Problem Chosen	2026HSB MCM/ICM Summary Sheet	Team Number
B		MI2601258

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Summary

Here is the summary of paper.

Please replace this text with your own summary. This summary should briefly describe the problem you are addressing, the methods you used, and the key results or conclusions you reached. Make sure to keep it concise and informative.

Keywords: KFC V50 Chicken

Contents

1 Intorduction

1.1 Background

In the contemporary era, artificial intelligence (AI) has emerged as one of the core domains of global technological competition, exerting profound and systemic influences on economic development, social progress, and national security. With the acceleration of a new wave of technological revolution and industrial transformation, AI technologies are fundamentally reshaping traditional industrial structures, modes of production, and governance systems, and have gradually become a key indicator of a nation's scientific strength and overall competitiveness.

Against this backdrop, countries around the world have elevated artificial intelligence to a strategic priority at the national level, continuously increasing investments in algorithmic research, computing infrastructure, data resource development, and the expansion of application scenarios, with the aim of securing a leading position in the global AI competitive landscape.

1.2 Problem Restatement

This study aims to quantitatively evaluate national artificial intelligence (AI) development capabilities, compare global competitiveness, and analyze future development trends through a systematic mathematical modeling framework. The problem is decomposed into four sequential and interrelated tasks:

Task 1: Factor Identification and Correlation Analysis

Relevant data are collected and integrated to identify the key factors influencing national AI development. These factors are quantified, and their intrinsic correlations and interaction mechanisms are analyzed using statistical and visualization methods.

Task 2: Comprehensive Evaluation and Ranking

Based on the quantified factors and their correlations obtained in Task 1, a multi-criteria evaluation model is constructed to assess and rank the AI competitiveness of ten selected countries.

Task 3: Competitiveness Trend Prediction

Using historical data from 2016 to 2025, the future evolution of AI development factors during the period 2026–2035 is predicted. The evaluation model established in Task 2 is then applied to analyze the dynamic changes in national competitiveness rankings over time.

Task 4: Optimal Fund Allocation Strategy

Under a fixed budget constraint of a 1 trillion yuan special fund, a multi-objective optimization model is developed to determine the optimal allocation of resources across AI development factors, with the goal of maximizing China's comprehensive AI competitiveness by 2035.

By sequentially accomplishing these tasks, this study provides a coherent framework for factor identification, comparative evaluation, future trend analysis, and strategic decision support in the global AI competition landscape.

1.3 Our Work

这是我们的工作介绍

2 Basic Assumption

To ensure the feasibility, consistency, and interpretability of the proposed models, the following basic assumptions are made.

► **Hypothesis 1: Assume that national AI development capability is a latent attribute that can be approximated by a finite set of observable and quantifiable indicators.**

Legitimacy: At the national level, AI development is manifested through measurable outcomes and resource inputs recorded in public statistics. Although the true capability cannot be observed directly, its major characteristics can be reasonably inferred from aggregated, quantifiable indicators.

► **Hypothesis 2: Assume that all indicators within the same evaluation year are cross-sectionally consistent.**

Legitimacy: Although data may be collected from slightly different release years, AI development is a long-term process. Minor temporal discrepancies do not significantly affect national-level competitiveness comparisons and help simplify the modeling process.

► **Hypothesis 3: Assume that the indicators are independent of each other in the weighting and evaluation stages.**

Justification : While interactions among indicators exist, explicitly modeling such dependencies would increase complexity and reduce interpretability. Treating indicators as independent avoids double counting and ensures the applicability of entropy-based and multi-criteria evaluation methods.

► **Hypothesis 4: Assume that the fundamental mechanisms of AI development remain stable during the forecasting and optimization period.**

Justification : National AI strategies, infrastructure construction, and talent cultivation generally evolve gradually. This stability makes trend-based prediction and investment optimization reasonable and analytically tractable.

3 Symbols

4 Data Explanation

4.1 Data Description and Sources

The dataset covers a lot of representative countries and consists of multiple quantitative indicators describing national AI development capability. For organizational clarity, the indicators were grouped into six dimensions reflecting different aspects of AI development. All data corresponded to the same evaluation period and were obtained from publicly available and widely recognized sources, ensuring cross-country comparability.

4.2 Data Preprocessing

Basic preprocessing was conducted prior to analysis. Minor missing or abnormal values were handled through reasonable estimation and consistency checks. All indicators were defined as benefit-type variables and were normalized to eliminate dimensional differences before being used in subsequent models.

5 Task 1: Analysis of AI Development Factors

Task 1 aims to *reveal the internal structure* of national AI capability from the 24-indicator system. Rather than prespecifying causal links, we use cross-country co-movement to identify (i) tightly coupled factor groups, (ii) dominant low-dimensional directions, and (iii) a small set of high-leverage indicators. These structural outputs support Task 2 (objective evaluation) and inform Task 4 (synergy-aware constraints).

5.1 Quantification of Key Indicators

Let the min–max normalized indicator matrix be

$$X = [x_{ij}] \in \mathbb{R}^{n\times p}, \qquad n = 10,\ p = 24, \tag{1}$$

where x_{ij} is the normalized value of indicator j for country i. To remove scale effects across heterogeneous indicators, we apply

$$x_{ij} = \frac{x_{ij}^{\text{raw}} - \min(x_j)}{\max(x_j) - \min(x_j)} \in [0, 1]. \tag{2}$$

Matrix X is the common input for correlation, clustering, and PCA in this task.

5.2 Correlation Structure and Interaction Mechanism

Correlation map and strong-link set. We quantify linear association by Pearson correlation:

$$r_{jk} = \frac{\sum_{i=1}^{n}(x_{ij} - \bar{x}_j)(x_{ik} - \bar{x}_k)}{\sqrt{\sum_{i=1}^{n}(x_{ij} - \bar{x}_j)^2}\sqrt{\sum_{i=1}^{n}(x_{ik} - \bar{x}_k)^2}}, \qquad R = [r_{jk}] \in \mathbb{R}^{p\times p}. \tag{3}$$

To focus on interpretable dependencies, we define the strong-correlation edge set

$$\mathcal{E} = \{(j, k) \mid |r_{jk}| > \tau,\ j < k\}, \tag{4}$$

where τ is a fixed threshold (used consistently in Task 4 to impose synergy constraints). The heatmap in Fig. 1a shows a dense positive-correlation backbone, suggesting that talent, R&D investment, market scale, and compute infrastructure often advance jointly.

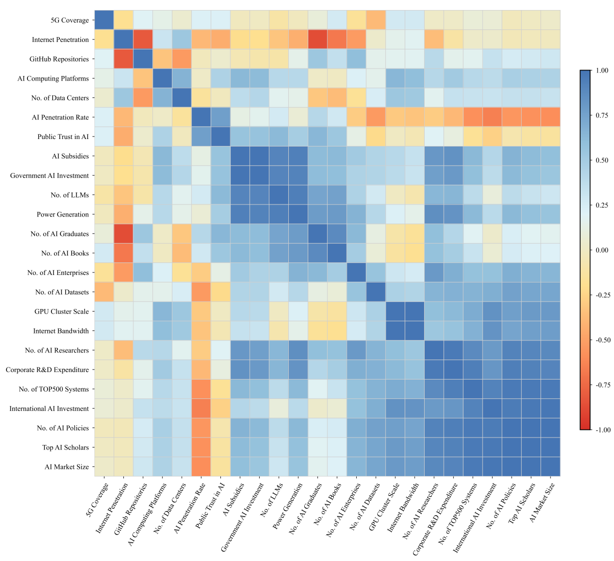
Hierarchical clustering (group-level structure). To move beyond pairwise links, we cluster indicators using correlation distance

$$d_{jk} = 1 - |r_{jk}|, \tag{5}$$

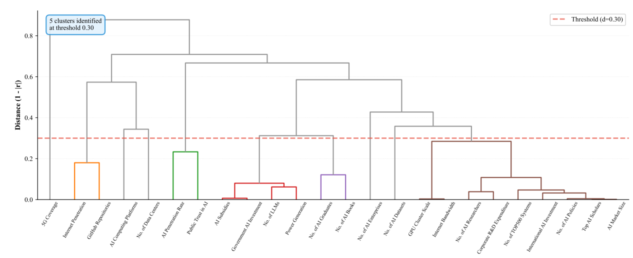
and average linkage between clusters C_a and C_b:

$$D(C_a, C_b) = \frac{1}{|C_a||C_b|} \sum_{j\in C_a} \sum_{k\in C_b} d_{jk}. \tag{6}$$

The dendrogram in Fig. 1b recovers coherent modules, typically separating (i) *investment–market–infrastructure* factors from (ii) *talent–knowledge production* factors. This validates that the indicator system is multidimensional but internally coordinated.



(a) Correlation heatmap of 24 indicators.



(b) Hierarchical clustering dendrogram.

Figure 1: Pairwise association and group structure of AI development factors.

Principal component structure (dominant dimensions). High correlations imply redundancy, so we use PCA to extract dominant directions. Let

$$\tilde{X} = X - \mathbf{1}\bar{X}^T, \qquad C = \frac{1}{n-1}\tilde{X}^T\tilde{X}, \tag{7}$$

and eigen-decompose

$$C = V\Lambda V^T. \tag{8}$$

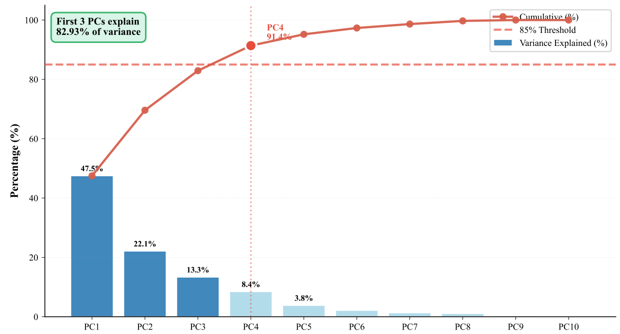
We retain the smallest m components that explain a high share of variance (in our results, the first four PCs explain $> 90\%$; see Fig. 2a). This indicates that cross-country AI capability differences can be summarized by a low-dimensional latent structure.

Factor importance and interaction network. We quantify indicator importance by combining squared loadings and explained variance:

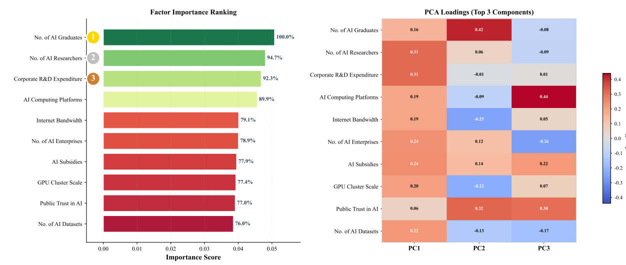
$$I_j = \sum_{k=1}^{m} v_{jk}^2 \cdot \frac{\lambda_k}{\sum_{\ell=1}^{p} \lambda_\ell}. \tag{9}$$

Fig. 2b shows that a limited subset (typically talent, frontier R&D, and high-end compute) contributes most to the explained variation. Finally, the strong-link network induced by $\mathcal{E}$ visualizes system-level coupling: hub indicators (often infrastructure and investment) connect multiple modules, consistent with a coordinated development mechanism (Fig. 2c).

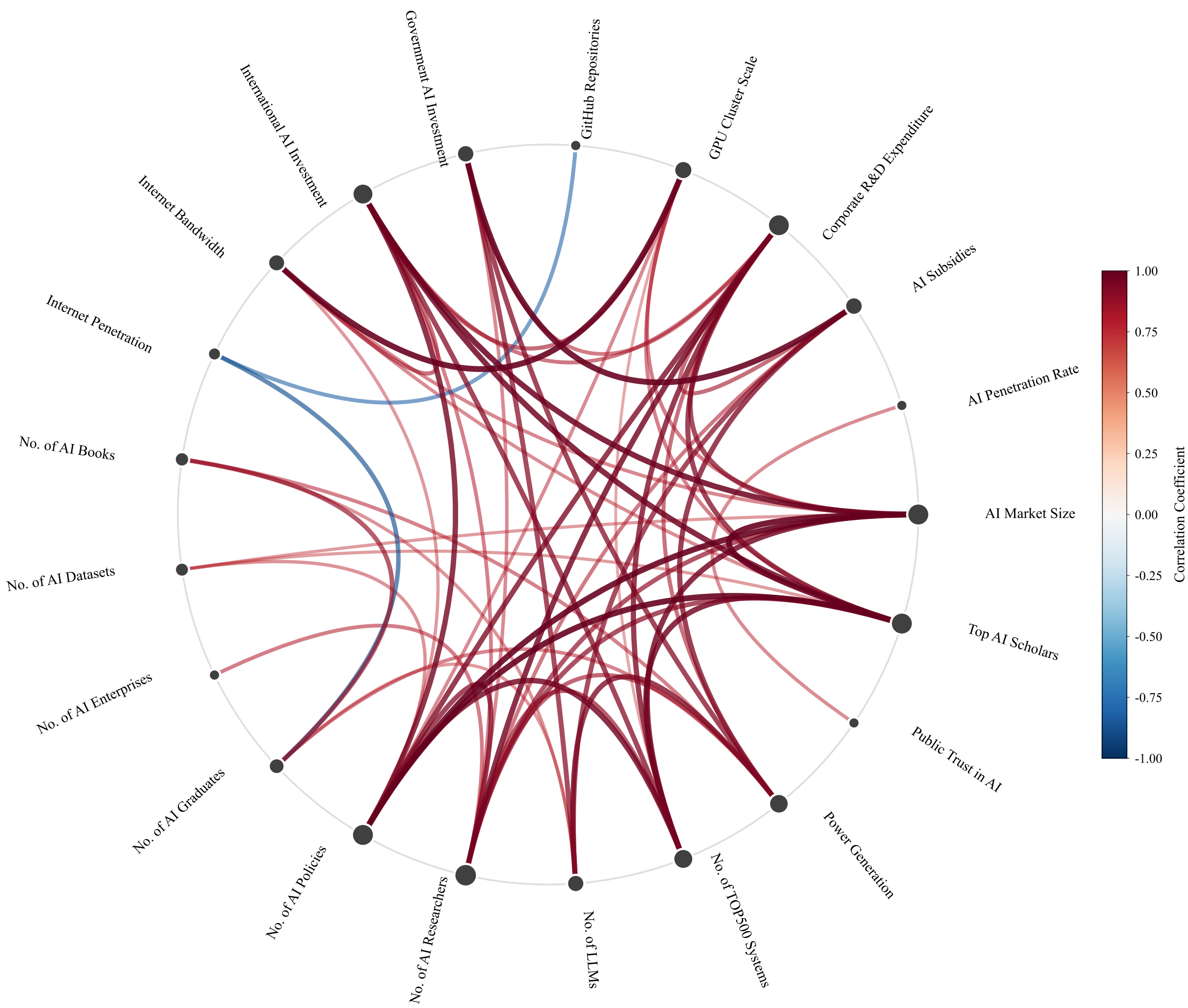
Summary of Task 1. Task 1 identifies a dense correlation backbone, coherent indicator modules, and a low-dimensional dominant structure. These findings motivate (i) objective aggregation in Task 2 and (ii) synergy-aware design in Task 4 using $\mathcal{E}$.



(a) Variance explained by PCs.



(b) Importance ranking I_j.



(c) Strong-correlation interaction network.

Figure 2: Low-dimensional structure and key drivers of AI development capability.

6 Task 2: Evaluation of National AI Competitiveness in 2025

With the indicator structure established in Task 1, Task 2 produces a *single, comparable competitiveness score* for each country in 2025. The design principle is to keep the evaluation standard objective and reproducible: entropy weights determine indicator importance from data dispersion, TOPSIS aggregates performance relative to ideal benchmarks, and GRA provides a structural cross-check.

6.1 Comprehensive Evaluation Methodology

Let the normalized indicator matrix for evaluation be

$$X' = \left(x'_{ij}\right)_{n\times p}, \qquad n = 10,\ p = 24, \tag{10}$$

where all indicators are treated as benefit-type (larger is better).

(1) Entropy weight method (EWM). Define

$$p_{ij} = \frac{x'_{ij}}{\sum_{i=1}^{n} x'_{ij}}, \qquad 0 \ln 0 := 0, \tag{11}$$

$$e_j = -k \sum_{i=1}^{n} p_{ij} \ln p_{ij}, \qquad k = \frac{1}{\ln n}, \tag{12}$$

and the entropy weight

$$w_j = \frac{1 - e_j}{\sum_{j=1}^{p}(1 - e_j)}. \tag{13}$$

Indicators with higher cross-country dispersion obtain larger weights.

(2) TOPSIS aggregation. Construct the weighted matrix

$$v_{ij} = w_j x'_{ij}, \tag{14}$$

with ideal solutions

$$A_j^+ = \max_i v_{ij}, \qquad A_j^- = \min_i v_{ij}. \tag{15}$$

Distances to the ideals are

$$D_i^\pm = \sqrt{\sum_{j=1}^{p}(v_{ij} - A_j^\pm)^2}, \tag{16}$$

and the closeness score is

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \in [0, 1]. \tag{17}$$

(3) Grey relational analysis (GRA) validation and fusion. Let the ideal profile be $v_{0j} = \max_i v_{ij}$ and define

$$\Delta_{ij} = |v_{0j} - v_{ij}|, \quad \Delta_{\min} = \min_{i,j} \Delta_{ij}, \quad \Delta_{\max} = \max_{i,j} \Delta_{ij}. \tag{18}$$

The grey relational coefficient and degree are

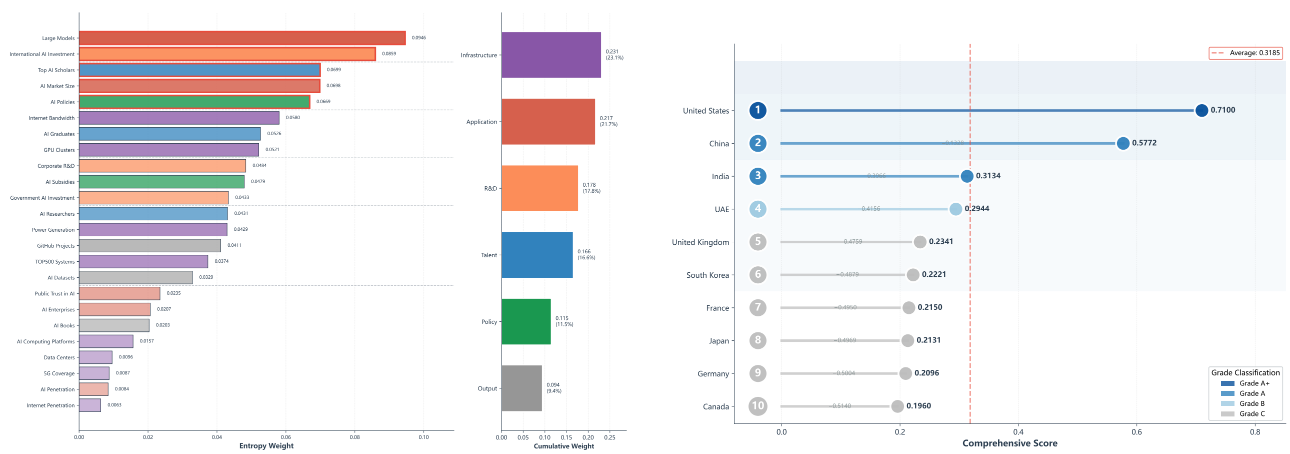
$$\xi_{ij} = \frac{\Delta_{\min} + 0.5\Delta_{\max}}{\Delta_{ij} + 0.5\Delta_{\max}}, \qquad \gamma_i = \frac{1}{p}\sum_{j=1}^{p} \xi_{ij}. \tag{19}$$

To combine distance-based performance (C_i) and structural similarity (γ_i), we use

$$S_i = \frac{C_i + \gamma_i}{2}. \tag{20}$$

6.2 Results and Comparative Analysis

Fig. 3 summarizes the weight pattern (left) and the 2025 competitiveness ranking by TOPSIS (right). The leading tier is clearly separated, while mid- and lower-tier countries form a tighter cluster.



(a) Entropy weight distribution. (b) TOPSIS ranking (2025).

Figure 3: Key outputs of Task 2: indicator weights and the 2025 ranking.

Table 1: TOPSIS Comprehensive Evaluation Results (2025)

Country	D_i^+	D_i^-	TOPSIS Score C_i	Rank
United States	0.0978	0.1744	0.6407	1
China	0.1320	0.1377	0.5104	2
India	0.2006	0.0533	0.2098	3
UAE	0.1998	0.0449	0.1836	4
United Kingdom	0.2040	0.0225	0.0995	5
South Korea	0.2063	0.0165	0.0740	6
France	0.2065	0.0153	0.0688	7
Japan	0.2064	0.0141	0.0640	8
Germany	0.2063	0.0138	0.0625	9
Canada	0.2091	0.0090	0.0414	10

Table 2: Final AI Competitiveness Ranking (2025) by Fusion Score

Country	TOPSIS Rank	GRA Rank	TOPSIS C_i	GRA γ_i	Fusion S_i	Grade
United States	1	1	0.6407	0.7793	0.7100	A+
China	2	2	0.5104	0.6440	0.5772	A
India	3	3	0.2098	0.4170	0.3134	A
UAE	4	4	0.1836	0.4052	0.2944	B
United Kingdom	5	6	0.0995	0.3686	0.2341	C
South Korea	6	5	0.0740	0.3703	0.2221	C
France	7	8	0.0688	0.3612	0.2150	C
Japan	8	7	0.0640	0.3623	0.2131	C
Germany	9	9	0.0625	0.3567	0.2096	C
Canada	10	10	0.0414	0.3506	0.1960	C

Reliability note. TOPSIS and GRA rankings are highly consistent (Spearman $\rho_s = 0.9758$, $p < 0.001$). Under ±30% weight perturbations, most countries vary by at most one rank, indicating stable ordering under moderate uncertainty.

7 Task 3: Forecasting AI Competitiveness (2026–2035)

Task 3 extends the 2025 evaluation to a dynamic horizon. The key rule is consistency: *the evaluation mechanism (weights and TOPSIS) is fixed*, and only the indicator trajectories evolve. Therefore, any ranking change during 2026–2035 can be attributed to data-driven indicator dynamics rather than altered standards.

7.1 Indicator-Level Trend Prediction

Let $x_{i,j,t}$ be indicator j of country i in year t. For each country–indicator series over 2016–2025, we forecast $\hat{x}_{i,j,t}$ for $t = 2026, \dots, 2035$ independently.

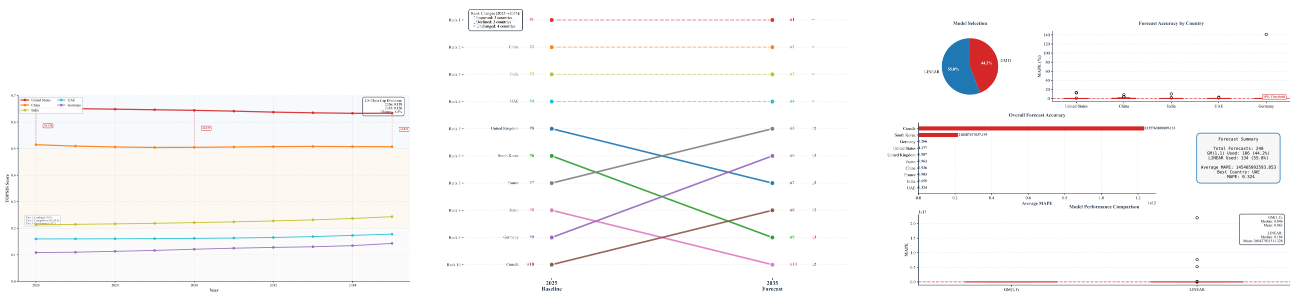
Given short sequences ($T = 10$), GM(1,1) is used as the primary model. When GM(1,1) backtesting is unsatisfactory, a constrained linear trend model is used as a fallback under the same non-negativity and truncation rules. One-step-ahead validation (train 2016–2024, predict 2025) uses MAPE as the main metric. In our pipeline, GM(1,1) covers 44.17% of the 240 country–indicator series, while the fallback is used for 55.83%, with a median MAPE of 0.1035.

7.2 Annual Evaluation and Score Evolution

After forecasting, we construct the predicted indicator matrix for each year t:

$$\hat{X}_t = \left(\hat{x}_{i,j,t}\right)_{n\times p}.$$

We keep the entropy weights from Task 2 fixed as $W = (w_1, \dots, w_p)$, and apply the same TOPSIS procedure to obtain the annual closeness scores $C_{i,t} \in [0, 1]$.



(a) Score gaps (2026–2035). (b) 2025 vs. 2035 slope chart. (c) Forecast diagnostics panel.

Figure 4: Forecasting and evaluation diagnostics for Task 3.

Table 3 reports the TOPSIS scores for representative years (2026, 2030, 2035), while Fig. 4a visualizes the score convergence and the evolution of cross-country gaps.

Table 3: Selected TOPSIS scores $C_{i,t}$ for 2026, 2030, and 2035.

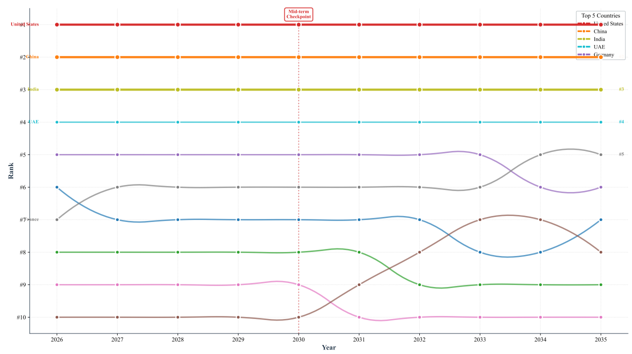
Country	2026	2030	2035
United States	0.653	0.644	0.633
China	0.515	0.505	0.507
India	0.213	0.221	0.244
United Arab Emirates	0.160	0.162	0.178
France	0.069	0.080	0.168
Germany	0.108	0.121	0.143
United Kingdom	0.069	0.073	0.102
Canada	0.042	0.057	0.101
South Korea	0.055	0.066	0.097
Japan	0.054	0.060	0.093

7.3 Ranking Evolution and Stability

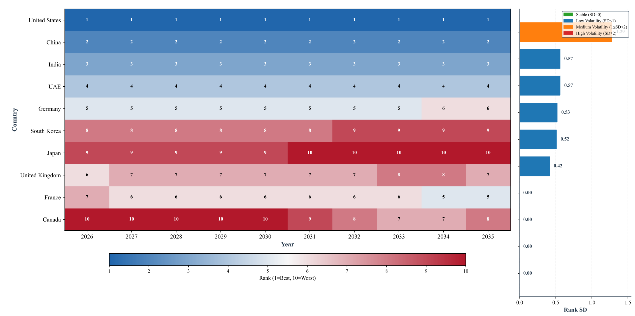
Countries are ranked annually by $C_{i,t}$. Fig. 5 shows both the ranking trajectories (bump chart) and the stability heatmap. The top tier remains stable, while rank swaps occur mainly among closely competing mid-/lower-tier countries.

7.4 Interpretation and Robustness

Because weights and evaluation rules are fixed, ranking changes come solely from predicted indicator trajectories. Observed swaps are local (small score gaps) rather than structural reversals, consistent with the convergence pattern in Fig. 4a. Forecast reliability is supported by the diagnostics in Fig. 4c.



(a) Bump chart (2026–2035).



(b) Rank stability heatmap.

Figure 5: Ranking evolution and stability over the forecast horizon.

Table 4: Rank stability summary (2026–2035).

Country	AvgRank	StdRank	BestRank	WorstRank
United States	1.00	0.00	1	1
China	2.00	0.00	2	2
India	3.00	0.00	3	3
United Arab Emirates	4.00	0.00	4	4
Germany	5.20	0.40	5	6
France	5.90	0.54	5	7
United Kingdom	7.10	0.54	6	8
South Korea	8.40	0.49	8	9
Canada	8.90	1.22	7	10
Japan	9.50	0.50	9	10

7.5 Summary

Task 3 couples indicator-level forecasting with the fixed Task 2 evaluation to project 2026–2035 competitiveness. The results suggest stable global leadership, gradual score convergence, and limited, interpretable mid-tier rank changes, providing the scenario baseline required by Task 4.

8 Task 4: Optimization of AI Development Investment Strategy

Tasks 1–3 establish a consistent pipeline: indicators → objective weights → TOPSIS scores → multi-year scenario. Task 4 turns this pipeline into a decision problem. Starting in 2026, China allocates an additional *1 trillion RMB* special fund, and the goal is to maximize China's *2035* comprehensive AI competitiveness under the *same* evaluation standard and comparison set.

8.1 Model Formulation and Constraints

Decision variables and budget. Let $\mathbf{I} = (I_1, \ldots, I_p)^\top$ be the allocation across $p = 24$ indicators. To match the policy budget and the numerical outputs, we measure investment in *hundred-million RMB*

(亿元). Thus, the total budget is

$$\sum_{j=1}^{p} I_j = B, \qquad B = 10000\ (\text{亿元}). \tag{21}$$

Objective (fixed evaluation standard). Let $S_{\mathrm{CN}}(\cdot)$ denote China's TOPSIS closeness coefficient under the fixed weight vector $\mathbf{w}$ obtained in Task 2. The optimization objective is

$$\mathbf{I}^* = \arg\max_{\mathbf{I}}\ S_{\mathrm{CN}}\Big(X^{2035}(\mathbf{I}); \mathbf{w}\Big), \tag{22}$$

where $X^{2035}(\mathbf{I})$ is the 2035 evaluation matrix: all non-China rows are fixed at the Task 3 scenario values, and only China's row is updated by the investment response.

Inputs from previous tasks.

$$\mathbf{w} \leftarrow \text{Task 2 (EWM weights)}, \tag{23}$$
$$\mathbf{x}_{\mathrm{CN}}^{\mathrm{base}} \leftarrow \text{Task 3 (China baseline trajectory)}, \tag{24}$$
$$X_{2035}^{\mathrm{scen}} \leftarrow \text{Task 3 (2035 scenario for all countries)}, \tag{25}$$
$$\mathcal{E} \leftarrow \text{Task 1 (strong correlation structure)}. \tag{26}$$

Investment–indicator response (diminishing returns & time lag). For indicator j, introduce: unit cost C_j, time-lag discount γ_j, and saturation upper bound L_j. The investment-induced increment is modeled by

$$\Delta x_j(\mathbf{I}) = \frac{I_j}{C_j}\left(1 - \frac{x_j^{\mathrm{base}}}{L_j}\right)\gamma_j, \qquad j = 1, \ldots, p, \tag{27}$$

and the post-investment level is truncated by feasibility:

$$x_{\mathrm{CN},j}^{2035}(\mathbf{I}) = \min\left\{x_j^{\mathrm{base}} + \Delta x_j(\mathbf{I}),\ L_j\right\}. \tag{28}$$

Upper bounds follow a relative-competitiveness rule:

$$L_j = \begin{cases} 1.5\, x_{j,2025}^{\mathrm{CN}}, & x_{j,2025}^{\mathrm{CN}} \ge x_{j,2025}^{\mathrm{US}}, \\ 3.0\, x_{j,2025}^{\mathrm{US}}, & x_{j,2025}^{\mathrm{CN}} < x_{j,2025}^{\mathrm{US}}, \end{cases} \qquad L_j \le 100 \text{ (ratio-type indicators)}. \tag{29}$$

Time-lag discounts are grouped as $\gamma_j \in \{1.0, 0.8, 0.6\}$ for short-/medium-/long-horizon effects.

TOPSIS evaluation (same as Task 2). Let $X = X^{2035}(\mathbf{I})$. Using vector normalization,

$$\tilde{X} = XD^{-1}, \quad D = \mathrm{diag}\big(\|X_{:,1}\|_2, \ldots, \|X_{:,p}\|_2\big), \tag{30}$$

$$V = \tilde{X}\,\mathrm{diag}(\mathbf{w}), \quad \mathbf{v}^+ = \max_i V_{i,:}, \quad \mathbf{v}^- = \min_i V_{i,:}, \tag{31}$$

$$D_i^{\pm} = \|V_{i,:} - \mathbf{v}^{\pm}\|_2, \qquad S_i = \frac{D_i^-}{D_i^+ + D_i^-}. \tag{32}$$

The objective (22) maximizes S_{CN}.

Constraints. (1) Budget and bounds:

$$\sum_{j=1}^{p} I_j = B, \qquad I_{\min} \le I_j \le I_{\max}. \tag{33}$$

(2) Synergy constraints (from Task 1 strong links). To avoid structurally imbalanced growth, we impose ratio-type coupling constraints:

$$\begin{aligned} x_{\text{Large Models}} &\le 200\, x_{\text{GPU}}, \\ x_{\text{Top AI Scholars}} &\le 5.0\, x_{\text{Researchers}}, \\ x_{\text{AI Publications}} &\le 0.24\, x_{\text{Researchers}}, \\ x_{\text{AI Enterprises}} &\le 78\, x_{\text{AI Market}}, \\ x_{\text{AI Datasets}} &\le 0.75\, x_{\text{Enterprise R\&D}}. \end{aligned} \tag{34}$$

Solution method. The nonlinear constrained program is solved by SLSQP with equal-allocation initialization $I_j = B/p$, maximum 500 iterations, and tolerance 10^{-6}.

8.2 Optimal Allocation Results and Insights

All allocations below are in 亿元.

Overall allocation pattern. The optimized plan prioritizes *infrastructure–policy–market*, with secondary emphasis on enterprise R&D and high-end talent. Table 5 and Fig. 6 summarize the TAPRIO dimension distribution.

Table 5: Dimension-level distribution of the 1 trillion RMB special fund.

Dimension	Investment (亿元)	Share (%)
Infrastructure (I)	3232.64	32.33
Talent (T)	1739.28	17.39
Policy (P)	1739.11	17.39
Application (A)	1512.40	15.12
R&D (R)	1264.80	12.65
Output (O)	511.84	5.12

Indicator-level priorities. Top-10 funded indicators account for the majority of the budget (Table 6), and Fig. 7 visualizes the allocation rank.

Full 24-indicator allocation (reproducibility).

Indicator improvements under the response function. Using Eqs. (27)–(28), we compute China's post-investment indicator levels in 2035. Table 8 reports selected indicators (baseline vs. post-investment), and Fig. 8 visualizes growth rates (log-scale).

Impact on 2035 TOPSIS competitiveness (within-year comparison). Under the fixed TOPSIS procedure (Task 2) and the 2035 comparison set (Task 3 scenario), China's post-investment closeness coefficient is

$$S_{\text{CN}}^{2035,\text{post}} = 0.54717. \tag{35}$$

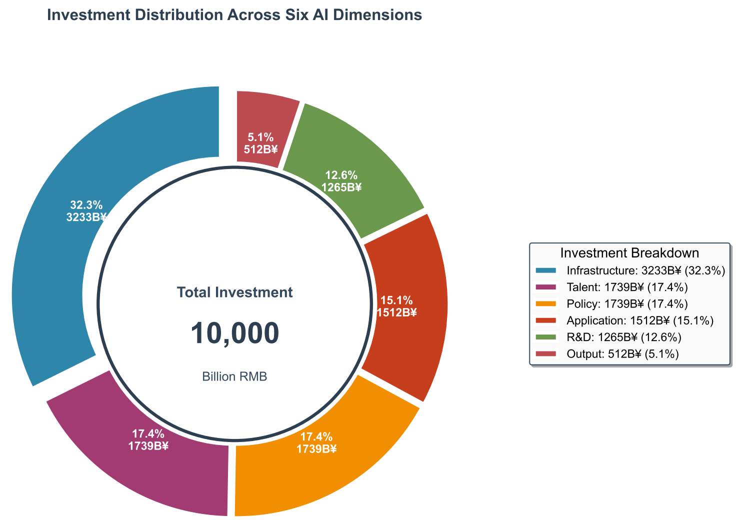


Figure 6: Dimension-level investment distribution (donut chart).

Table 6: Top-10 funded indicators under the optimized allocation.

Rank	Indicator	Investment (亿元)	Share (%)
1	GPU cluster scale	1500.00	15.00
2	Number of AI policies	1474.23	14.74
3	AI market size	1121.23	11.21
4	Enterprise R&D expenditure	927.66	9.28
5	Top AI scholars	820.92	8.21
6	AI researchers	816.90	8.17
7	TOP500 supercomputer count	731.54	7.32
8	GitHub AI-related projects	308.86	3.09
9	Number of data centers	281.74	2.82
10	Internet bandwidth	232.86	2.33

From Task 3 (no additional investment), China's 2035 baseline score is $C_{\mathrm{CN},2035} = 0.507$ (Table 3), so the optimized plan yields an improvement of approximately +0.040 under the same 2035 benchmark environment.

Complementary diagnostics and policy translation. Fig. 9 links the optimized allocation to (i) dimension-level changes and (ii) investment efficiency patterns.

Actionable recommendations.

1. **Strategic capacity foundation (I & P):** prioritize GPU clusters, TOP500 capacity, data centers, and a coherent policy package to avoid compute and governance bottlenecks.

2. **Innovation production engine (A & R):** expand AI market size and enterprise R&D to convert funded capacity into scalable applications and industrial output.

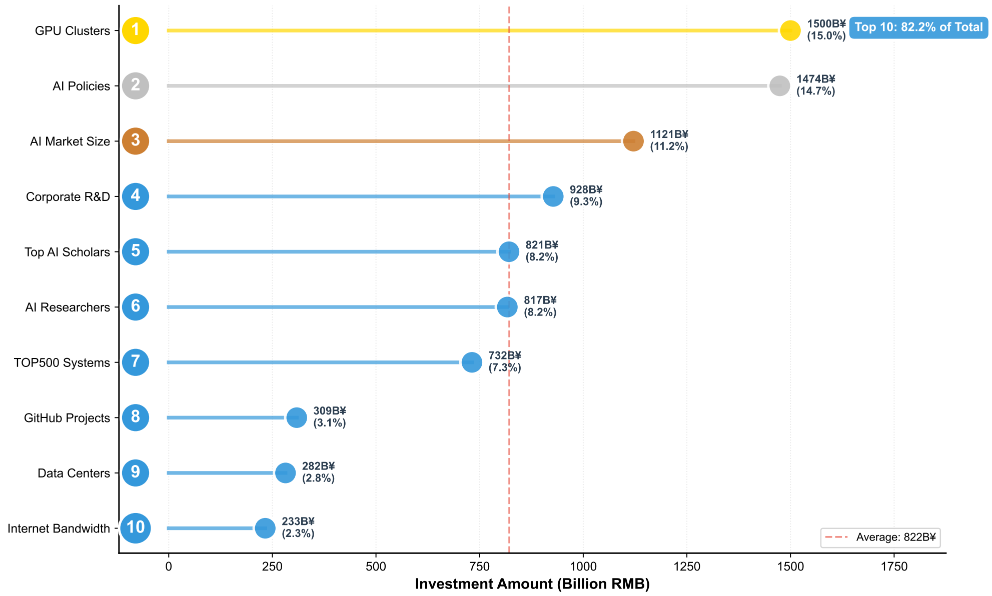


Figure 7: Top-10 indicator investments (lollipop chart).

Table 7: Full investment allocation across all 24 indicators.

Rank	Indicator	Investment (亿元)	Share (%)
1	GPU cluster scale	1500.000	15.000
2	Number of AI policies	1474.225	14.742
3	AI market size	1121.225	11.212
4	Enterprise R&D expenditure	927.661	9.277
5	Top AI scholars	820.922	8.209
6	AI researchers	816.904	8.169
7	TOP500 supercomputer count	731.544	7.315
8	GitHub AI-related projects	308.863	3.089
9	Number of data centers	281.743	2.817
10	Internet bandwidth	232.859	2.329
11	Number of AI enterprises	218.799	2.188
12	International AI investment	189.042	1.890
13	AI subsidy amount	149.758	1.498
14	Government AI investment	148.102	1.481
15	AI computing platforms	145.773	1.458
16	Electricity production	138.211	1.382
17	AI application penetration	122.376	1.224
18	AI social trust	115.123	1.151
19	Number of AI datasets	101.499	1.015
20	Number of AI books	101.482	1.015
21	Number of AI graduates	101.459	1.015
22	5G coverage rate	101.438	1.014
23	Internet penetration rate	101.075	1.011
24	Number of large models	50.000	0.500

Table 8: Selected indicator changes from baseline (2026) to post-investment level (2035).

Indicator	Baseline 2026	Post-invest 2035	Increment	Growth (%)
GitHub AI-related projects	5094.574	99000.000	93905.426	1843.244
AI graduates	70.000	97.500	27.500	39.286
GPU cluster scale	3.967	32.968	29.001	731.056
Internet bandwidth	1.607	6.201	4.594	285.874
Number of AI policies	72.933	270.580	197.647	270.998
AI researchers	279.342	900.000	620.658	222.186
TOP500 supercomputer cnt	83.200	205.780	122.580	147.332
AI market size	138.000	295.159	157.159	113.883
AI enterprises	5901.133	11830.887	5929.754	100.485
Enterprise R&D exp.	665.333	1172.337	507.004	76.203

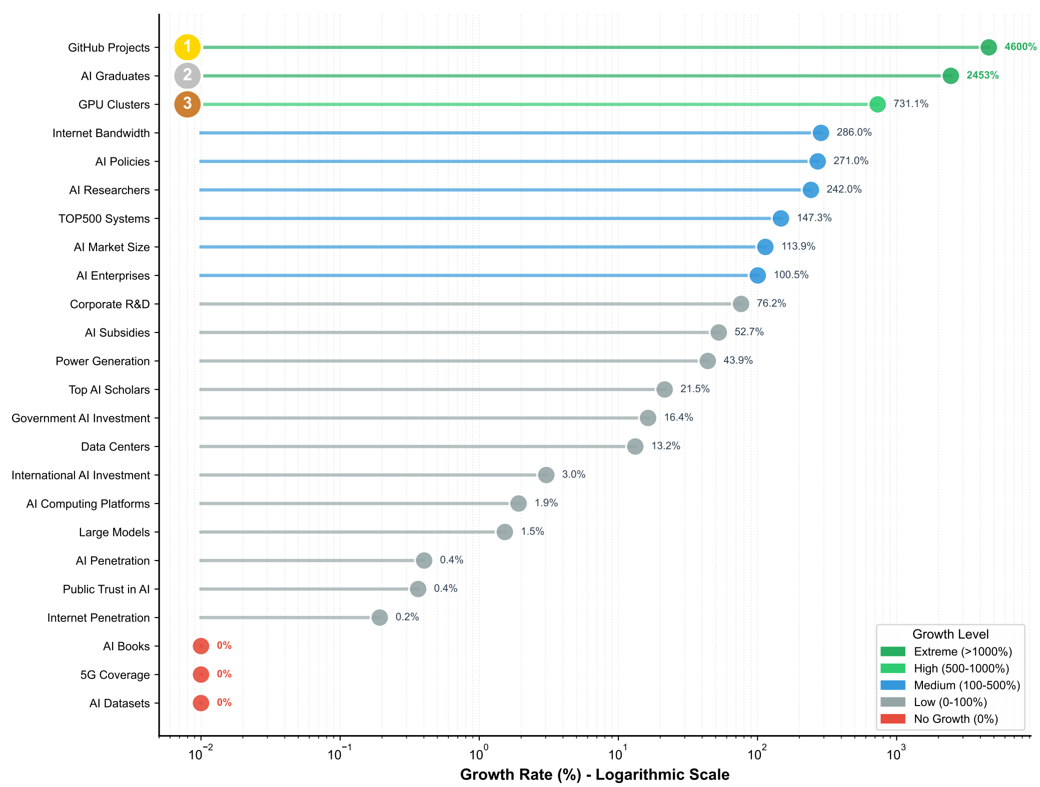
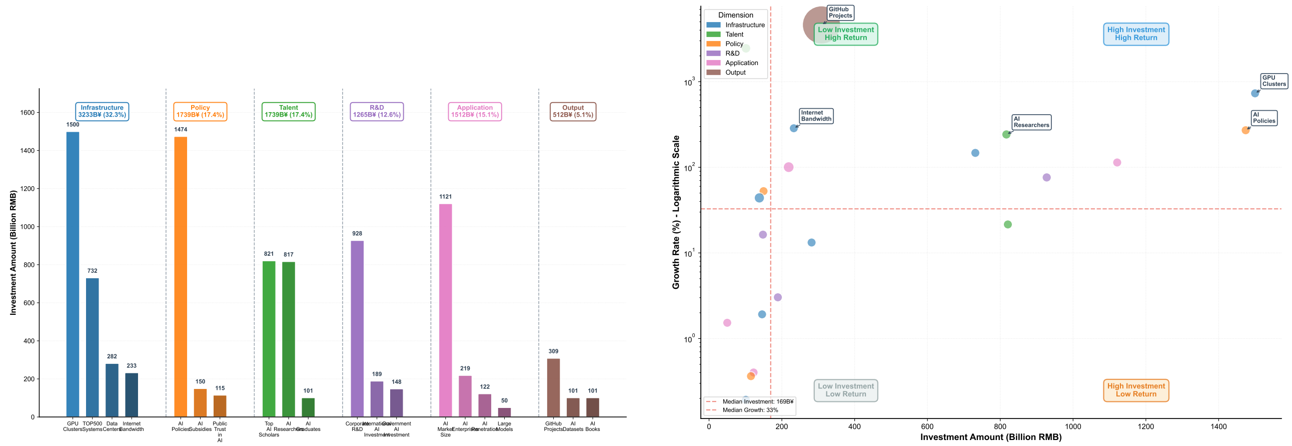


Figure 8: Indicator growth rates under the optimized investment (log-scale lollipop).



(a) TAPRIO dimension comparison (2035). (b) Efficiency quadrant (bubble chart).

Figure 9: Interpretation tools for the optimized investment plan.

3. **Talent upgrading (T):** target high-end researchers and top scholars as multipliers, consistent with the synergy constraints in (34).

All results above are generated under the fixed Task 2 evaluation scheme and the Task 3 2035 scenario, ensuring model consistency and reproducibility.

9 Conclusions and Implications

This study develops a unified, data-driven modeling framework to evaluate, compare, forecast, and optimize national artificial intelligence (AI) development capability. By maintaining a consistent indicator system and a fixed evaluation rule throughout all tasks, the proposed framework forms a closed analytical loop that ensures cross-country and cross-period comparability, as well as full traceability of results.

From a methodological perspective, the factor identification and structural analysis reveal that AI development is not driven by isolated indicators, but by a tightly coupled system involving infrastructure capacity, human capital, policy environment, and innovation output. The composite evaluation results for 2025 demonstrate clear stratification among countries, reflecting persistent structural advantages rather than short-term fluctuations. Extending the analysis to the 2026–2035 horizon, the forecasting task shows that, under stable structural conditions, global AI competitiveness rankings exhibit strong inertia, with only limited position changes among mid-tier countries. This finding suggests that AI leadership is path-dependent and difficult to overturn without sustained, long-term investment.

Robustness and error diagnostics further support the reliability of the conclusions. High rank-order consistency ($\rho_s = 0.9758$) and a moderate median prediction error (median MAPE ≈ 0.1035) indicate that the results are not sensitive to specific parameter settings or single-model assumptions. Consequently, the observed ranking patterns and trends can be regarded as structurally driven rather than model-induced artifacts.

On this basis, the investment optimization task translates analytical results into actionable policy insights. Under the assumption of an additional one-trillion-yuan budget for China starting in 2026, the optimal allocation strategy emphasizes an infrastructure-first approach, complemented by coordinated investment in talent cultivation and policy support. This allocation pattern reflects the high marginal contribution of foundational capacity to long-term AI competitiveness, while highlighting the necessity of institutional and human capital alignment.

Several limitations should be acknowledged. First, the analysis relies on publicly available and lagged data, which may not fully capture emerging technological breakthroughs. Second, the forecasting results are conditional on a stable structural assumption and do not account for disruptive policy shifts or technological shocks. Despite these limitations, the proposed framework provides a transparent, extensible, and reproducible decision-support tool for evaluating national AI competitiveness and guiding strategic investment planning.

Overall, this study offers both a quantitative assessment of the current global AI landscape and a forward-looking perspective on its evolution, with implications for policymakers seeking to design evidence-based and strategically coherent AI development strategies.