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Prediction and analysis of AI talent demand in Fujian Province's ordinary highway industry based on bayesian regression principle

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Abstract: The supply of high-quality talent plays a decisive role in the sustainable development of the highway industry. To accurately capture trends in AI-highway engineering interdisciplinary talent and to inform talent cultivation and policy formulation in higher education, this study analyzes data from Fujian Province spanning 2019–2024, including the total number of highway engineering professionals, total industry investment, talent attrition, and the supply of college graduates. A Bayesian regression model is employed for predictive analysis. The results indicate that parameter estimates are consistent with prior assumptions, the sampling process is stable, inter-chain convergence is satisfactory, and parameter estimates are reliable. The posterior distributions are approximately normal, and the Markov chain Monte Carlo (MCMC) trajectories exhibit random behavior without discernible trends, indicating good chain mixing and robust posterior estimation. Overall, demand for AI interdisciplinary talent in the highway engineering sector of Fujian Province shows a significant upward trend. Under the baseline scenario, the total industry workforce is projected to reach 5,351 by 2029, including 1,605 AI interdisciplinary professionals, representing a cumulative increase of 687 over five years. In the optimistic scenario, driven by increased investment, reduced drain, and growth in graduate supply, the workforce is expected to expand to 6,508 by 2029, with 1,952 AI interdisciplinary professionals, a cumulative increase of 999 over five years. Even in the pessimistic scenario, despite adverse conditions such as reduced investment and higher turnover leading to a workforce decline to 4,743 by 2029, the number of AI interdisciplinary professionals is projected to continue growing, reaching 1,423, with a cumulative increase of 522 over five years. These results demonstrate that the Bayesian regression model effectively quantifies the dynamic effects of total highway industry investment, brain drain, and graduate supply on workforce scale, and that the forecasts are consistent with practical industry constraints.

Keywords: transportation; highway engineering; AI interdisciplinary talent prediction; demand forecasting; bayesian regression model

1 Introduction

In recent years, as transportation infrastructure construction in China has steadily advanced, the demand for professional and technical personnel in the highway engineering sector has continued to rise [1-2]. With the rapid integration of emerging technologies—such as artificial intelligence (AI) and big data—into various processes including construction management, structural health monitoring, progress tracking, and cost and resource optimization, the need for cross-disciplinary and hybrid talent has grown at an unprecedented rate [3-4]. However, the growth in the number of engineering graduates has remained sluggish, making it difficult for the supply of new professionals to keep pace with the industry's increasing demand for AI-related composite talent. Accurately understanding the evolving trends in talent demand, particularly forecasting the scale of future needs for AI-highway engineering cross-disciplinary professionals, is therefore of great importance not only for strategic industry planning but also for informing talent development and policy-making in higher education institutions.

AI technology is profoundly reshaping the business models of highway construction and management, and extensive research has been conducted both domestically and internationally. Zhou et al.

[5] proposed a vectorized road-generation model based on the Transformer architecture, which produces high-precision road networks driven by geographic map data (e.g., elevation, vegetation). The incorporation of a density-map generation network and an attention mechanism significantly enhances design efficiency and interactivity. During the construction phase, AI technologies support automated scheduling, construction robotics, and real-time monitoring, thereby improving resource allocation and construction efficiency. Clerc et al. [6] developed an AI edge computing system based on 18 nm FD-SOI chips that enables real-time (15 fps) and energy-efficient (14.8 μ J per inference) road surface monitoring, providing critical hardware support for intelligent construction equipment. Zhao et al. [7] assessed the economic benefits of artificial intelligence technologies in urban intelligent transportation systems and found that AI applications significantly reduce road investment costs while supporting sustainable urban development and enhancing traffic safety. Yan et al. [8] systematically introduced the principles of various generative AI technologies, categorized intelligent transportation system (ITS) tasks into four groups—traffic perception, traffic prediction, traffic simulation, and traffic decision-making—and demonstrated how generative AI addresses key challenges across these task categories.

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In the maintenance and inspection stage, deep learning-based image recognition technologies can rapidly detect structural defects in bridges and tunnels. Busgaib Goncalves et al. [9] utilized smartphone cameras combined with CNN (Convolutional Neural Network) models to detect pavement cracks and potholes (mAP = 0.54), demonstrating the feasibility of using consumer-grade devices. In the maintenance management stage, AI-driven predictive maintenance models can provide early warnings of road deterioration and reduce overall maintenance costs. Qu Zhe [10] proposed an ETC+ digital maintenance platform based on AIoT, which achieves full-cycle monitoring of maintenance processes through BeiDou positioning and edge computing.

Regarding talent demand forecasting, numerous scholars have applied various predictive methods, including grey prediction models, BP neural networks, and autoregressive integrated moving average (ARIMA) models. Zhang Tingting [11], Hong Xiulai [12], and others employed the grey GM(1,1) model to predict the number of marketing graduates cultivated by Guilin University A and the demand of health human resources talents in Tianjin. Fan Dan [13], Shen Yu [14], and colleagues used BP neural networks to estimate the demand for exhibition-related talent in Chengdu and technical/skilled personnel in Shanxi Province. Yu [15], Liu Tianyue [16], and others predicted the monthly job demand in a municipal talent market over a three-year period using the ARIMA model. Sun [17] proposed a hybrid GM(1,1)–BP neural network model for forecasting talent demand in the information service industry. Tang et al. [18] employed a combination of talent density analysis, trend extrapolation, and regression methods to quantitatively forecast the demand for air transport professionals in Yunnan Province for 2030 and 2040. Their results indicate that air transport employment in Yunnan Province is expected to increase substantially in the future, accompanied by a continuous rise in talent density.

In summary, existing talent demand forecasting models have achieved promising results in fields such as marketing, civil aviation, and economic management. However, their application to talent demand prediction in the highway industry remains limited, and systematic forecasts of cross-disciplinary talent needs at the intersection of highway engineering and AI are even rarer. The integrated development of highway engineering and AI is affected by multiple stochastic factors—including fluctuations in talent numbers, shifts in policy orientation, and variations in industrial investment—resulting in substantial inherent uncertainty. Drawing on statistical data from Fujian Province's highway industry from 2019 to 2024, supplemented by expert interview insights, this study employs a Bayesian regression model to forecast overall talent demand and AI-related cross-disciplinary talent demand in the highway sector from 2025 to 2029. The results provide a scientific foundation for medium- and short-term talent planning in Fujian Province's highway industry.

2 Introduction to prediction methods

2.1 The principle of Bayesian regression prediction

Bayesian regression models perform inference by formulating regression problems within a Bayesian framework. Unlike traditional frequentist statistical methods, Bayesian approaches can effectively handle small-sample datasets, generate full posterior distributions of parameters, quantify prediction uncertainty in a rigorous manner, and naturally incorporate prior knowledge. The core of this approach is Bayesian theorem, which can be expressed as follows:

$$P(\theta|D) = \frac{P(D|\theta)P(\theta)}{P(D)} \quad (1)$$

where, $P(\theta|D)$ is the posterior probability distribution, which represents the probability distribution of the parameter θ after ob-

serving the data D . $P(D|\theta)$ is the likelihood function, which represents the probability of observing data D under the condition of given parameter θ . $P(\theta)$ is a prior probability distribution, which reflects the belief or hypothesis of the parameter θ before the observation data. $P(D)$ is the marginal likelihood, which is the marginal probability of the data.

$P(D)$ is typically treated as a normalization constant, and its calculation is given by:

$$P(D) = \int P(D|\theta)P(\theta)d\theta \quad (2)$$

In practical applications, the marginal likelihood $P(D)$ is often difficult to compute directly. However, Bayesian methods can sample from the posterior distribution $P(\theta|D)$ using numerical techniques—such as Markov Chain Monte Carlo (MCMC)—without requiring explicit evaluation of $P(D)$.

The linear Bayesian regression model can be expressed mathematically as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \sigma \quad (3)$$

where, $\sigma \sim N(0, \sigma^2)$. The model parameters β_0 , β_1 , β_2 , and β_3 are treated as random variables, and their posterior distributions are estimated using Bayesian inference.

2.2 Research basic data

The data used in this study—including the total number of employees in the ordinary highway industry of Fujian Province, the number of brain drain, and the total investment in the provincial highway industry—were obtained from internal statistics of provincial institutions, such as the Provincial Highway Development Center and Fujian Provincial Transportation Human Resources Co., Ltd. The number of college graduates refers to graduates from highway engineering-related programs at universities such as Fuzhou University, Fujian Agriculture and Forestry University, and Fujian University of Technology over the past six years. The specific statistical results are presented in Table 1.

Table 1 Basic data sheet.

Year	Total number of employees	Total investment (billion yuan)	Brain drain	Number of college graduates
2019	4 210	381	28	532
2020	4 255	390.5	28	532
2021	4 300	400	28	532
2022	4 545	400	30	519
2023	4 762	399	20	536
2024	4 965	398	30	651

Given the absence of explicit statistics on the number of AI-highway engineering interdisciplinary professionals in existing highway enterprises and management agencies, this study estimates the overall penetration rate of AI interdisciplinary talent in the highway engineering sector by integrating projections of future talent demand with insights obtained from extensive expert interviews.

A total of 12 experts were interviewed, including three researchers from the Department of Transportation, four senior engineers from highway construction enterprises, two industry talent-planning consultants, and three university professors specializing in intelligent transportation. All participants had at least 10 years of industry experience and demonstrated expertise in AI applications or talent planning. Semi-structured interviews were conducted, focusing on (i) the current status of AI applications across different segments of the highway industry and (ii) the reasonable range of AI-related talent penetration in these segments over the next five years. The results indicate a high level of consensus among experts regarding the AI talent penetration rate, with an average of $5\% \pm 1\%$; however, minor differences were observed in assessments of penetration between the planning and design stage and the con-

struction stage. To enhance model robustness, the median value of expert opinions was adopted as the parameter setting. Accordingly, the overall penetration rate of AI–highway engineering interdisciplinary talent in the highway industry is assumed to increase annually, with a base-year value of 5%, an annual increase of 2% in the current period, and an annual increase of 3% in the forecast period.

According to expert interviews, although AI has contributed to current planning and design processes (e.g., through optimization algorithms), its overall presence in the highway industry remains relatively low, and the proportion of AI professionals is limited. AI applications in construction are also restricted, with a similarly low proportion of technical personnel. By contrast, AI is widely applied in maintenance and inspection (e.g., image recognition and predictive maintenance) as well as in operation management (e.g., intelligent transportation systems). Based on the current application levels, technological maturity, and adoption trends of AI in the highway industry, the penetration rates of AI professionals across the four domains—planning and design, construction, maintenance and inspection, and operation management—are summarized in Table 2.

Table 2 The penetration rate of AI talents in each link.

Link	Planning and design	Construction	Maintenance inspection	Operation management
Proportion	12%	20%	40%	28%

3 Establishment of the predictive model

3.1 Data preprocessing

The talent dataset in the highway industry comprises the dependent variable, the total number of employees, and the independent variables, including the annual total investment in the highway industry (in billions of yuan), the number of brain drain, and the number of college graduates in relevant fields. Due to substantial differences in the scales of these variables, all variables are standardized.

$$x_{\text{std}} = \frac{x - \bar{x}}{s_x} \quad (4)$$

where, $\bar{x}$ denotes the sample mean; s_x represents the sample standard deviation. Standardization allows the influence coefficients of different variables to be comparable and improves the efficiency of MCMC sampling.

3.2 Model setting

This study develops a Bayesian linear regression model in which the number of employees serves as the dependent variable, with standardized total investment, brain drain, the number of college graduates, and other relevant variables as independent variables.

The mathematical representation of the regression model is:

$$y_{\text{std}} = \beta_0 + \beta_{\text{inv}} x_{\text{inv, std}} + \beta_{\text{inv}} x_{\text{loss, std}} + \beta_{\text{grad}} x_{\text{grad, std}} + \sigma \quad (5)$$

where, y_{std} is the standardized number of employees; $x_{\text{inv, std}}$, $x_{\text{loss, std}}$, $x_{\text{grad, std}}$ are standardized independent variables, representing the total investment in the highway industry, the number of brain drain, and the number of college graduates, respectively. β_0 is the intercept; β_{inv} , β_{loss} , β_{grad} are regression coefficients, representing the effects of total investment, brain drain, and the number of college graduates on the total number of employees, respectively. $\sigma \sim \text{Half-Cauchy}(1)$ is the error term, following a half-Cauchy distribution with a scale parameter of 1.

The Bayesian model needs to specify a prior distribution for all parameters. In this study, based on domain knowledge and preliminary data analysis, the following priors are set.

Empirical research by Park et al. [19], based on multi-regional data from the United States, demonstrates that transportation infrastructure investment contributes to economic growth through both

direct and indirect channels, including positive effects on employment via productivity gains and labor market improvements. Accordingly, this study specifies a normal prior distribution with a positive mean for the investment input coefficient to capture the expected positive effect of investment on the growth of talent demand. To avoid excessive reliance on subjective judgment, the prior standard deviation is set to 1, thereby allowing for parameter uncertainty. Chen et al. [20] further show that higher education significantly enhances both employment opportunities and job quality among young people. As college graduates constitute a major source of new talent supply for the industry, their positive influence on the size of the industrial workforce has been well established in the human capital literature. Consequently, a normal prior distribution with a positive mean is assigned to the graduate coefficient to reflect the contribution of college graduates to the replenishment of industry talent. In contrast, brain drain represents the outflow of highly skilled and experienced workers from the industry and, from a human capital supply perspective, constrains workforce size. Therefore, the brain drain coefficient is specified as negative to represent its inhibitory effect on industry employment.

Based on the preceding analysis, the prior distribution parameters specified in this study are as follows:

The intercept term is assigned a normal prior: $\beta_0 \sim N(0, 10)$, the total investment coefficient follows a weakly informative positive prior: $\beta_{\text{inv}} \sim N(0.5, 1)$, the brain drain coefficient is specified with a weakly informative negative prior: $\beta_{\text{loss}} \sim N(-0.2, 1)$, and the college graduates coefficient is assigned a moderately informative positive prior: $\beta_{\text{grad}} \sim N(0.8, 1)$.

3.3 Posterior distribution

In Bayesian analysis, the posterior distribution often lacks an analytical solution. Therefore, this study employs MCMC method for numerical approximation. By combining the advantages of Bayesian inference with MCMC simulation, parameter estimation can be effectively conducted for nearly all models with stochastic components. Based on the specified prior distributions, historical sample data are used in Bayesian sampling to perform parameter inference, allowing the posterior distribution characteristics of each parameter to be obtained.

3.4 Prediction method

Based on the obtained posterior distributions of the model parameters, three scenarios are established to predict the number of AI talents from 2025 to 2029:

(1) Baseline scenario: Annual total investment in the highway industry remains at 400 billion yuan, brain drain remain at 28 per year, and the number of college graduates increases by 2% annually.

(2) Optimistic scenario: Annual total investment in the highway industry increases by 2% per year, brain drain decrease annually to as low as 22 per year, and the number of college graduates increases by 4% per year.

(3) Conservative scenario: Annual total investment in the highway industry decreases by 1% per year, brain drain s increase annually to a maximum of 34 per year, and the number of college graduates grows by 1% per year.

(4) The prediction process employs the MCMC method, drawing a large number of samples from the posterior distributions of the parameters to calculate the predicted results.

4 Analysis of prediction results

4.1 Descriptive statistics and correlation analysis

Based on the descriptive statistics of each research variable presented in Table 3, during the period from 2019 to 2024, the average total number of employees in the highway industry was

Table 3 Descriptive statistical results of research variables.

	Year	Total number of employees	Total investment (billion yuan)	Brain drain	Number of college graduates
Parameter	6	6	6	6	6
Average value	2 021.50	4 506.17	394.75	27.33	550.33
Standard deviation	1.87	306.85	7.63	3.72	49.66
Minimum	2 019.00	4 210.00	381.00	20.00	519.00
25%	2 020.25	4 266.25	392.38	28.00	532.00
50%	2 021.50	4 422.50	398.50	28.00	532.00
75%	2 022.75	4 707.75	399.75	29.50	535.00
Maximum	2 024.00	4 965.00	400.00	30.00	651.00

4,506, ranging from a minimum of 4,210 in 2019 to a maximum of 4,965 in 2024, indicating a stable growth trend. The average annual total investment was 39.475 billion yuan, and the average number of college graduates was 550.

The correlation analysis results for the research variables are presented in Table 4. The total number of employees exhibits a significant positive correlation with the year, the total investment in

the highway industry, and the number of college graduates, with correlation coefficients of 0.965, 0.584, and 0.723, respectively. The strong correlation between year and the total number of employees suggests that the workforce in the highway industry has demonstrated a stable growth trend in recent years. Conversely, the total number of employees shows a weak negative correlation (−0.184) with brain drain.

Table 4 Study the correlation coefficient matrix of variables.

	Year	Total number of employees	Total investment (billion yuan)	Brain drain	Number of college graduates
Year	1.000	0.965	0.774	−0.172	0.639
Total number of employees	0.965	1.000	0.584	−0.184	0.723
Total investment in highway industry	0.774	0.584	1.000	−0.120	0.177
The number of brain drain in enterprises	−0.172	−0.184	−0.120	1.000	0.274
Number of college graduates	0.639	0.723	0.177	0.274	1.000

4.2 Parameter estimation of Bayesian model

The model employs the PyMC library to perform efficient sampling using the No-U-Turn Sampler (NUTS) algorithm, with 2,000 samples per chain, 4 parallel chains, and a total of 8,000 samples. The NUTS sampler provides high sampling efficiency

and low autocorrelation, which substantially increases the effective sample size (ESS). The resulting ESS values range from 2,161.607 to 6,280.297. The model outputs include the posterior distribution characteristics of the parameters (Table 5), the posterior distribution densities (Fig. 1) and the MCMC chain trajectories (Fig. 2).

Table 5 The posterior distribution characteristics of Bayesian regression model parameters.

Parameter	Average value	Standard deviation	HDI 2.5%	HDI 97.5%	Ess_bulk	Ess_tail	$\hat{R}$
Intercept term	−0.003	0.399	−0.757	0.837	6 463.347	4 007.149	1.001
Investment coefficient	0.424	0.355	−0.297	1.151	5 985.806	3 977.292	1.001
loss coefficient	−0.322	0.362	−1.078	0.392	7 183.445	4 365.163	1.001
Graduate coefficient	0.742	0.371	−0.015	1.499	6 767.561	4 499.56	1.001
Error term σ	0.868	0.445	0.299	1.732	2 053.141	2 899.021	1.002

As shown in Table 5, the mean values of the investment coefficient and the graduate coefficient are 0.424 and 0.742, respectively, both positive, indicating that the level of investment in the highway industry and the supply of college graduates positively affect the total number of employees. The mean value of the drain coefficient is −0.322, suggesting that talent loss negatively impacts the total number of employees. The 95% HDI interval of the graduate coefficient is [−0.015, 1.499], and the 95% HDI interval of the investment coefficient is [−0.277, 1.113]. Although it crosses zero, the mean value still shows a positive correlation trend. The 95% HDI for the drain coefficient is [−1.078, 0.392], primarily negative, confirming its adverse effect on the total number of employees. The mean value of the intercept term is close to zero, suggesting no systematic bias in the standardized model. The mean value of the error term σ is 0.868, indicating relatively small residual fluctuations and stable overall model fit. High values of ESS_bulk and ESS_tail further indicate that both the mean and quantile estimates of parameters are stable, and the MCMC sampling process converged well, validating the reliability of the posterior distributions. The convergence index $\hat{R}$ ranges from 1.001 to 1.002 across parameter chains, below the 1.1 threshold, indicating good model convergence.

Fig. 1 is the posterior distribution density map. The distribution of each parameter is close to normal, and σ is right-skewed, which conforms to the Half-Cauchy prior characteristics. Fig. 2 is the sampling trajectory diagram of MCMC chain. The trajectory dia-

gram shows that the sampling path of each chain is random and has no obvious trend. The mixing between chains is good, and there is no obvious periodicity or trend. All chains fluctuate stably in the parameter space, indicating that the sampling process converges well.

Overall, the estimated model parameters align with the prior assumptions: investment and graduate variables exert a positive effect, whereas the drain variable has a negative effect. Moreover, the MCMC sampling process is stable, inter-chain convergence is satisfactory, and the parameter estimates are reliable.

4.3 Posterior distribution evaluation

The model employs the cumulative distribution function (CDF) to compare observed values with posterior predicted values. The posterior prediction results are presented in Fig. 3, where the horizontal axis represents the standardized number of employees and the vertical axis represents cumulative probability. The figure shows that the observed values largely fall within the posterior predictive distribution, indicating good agreement between the model predictions and the actual data. Additionally, the mean of the posterior predictions closely aligns with the observed values, suggesting that the model fits the existing data well.

Overall, the Bayesian model demonstrated strong performance on the small-sample data, achieving an R^2 of 0.8456. The MCMC diagnostic indicators indicated good convergence, and the posterior parameter estimates were reliable.

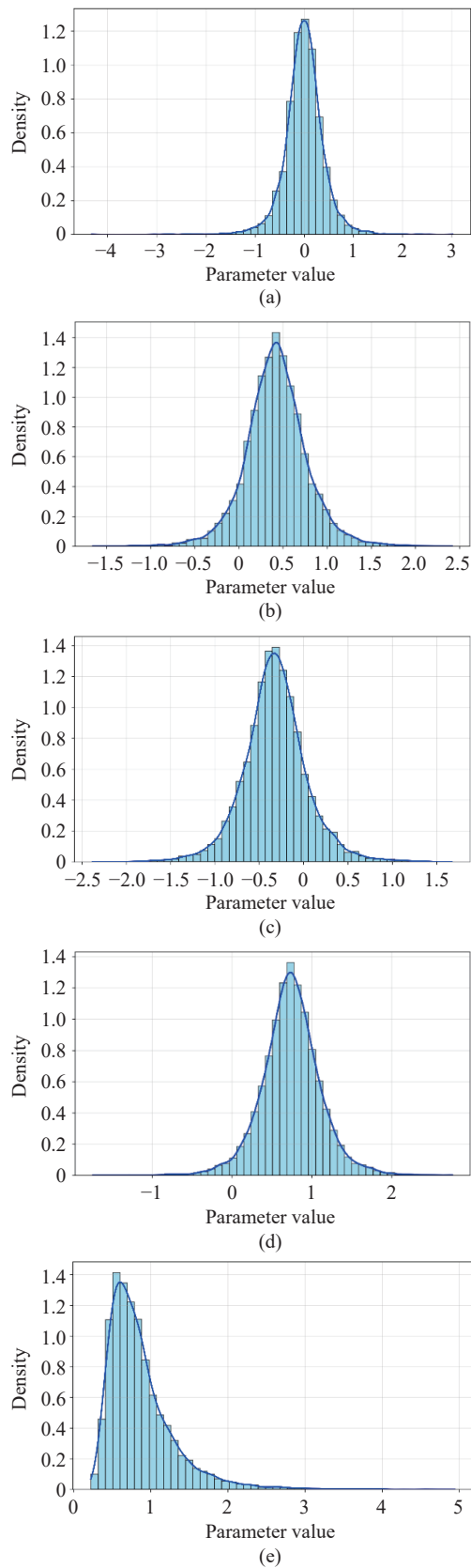


Fig. 1 Posterior distribution density. (a) Intercept term; (b) Investment coefficient; (c) Loss coefficient; (d) Graduate coefficient; (e) Error term σ .

4.4 Prediction result

The number of talents in the general highway industry from 2025 to 2029 was predicted under three scenarios using the

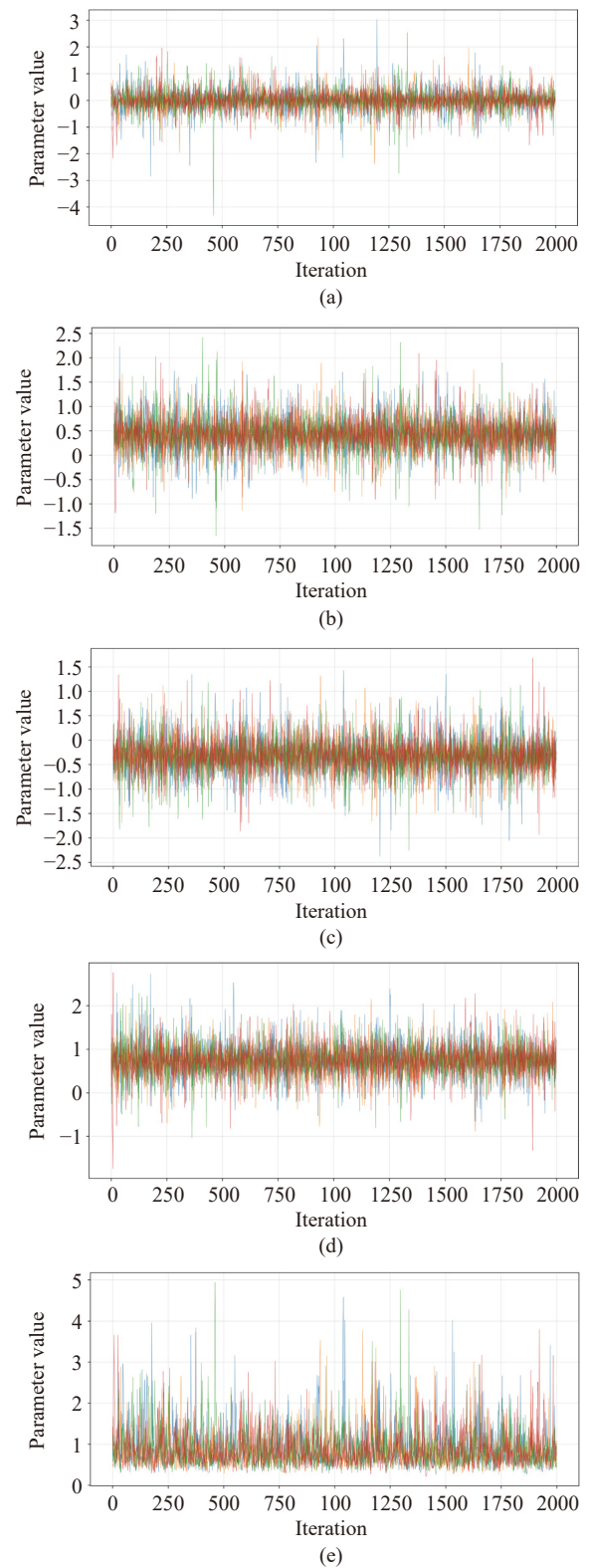


Fig. 2 MCMC chain sampling trajectory. (a) Intercept term; (b) Investment coefficient; (c) Loss coefficient; (d) Graduate coefficient; (e) Error term σ .

Bayesian model. The prediction results are presented in Fig. 4.

Table 6 presents the forecasted total number of employees from 2025 to 2029 under the baseline scenario. The total workforce is projected to grow steadily, increasing from 5,098 in 2025 to 5,351 in 2029, representing a cumulative increase of 253 over the five-year period. The number of AI cross-disciplinary talents is expected to rise from 918 to 1,605.

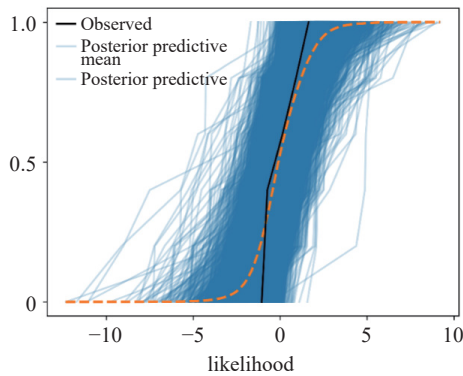


Fig. 3 A posteriori prediction test chart.

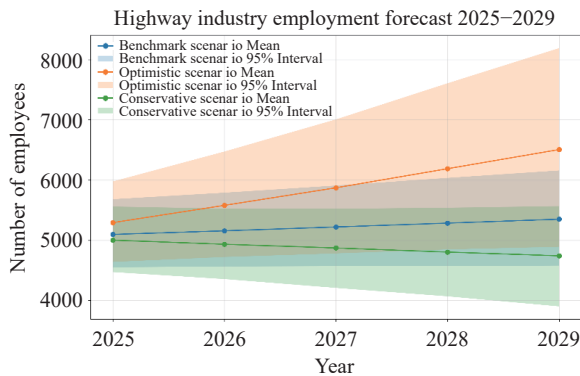


Fig. 4 2025–2029 industry total talent forecast results chart.

Table 7 presents the forecasted total number of employees from 2025 to 2029 under the optimistic scenario. The total workforce is projected to grow rapidly, increasing from 5,294 in 2025 to 6,508 in 2029, representing a cumulative increase of 1,214 over the five-year period. The number of AI cross-disciplinary talents is expected to rise from 953 to 1,952. This growth in the total workforce is primarily driven by the combined effects of increased investment, reduced brain drain, and the rising number of college graduates.

Table 8 presents the forecasted total number of employees from 2025 to 2029 under the conservative scenario. The total workforce is projected to decline gradually, decreasing from 5,003 in 2025 to 4,743 in 2029, representing a cumulative reduction of 260 over the

five-year period. Nevertheless, the number of AI cross-disciplinary talents is expected to continue growing, rising from 901 to 1,423. The decline in the total workforce is primarily attributable to the combined effects of reduced investment, increased brain drain, and limited growth in the number of college graduates. In contrast, the growth in AI cross-disciplinary talents is mainly driven by the advancement of AI technology and the increasing penetration rate of AI talents.

Based on the penetration rates of AI talents in each segment presented in Table 2, Table 9 summarizes the predicted demand for AI cross-disciplinary talents in the four key areas of the highway industry—planning and design, construction, maintenance and inspection, and operation management—under the three scenarios.

5 Conclusion

(1) The Bayesian regression model is a multivariate statistical model that incorporates multiple independent variables, including total investment, brain drain, and the number of college graduates. It estimates the posterior distributions of the parameters by combining prior distributions with observed data, thereby quantifying the dynamic effects of investment, drain, and graduates on the total number of employees. This approach produces predictions that better reflect the actual constraints of the industry, yielding more conservative and reliable results.

(2) The estimated model parameters align with the expected directions of the prior assumptions. The MCMC sampling process is stable, inter-chain convergence is satisfactory, and the parameter estimates are reliable. The posterior distributions of the parameters are approximately normal. The sampling trajectories of the MCMC chains are random, with no discernible trends, and inter-chain mixing is good, confirming stable convergence. Furthermore, the mean posterior predictions closely match the observed values, indicating that the model predictions are consistent with the actual data and that the model demonstrates a good fit.

(3) The predictions from the Bayesian regression model indicate a substantial growth in the demand for AI cross-disciplinary talents in the highway engineering sector in Fujian Province. Under the baseline scenario, the total workforce is projected to reach 5,351 by 2029, including 1,605 AI cross-disciplinary talents, representing a cumulative increase of 687 over five years. In the optimistic scenario, driven by increased investment, reduced brain drain, and a rise in the number of graduates, the total workforce is expected to reach 6,508 by 2029, with 1,952 AI cross-disciplinary

Table 6 Prediction of the number of employees in 2025–2029 under the baseline scenario.

Year	Total number of employees	95 % prediction interval	Total investment (billion yuan)	Brain drain	Number of college graduates	Total number of AI cross talents
2025	5 098	[4 552, 5 683]	400	28	664	918
2026	5 158	[4 566, 5 791]	400	28	677	1 083
2027	5 222	[4 571, 5 910]	400	28	691	1 253
2028	5 286	[4 574, 6 037]	400	28	705	1 427
2029	5 351	[4 580, 6 160]	400	28	719	1 605

Table 7 Prediction of the number of employees in 2025–2029 under optimistic scenarios.

Year	Total number of employees	95 % prediction interval	Total investment (billion yuan)	Brain drain	Number of college graduates	Total number of AI cross talents
2025	5 294	[4 642, 5 978]	408	28	677	953
2026	5 581	[4 724, 6 475]	416	27	704	1 172
2027	5 873	[4 783, 7 009]	424	26	732	1 410
2028	6 190	[4 850, 7 609]	433	25	762	1 671
2029	6 508	[4 893, 8 193]	442	24	792	1 952

Table 8 Prediction of the number of employees in 2025–2029 under conservative scenarios.

Year	Total number of employees	95 % prediction interval	Total investment (billion yuan)	Brain drain	Number of college graduates	Total number of AI cross talents
2025	5 003	[4 473, 5 561]	396	28	658	901
2026	4 935	[4 357, 5 527]	392	29	664	1 036
2027	4 873	[4 210, 5 524]	388	30	671	1 170
2028	4 805	[4 070, 5 541]	384	31	677	1 297
2029	4 743	[3 903, 5 568]	380	32	684	1 423

Table 9 The predicted value of AI talents in each link.

Scenario	Year	Planning and design	Construction	Maintenance inspection	Operation management	Total number of AI cross talents
Baseline scenario	2025	110	184	367	257	918
	2026	130	217	433	303	1 083
	2027	150	251	501	351	1 253
	2028	171	285	571	400	1 427
	2029	193	321	642	449	1 605
Optimistic scenarios	2025	114	191	381	267	953
	2026	141	234	469	328	1 172
	2027	169	282	564	395	1 410
	2028	201	334	669	468	1 671
	2029	234	390	781	547	1952
Conservative scenarios	2025	108	180	360	252	901
	2026	124	207	415	290	1 036
	2027	140	234	468	327	1 170
	2028	156	259	519	363	1 297
	2029	171	285	569	398	1 423

talents, corresponding to a cumulative increase of 999 over five years. Even under the conservative scenario, despite a projected decline in total workforce to 4,743 by 2029 due to factors such as reduced investment and increased drain, the number of AI cross-disciplinary talents is still expected to grow, reaching 1,423, with a cumulative increase of 522 over the five-year period.

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Declaration of competing interest

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Author contribution statement

Yu Liang: writing-original draft, conceptualization, data curation methodology, software. Yanqun Yang: writing-review and editing, methodology. Shoujie Huang: data curation, investigation, software. Zhandong Zhu: data curation, software. Qingxiong Wu: writing-review and editing, funding acquisition, methodology.

Data availability statement

All data, models, and code generated or used during the study appear in the submitted article.

Use of AI statement

During the preparation of this research, we used Chatgpt to improve grammar and readability. After using this tool, we reviewed and edited the content as needed and take full responsibility for content of the publication.

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