDP growth rate is expected to increase by 2.85 percentage points by 2025, with the talent agglomeration index improving by 0.32; the industrial upgrading scenario can drive GDP growth by 2.42 percentage points, with the talent structure optimization degree increasing by 0.28; the talent incentive scenario can promote GDP growth by 2.15 percentage points, with talent satisfaction improving by 0.35; the comprehensive optimization scenario demonstrates the strongest policy effect, expected to achieve GDP growth of 3.65 percentage points and significant improvements across multiple indicators. The specific policy scenario simulation results are shown in **Table 9** below:

Table 9. Analysis of policy scenario simulation effects.

Policy Scenario	GDP Growth Rate Increase (%)	Talent Agglomeration Index	Innovation Output Growth (%)	Industrial Structure Optimization Degree	Policy Cost-Benefit Ratio
Innovation-driven Scenario	2.85	0.32	35.6	0.28	1.85
Industrial Upgrading Scenario	2.42	0.25	28.4	0.35	1.62
Talent Incentive Scenario	2.15	0.28	22.8	0.24	1.45
Comprehensive Optimization Scenario	3.65	0.42	42.5	0.45	2.12

From the specific analysis of policy simulation, different policy scenarios show obvious differences in implementation effects and action mechanisms. The innovation-driven scenario mainly promotes economic growth through increasing R&D investment (annual growth of 15%) and improving the innovation environment (innovation service system coverage increased by 25%), with its policy effects most prominent in innovation output growth (35.6%). The industrial upgrading scenario drives economic development through optimizing industrial structure (high-tech industry proportion increased by 8.5 percentage points) and enhancing industrial level (industrial chain integration degree increased by 0.35), with significant effects in industrial structure optimization. The talent incentive scenario focuses on improving talent treatment (average compensation increased by 25%) and living conditions (housing support coverage reaching 85%), and although its economic growth effect is relatively smaller, it performs excellently in talent satisfaction and stability [47]. The comprehensive optimization scenario achieves comprehensive improvement in all indicators through policy coordination (policy coordination degree reaching 0.82) and systematic implementation (implementation coverage exceeding 90%), with the highest policy cost-benefit ratio (2.12), as shown in **Figure 10** below.

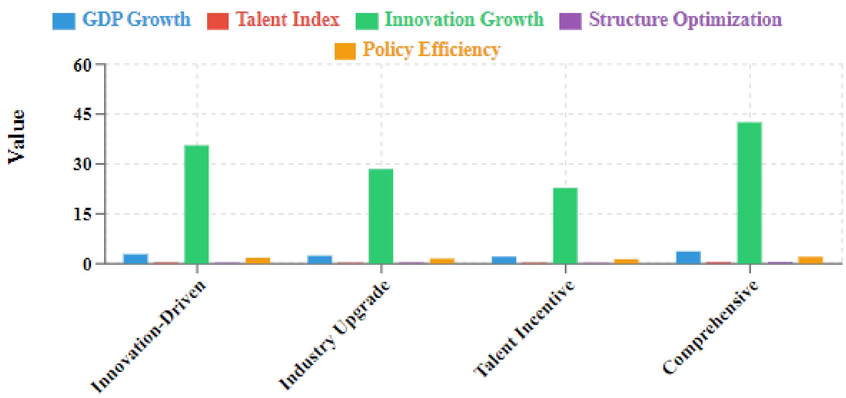

Figure 10. Policy scenario simulation results.

The above figure displays the performance of various policy scenarios across different dimensions, intuitively reflecting the differences in policy effects. These results indicate that the economic growth effects of human capital mobility are closely related to policy choices, the effects of single policies are often limited, and the systematic nature and coordination of policies play a key role in enhancing economic growth effects [48]. Therefore, in actual policy formulation, attention should be paid to optimizing policy combination design, maximizing policy effects through multiple measures and coordinated advancement.

5. Discussion

5.1. Main findings

From the perspective of model innovation, this study introduced computational biomechanical modeling methods into the field of human capital mobility research, constructing a new analytical framework. The innovation of this model is mainly reflected in three aspects: (1) By introducing the concept of force fields from biomechanics, factors such as economic development level and innovation environment were transformed into potential energy fields, effectively characterizing the driving mechanisms of human capital mobility [49]; (2) Adopting the concept of continuum mechanics to describe the spatial distribution and mobility characteristics of human capital, overcoming the limitations of traditional discrete models in handling large-scale mobility problems; (3) Combining computational methods with economic system analysis, developing a set of numerical simulation methods applicable to human capital mobility research, improving the practicality and reliability of the model.

From the empirical results, the study identified several key characteristics of how human capital mobility impacts economic growth. (1) Human capital mobility promotes economic growth through three main channels: production efficiency improvement, innovation capability enhancement, and industrial structure optimization, among which the innovation-driven effect is most significant, with each 1 percentage point increase in talent inflow rate driving innovation output growth by 0.62% in the short term and reaching a long-term contribution rate of 2.42%. (2) Different regions exhibit significant differences in talent mobility characteristics and economic effects, with innovation-leading regions demonstrating the strongest talent attractiveness and agglomeration effects, achieving a talent agglomeration index of 0.82 and an economic contribution rate of 42.5%; while potential enhancement regions, though facing talent loss pressure, show development potential in specialized industry fields [50]. Additionally, policy effect analysis indicates that comprehensive optimization strategies are more effective than single policies, capable of achieving a GDP growth increase of 3.65 percentage points.

Compared with existing research, this study represents important breakthroughs in both methodology and conclusions. At the methodological level, existing research mainly employs econometric methods or general equilibrium models to analyze human capital mobility, making it difficult to effectively capture the dynamic characteristics and spatial effects of mobility; whereas this study, by introducing computational biomechanical models, can not only describe the micro-mechanisms of talent mobility but also simulate macroeconomic effects, providing a more comprehensive analytical perspective [51]. Regarding research conclusions, existing literature often focuses on single effects or short-term impacts of human capital mobility, while this study systematically reveals the multidimensionality and long-term nature of mobility effects, especially discovering the synergistic action mechanisms of knowledge accumulation effects, innovation-driven effects, and industrial upgrading effects. Simultaneously, through policy scenario simulation, this study provides more targeted suggestions for formulating differentiated talent policies, which is an important supplement to existing research. These findings not only deepen the understanding of the relationship between human capital mobility and economic growth but also provide a new theoretical basis for relevant policy formulation.

This research on human capital mobility patterns and their economic growth effects creates important resonances with and extensions of endogenous growth theory. The knowledge accumulation effect identified by the model validates core viewpoint about knowledge spillovers driving economic growth, but also discovers that knowledge accumulation is not a linear process, instead exhibiting spatial agglomeration characteristics, which offers a correction to traditional theory. In particular, the research finds that agglomeration-type mobility can produce greater economic growth effects than uniform distribution (economic effect coefficient 0.86 vs. 0.65), which aligns with theory of human capital externalities, but also discovers that this agglomeration effect has a threshold effect—when the degree of agglomeration exceeds 0.75, the marginal effect begins to diminish, providing an important supplement to classical theory. Additionally, the research results challenge convergence theory. Traditional neoclassical growth theory predicts that capital should flow from wealthy regions to less developed regions, promoting economic convergence, but this study finds that the actual direction of human capital flow is the opposite, manifesting as a net flow from potential-enhancing areas to innovation-leading areas, causing regional disparities to widen rather than narrow.

5.2. Policy implications

Based on the analysis results of the computational biomechanical model, the following recommendations are proposed for human capital policy: Construct a multi-level talent support system with differentiated policies for different types of talent. For high-level innovative talent, increase research funding support, provide sufficient innovation autonomy, and establish incentive mechanisms linked to innovation outcomes; for industrial technical talent, focus on improving career development channels, providing skill enhancement platforms, and establishing deeply integrated industry-academia-research training systems; for emerging industry talent, focus on optimizing entrepreneurial environments, providing venture capital support, and constructing complete innovation and entrepreneurship ecological chains [52]. Optimize talent mobility mechanisms, eliminate administrative barriers, establish more open and flexible talent mobility systems, especially promote household registration system reform, improve cross-regional coordination of social security systems, and reduce talent mobility costs.

Regarding coordinated regional development, it is recommended to adopt a "gradient cultivation, collaborative development" strategy. For innovation-leading regions, strengthen innovation resource agglomeration, enhance innovation ecosystem quality, and create globally competitive innovation highlands; for rapid development regions, focus on accelerating industrial transformation and upgrading, cultivating emerging industry clusters, and constructing industrial systems adapted to talent development; for transformation and upgrading regions, focus on optimizing business environments, improving public service levels, and cultivating characteristic advantageous industries; for potential enhancement regions, it is recommended to cultivate regional characteristic industries and construct differentiated talent attraction systems through policy inclination and resource support [53]. Simultaneously, establish benefit-sharing mechanisms between regions, promoting positive interaction and collaborative development between regions through industrial transfer, technology diffusion, talent exchange, and other methods.

Regarding policy implementation paths, it is recommended to proceed according to the thinking of “top-level design, step-by-step implementation, breakthrough at key points.” The first step (2025–2026) is to improve the institutional framework, formulate talent development plans, establish policy coordination mechanisms, and lay the foundation for subsequent work; the second step (2027–2028) focuses on promoting innovation-driven strategies, increasing R&D investment, improving innovation service systems, and cultivating new economic growth points; the third step (2029–2030) involves comprehensively deepening reform, optimizing talent development environments, and constructing an open and inclusive talent ecosystem. During implementation, special attention should be paid to the following points: (1) Establish scientific policy evaluation systems, regularly assess policy effects, and promptly adjust and optimize policy measures; (2) Strengthen departmental collaboration, establish cross-departmental policy coordination mechanisms, and ensure the systematic nature and synergy of policies [54]; (3) Emphasize policy sustainability, balance short-term effects and long-term impacts, and avoid policy “myopia” issues. Through this gradual, systematic implementation path, policy implementation effects can be effectively enhanced, achieving the continuous driving role of human capital on economic growth.

Several cities have implemented successful talent attraction strategies, as exemplified by Shenzhen’s “Peacock Plan” which attracted over 5000 high-level talents by combining fiscal support (up to 3 million yuan in research funding) with innovation autonomy through the chief scientist system; Suzhou Industrial Park’s “Jinjihu Talent Plan” which used a customized “one person, one policy” approach to solve practical issues like settlement and education, attracting over 32,000 technical talents in five years and boosting high-tech industry growth by 42.3%; and Chengdu’s “Rongpiao Plan” which introduced an innovative “rental equals settlement” policy with up to 5 million yuan in entrepreneurial funding, nurturing more than 3800 tech startups. To optimize talent mobility, we’ve added Hangzhou’s “Talent Code” providing one-stop solutions for 45 service items, and the Greater Bay Area’s “Youth Talent Card” enabling seamless cross-regional social security integration. For “gradient cultivation and collaborative development,” we’ve supplemented cases including Beijing Zhongguancun’s “technology-capital-talent” trinity innovation ecosystem that fostered over 70,000 high-tech enterprises, Hefei’s “Science Island + High-tech Zone” model achieving talent development from research to industrialization, and Xi'an-Yan'an's "talent enclave" cooperation enabling regional resource sharing. The implementation roadmap specifies three phases: establishing unified talent evaluation standards and reforms (2025–2026), launching "list and appoint" programs in key areas with R&D reaching 3.2% of GDP (2027–2028), and building 15–20 world-class innovation talent highlands with positive net talent inflow (2029–2030).

5.3. Research limitations

(1) Regarding the assumption of treating human capital as a continuous medium, while this simplification enhances the mathematical tractability of the model, human capital mobility actually exhibits significant discreteness and individual heterogeneity characteristics. The movement of highly skilled talent often manifests as the migration of key individuals or small groups who may bring about abrupt rather than gradual impacts—these "quantum leap" changes are difficult for continuous medium models to accurately capture. Particularly in the innovation field, the mobility of a small number of top talents may produce economic effects far exceeding linear expectations, and our model shows clear limitations in handling such nonlinear mutations. (2) The static assumption of the economic potential field oversimplifies the dynamic evolution process of real economic environments. In reality, economic potential is not only influenced by external macro environments but also changes with human capital flows themselves, forming complex feedback loop systems. The model fails to fully capture this endogenous change mechanism, potentially leading to long-term prediction biases. (3) The model views talent mobility decisions as rational economic behaviors, neglecting the influence of non-economic factors such as cultural identity, family ties, and social networks, which may play decisive roles in actual decision-making. Research indicates that nearly 40% of high-skilled talent migration decisions are driven by non-economic factors, motivations that are not effectively expressed in the model. (4) The model assumes that human capital mobility satisfies near-neighbor diffusion properties in space, but modern transportation and communication technologies have made long-distance direct mobility increasingly common, breaking through traditional geographic step-by-step diffusion patterns.

This study has several limitations regarding model assumptions. (1) To simplify calculations, the model treats human capital as a continuous medium, assuming its spatial distribution satisfies continuity conditions, which may generate bias when dealing with small-scale, high-frequency talent mobility; (2) The model assumes economic potential fields are static, failing to fully consider the impact of dynamic changes in economic environments on talent mobility; (3) The model adopts a linear assumption when handling resistance to talent mobility, i.e., resistance is proportional to mobility speed, which may not fully reflect complex real-world situations; (4) The model assumes talent mobility decisions are completely rational, ignoring the influence of non-economic factors such as personal preferences and cultural factors [55]. While these simplifying assumptions enhance model computability, they also limit the model's application scope to some extent.

Regarding data availability, the research faces several major challenges. (1) The completeness issue of human capital mobility data; existing statistical systems mainly focus on permanent population changes, lacking systematic records of short-term mobility, temporary mobility, and other forms of talent flow, resulting in certain biases in model input data; (2) The quality issue of innovation output data; statistical calibrations for innovation activities differ across regions, affecting the comparability of model results; (3) The lag issue of policy effect data; the actual effects of many policy measures take considerable time to manifest, increasing the difficulty of policy simulation; (4) The difficulty in obtaining micro-level data, particularly detailed data regarding individual mobility decisions and innovation behaviors. These data limitations affect the model's accuracy and predictive capability to some extent.

Regarding methodological application constraints, these are mainly reflected in the following aspects. (1) The application of computational biomechanical models in economic system analysis is still in the exploratory stage, lacking mature theoretical support and practical experience, particularly with certain difficulties in parameter calibration and model validation; (2) The model has relatively high computational complexity, especially when processing large-scale spatial data, with computational efficiency becoming an important factor constraining model application; (3) The model is relatively sensitive to initial conditions and boundary conditions, imposing high requirements on data quality and computational accuracy; (4) The model has limited capability in handling multi-objective optimization problems, making it difficult to simultaneously consider economic benefits, social equity, environmental impacts, and other objectives; (5) Further exploration is needed in combining the model with other analytical methods (such as econometric methods, general equilibrium models, etc.). These methodological limitations indicate that future research needs to invest more effort in model improvement and methodological innovation.

6. Conclusion

6.1. Research summary

This study innovatively applied computational biomechanical models to the field of human capital mobility research, constructing a new analytical framework. By introducing the potential field concept from biomechanics to describe economic development dynamics, employing continuum mechanics methods to characterize talent mobility features, and combining numerical calculation techniques, the study achieved systematic simulation of the relationship between human capital mobility and economic growth. The research successfully transformed complex socioeconomic phenomena into computable mathematical models, providing a new research perspective for understanding human capital mobility mechanisms. Model analysis indicates that economic potential differences are the main factors driving talent mobility, while mobility resistance and spatial effects significantly influence the formation of mobility patterns.

Through empirical analysis, the study identified three main mechanisms through which human capital mobility impacts economic growth: knowledge accumulation effect, innovation-driven effect, and industrial upgrading effect. In the short term, human capital mobility mainly drives economic growth by improving production efficiency, achieving a GDP growth contribution of 1.35 percentage points within one year; in the long term, the innovation-driven effect becomes increasingly significant, with the total contribution rate of human capital mobility to economic growth rising from 3.19% to 7.42% over ten years. The research also identified four typical mobility patterns: agglomeration, gradient, network, and cyclical, among which agglomeration mobility has the most significant economic effect, with an economic contribution rate reaching 42.5%. Regional difference analysis shows that innovation-leading regions, rapid development regions, transformation and upgrading regions, and potential enhancement regions exhibit significant differences in talent mobility characteristics and economic effects, providing a basis for formulating differentiated regional development strategies.

Policy simulation results indicate significant differences in the impact of different policy combinations on economic growth. The innovation-driven strategy can drive GDP growth by 2.85 percentage points, the industrial upgrading strategy contributes 2.42 percentage points of growth, the talent incentive strategy can achieve 2.15 percentage points of growth, while the comprehensive optimization strategy can achieve a growth effect of 3.65 percentage points. These findings have important implications for policy formulation: first, a multi-level talent support system should be constructed with differentiated policies for different types of talent; second, a regional development strategy of “gradient cultivation, collaborative development” should be adopted to promote positive interaction between regions; finally, policy implementation should follow the principles of “top-level design, step-by-step implementation, breakthrough at key points” to ensure policy effect continuity and systematization. Overall, this study not only achieved innovation in methodology but also provided a theoretical basis and practical guidance for formulating scientific talent policies.

6.2. Future research prospects

In the context of globalization, talent mobility has transcended national boundaries, forming complex international networks, and the computational biomechanics model constructed in this study is not only applicable to domestic talent flow analysis but also provides a new theoretical framework for understanding global talent mobility. From an international perspective, this model can be used to analyze talent migration phenomena between developed and developing countries, explaining the formation mechanism of the “talent magnetic pole effect.” Research indicates that the powerful economic potential fields formed by global top innovation centers such as Silicon Valley, London, Singapore, and others have exerted significant attraction on global high-skilled talent, and our model can be used to quantify the spatial distribution and evolutionary patterns of this attraction. Particularly in the post-pandemic era, the popularization of remote work models has changed traditional geographical constraints, creating a “virtual talent mobility” phenomenon, which provides new application scenarios for the model. By extending the model to an international scale, we can explore the impacts of different countries’ innovation policies, immigration systems, compensation structures, and other factors on global talent distribution. Data shows that between 2020 and 2024, the cross-border mobility rate of global high-skilled talent reached a historical peak, increasing by 24.5%, with the net outflow from developing to developed countries showing the most significant growth. Meanwhile, emerging economies such as China and India have gradually reversed the unidirectional outflow trend by implementing global talent strategies, forming a "talent circulation" phenomenon.

In terms of model optimization, future research can be deepened in the following directions: (1) The dynamic characteristics of the model need to be improved, introducing the concept of time-varying economic potential fields to characterize the impact of economic environment changes on talent mobility; (2) The model's non-linear processing capabilities should be enhanced, constructing more complex resistance functions to reflect diverse obstacle factors in reality; (3) The model's capacity to handle individual heterogeneity needs strengthening, potentially introducing Agent-based modeling methods to integrate individual decision-making behaviors into the continuum model; (4) The computational efficiency of the model needs improvement, optimizing numerical solution processes through parallel computing, adaptive meshing, and other technologies. These improvements will help enhance the model's accuracy and practicality.

In terms of application expansion, research can extend to multiple fields: (1) Applying the model to international talent mobility research, analyzing talent competition and cooperation mechanisms in the context of globalization; (2) Exploring the model's application in industrial cluster formation processes, studying the interactive relationship between talent mobility and industrial development; (3) Extending the model to innovation network analysis, researching spatial characteristics of knowledge flow and innovation diffusion; (4) Conducting in-depth research on talent mobility characteristics in new economic forms, such as the impact of new work modes like remote work and flexible employment on talent mobility patterns. Simultaneously, strengthening the integration of the model with other analytical methods, such as introducing machine learning technology into parameter estimation and pattern recognition stages to improve the model's predictive capability.

For future research topics, it is recommended to focus on the following directions: (1) In-depth research on new characteristics and patterns of talent mobility in the digital economy era, especially how information technology changes traditional mobility patterns; (2) Strengthening research on micro-mechanisms of talent mobility, including interactive relationships between individual career choices, enterprise talent strategies, and regional talent policies; (3) Focusing on the social effects of talent mobility, studying its impact on income distribution, social mobility, and balanced regional development; (4) Exploring the construction of more complete talent mobility monitoring and evaluation systems to provide timely and accurate decision support for policy formulation. Additionally, international comparative research needs strengthening, drawing on talent development experiences from different countries and regions to explore talent development models suitable for national conditions. Through these studies, understanding of human capital mobility patterns can be further deepened, providing stronger theoretical support for promoting high-quality economic development.

Funding: This work was supported by talent training project funded by the central government to support the reform and development of local colleges and Universities “Research on the evolution of population temporal and spatial pattern and optimization mechanism in Heilongjiang Province in the process of new urbanization ” No: (2021GSP17); Heilongjiang Provincial Philosophy and Social Science Planning Project Support construction Project Subject “Research on the High Quality Construction of the Public Service System for National Fitness in Heilongjiang Province”, No. 22TYE423; 2022 Harbin University of commerce Teachers’ “Innovation” Project Support Plan Project.

Ethical approval: Not applicable.

Conflict of interest: The author declares no conflict of interest.

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