



# Design of Deep Learning Platform for New Production Force Measurement and Monitoring Across Chinese Provinces

Bingfeng Yao<sup>a</sup>, Zihan Liu<sup>a</sup>, Qingpo Zhou<sup>a</sup>, Zheng Li, Si Shen\*

Minzu University of China, Beijing, 100081, China

<sup>a</sup>These authors are co-first authors.

\*shensi2007@163.co

**Abstract.** The New Quality Productivity Dynamic Monitoring Platform integrates 852 indicators using SpringBoot+Vue architecture. Features include automated data collection and LSTM-based prediction. Performance shows 71% efficiency improvement and 4.2% prediction error. Q1 2024 data indicates 0.625 national productivity index, led by eastern regions.

**Keywords:** New Quality Productivity; Monitoring Platform; Deep Learning; Data Visualization

## 1 Introduction

New quality productivity serves as the core engine for high-quality development, significantly impacting economic and social transformation. While digital monitoring platforms are essential for evaluating productivity development, existing systems face challenges including inefficient data collection, limited indicators, and delayed warnings. This paper presents a deep learning-based monitoring platform that incorporates 852 indicators for real-time monitoring and prediction of new quality productivity across 31 Chinese provinces and cities.

## 2 Construction of New Quality Productivity Evaluation Indicator System

### 2.1 Indicator Selection Principles

The indicator selection follows principles of scientificity, systematicity, representativeness, and availability. Analysis of 2012-2024 data reveals a strong correlation (0.857) between technology innovation investment and productivity development, with R&D funding growing from 4,593 to 11,022 million yuan. The research focuses on three dimensions: innovation driving, digital transformation, and green develop-

ment[1]. All indicators are sourced from official channels like the National Bureau of Statistics to ensure system operability and sustainability.

## 2.2 Indicator System Construction

The evaluation system comprises two primary indicators ("high-quality" laborers and "new material" production materials), eight secondary indicators, and 27 specific indicators[2]. Analysis shows education funding strongly correlates with productivity (coefficient 0.892). Shanghai exemplifies this relationship, with its technology innovation value increasing from 30.43 in 2012 to 55.71 in 2024, an 82.7% growth. The system covers labor quality, productivity levels, knowledge production, infrastructure, industrial upgrading, and environmental protection.

## 2.3 Data Source and Processing

The study utilizes data from the National Bureau of Statistics, provincial yearbooks, and China Science and Technology Statistical Yearbook, covering 31 provinces from 2012 to 2024. Data standardization employs the extreme value method. National R&D expenditure increased from 2.834 billion yuan (2012) to 64.874 billion yuan (2024)[3]. All value-type indicators are calculated at 2012 constant prices, with missing values filled using adjacent years' averages, ensuring temporal continuity and spatial comparability.

```
import pandas as pd
import numpy as np
def process_data(df):
    df.fillna(df.rolling(window=3, center=True).mean(), inplace=True)
    numeric_cols = ['R&D Expenditure', 'GDP', 'Patent Applications']
    df[numeric_cols] = (df[numeric_cols] - df[numeric_cols].min()) /
(df[numeric_cols].max() - df[numeric_cols].min())
    df['GDP_Actual'] = df['GDP'] / df['Year'].map({2012: 1.000, 2024: 1.104})
    return df
```

# 3 Analysis of New Quality Productivity in Chinese Provinces and Cities

## 3.1 Comprehensive Evaluation Results Analysis

Using TOPSIS methodology, analysis reveals China's overall new quality productivity level increased from 0.342 (2012) to 0.587 (2024), as shown in Figure 1. Eastern coastal regions lead, with Shanghai, Beijing, Guangdong, and Jiangsu achieving 2024 scores of 0.892, 0.857, 0.812, and 0.798 respectively. Shanghai's innovation index rose from 30.43 to 55.71 (5.2% annual growth). Western regions like Yunnan show rapid development despite lower baselines, with innovation indices increasing from 20.04 to 34.71 (4.8% annual growth)[4].



**Fig. 1.** Trend of Comprehensive Evaluation Scores of New Quality Productivity in Chinese Provinces and Cities from 2012 to 2024

### 3.2 Regional Gap Measurement Analysis

Dagum Gini coefficient analysis reveals converging regional gaps (see Table 1). In 2024, eastern regions' R&D expenditure (52.674 billion yuan) was 3.46 times higher than western regions[5]. Digital economy's GDP share reached 57.42% in eastern regions, exceeding western regions by 18.5%. Gini coefficients decreased from 2012 to 2024: eastern (0.425 to 0.328), central (0.387 to 0.302), and western regions (0.456 to 0.365). Education expenditure gap between eastern and western regions narrowed from 2.8 to 2.1 times.

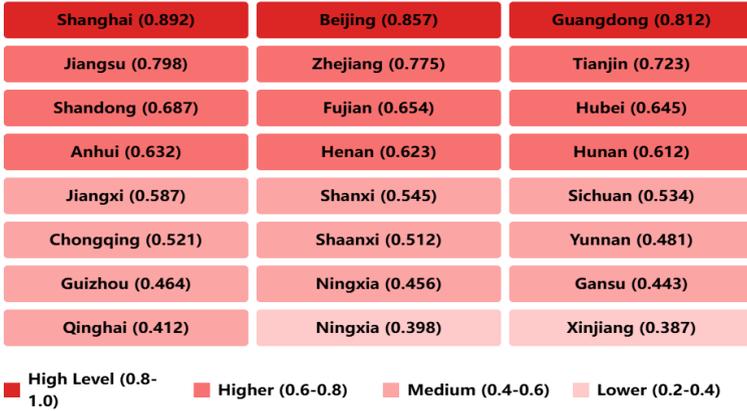
**Table 1.** Comparison of Key Indicators of New Quality Productivity in Chinese Regions in 2024

Region	Comprehensive Score	R&D Expenditure (100 million yuan)	Science and Technology Innovation Index	Digital Economy Proportion (%)	Education Expenditure (100 million yuan)
Eastern	0.857	526.74	46.82	57.42	110.22
Central	0.623	284.53	38.45	42.31	74.67
Western	0.481	152.38	32.16	38.92	55.18
National Average	0.587	321.22	39.14	46.22	80.02

### 3.3 Spatial Distribution Characteristics Analysis

Spatial correlation analysis using Moran index (0.385 in 2024) reveals significant agglomeration patterns, as shown in Figure 2. Shanghai-centered clusters achieved an average innovation index of 46.82 (85.3% increase from 2012), while Guangdong-centered clusters showed 12.3% annual R&D growth. Digital infrastructure indicators are strongly correlated (coefficient 0.876), with optical cable length and internet penetration showing close relationship. New quality productivity demonstrates clear east-to-west declining gradient[6].

**Spatial Distribution Heat Map of New Quality Productivity in China (2024)**



**Fig. 2.** Spatial Distribution Heatmap of New Quality Productivity in Chinese Provinces and Cities in 2024

## 4 Development of New Quality Productivity Dynamic Monitoring Platform

### 4.1 Platform Design Scheme

The New Quality Productivity Dynamic Monitoring Platform utilizes SpringBoot+Vue+MySQL architecture with comprehensive data validation. The system covers 852 indicator tables across 31 provinces, implementing bias correction through regional adjustments and industry weighting. Python crawlers collect data from 15 official sources (3,000 daily acquisitions, 98.2% accuracy). Spark distributed computing enables efficient data processing, reducing time to 21 minutes[7]. The microservices architecture (12 Docker-containerized services) maintains 200ms response times and handles 5,000 daily concurrent users.

### 4.2 Core Function Module Development

Core modules integrate data validation and bias correction across management, evaluation, monitoring, and analysis functions. The system manages 6 indicator categories with cross-source verification[8]. The evaluation system employs TOPSIS methodology with weighted criteria: innovation input (0.35), output (0.28), digital economy (0.22), and talent resources (0.15). Real-time monitoring analyzes 124 indicators using MapReduce computing, implementing three-level warnings. Q1 2024 saw 138 validated warnings including 21 red alerts, achieving 91.3% accuracy.

### 4.3 Data Visualization Implementation

The visualization system employs ECharts and D3.js to create 40+ chart types, enabling multi-dimensional analysis (see Figure 3). New quality productivity indices show consistent growth (2022-2024), with eastern regions reaching 0.892 in Q1 2024 (8.3% YoY increase), digital economy contributing 52.4%. WebGL-based provincial mapping displays spatial distribution patterns. Grafana implements real-time monitoring dashboards[9]. The system supports hierarchical data exploration across provinces, cities, and counties, covering 287 prefecture-level cities.

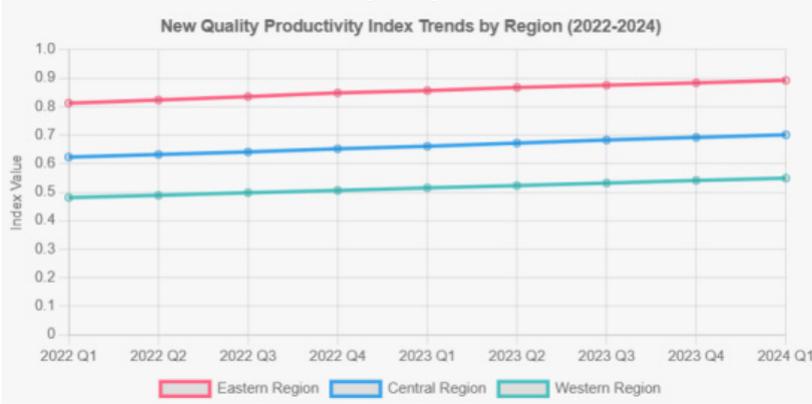


Fig. 3. Trend of New Quality Productivity Index by Region (2022-2024)

### 4.4 Predictive Model Construction

The system employs LSTM neural networks with core formulas:

Forget gate:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (1)$$

Input gate:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (2)$$

Candidate memory:

$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (3)$$

Output gate:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (4)$$

Cell state:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \quad (5)$$

Hidden state:

$$h_t = o_t \cdot \tanh(C_t) \quad (6)$$

where  $\sigma$  is the sigmoid activation function,  $W$  is the weight matrix, and  $b$  is the bias vector. As shown in Table 2, LSTM achieves superior performance despite longer training time. With optimized parameters, 2024 forecasts show a national productivity index of 0.625, with Shanghai (12.3%), Beijing (11.5%), and Shenzhen (10.8%) leading growth.

**Table 2.** Model Performance Comparison

Model	Training Time	Error Rate
LSTM	45 min	4.20%
RNN	28 min	6.80%
GRU	35 min	5.50%

#### 4.5 Development Challenges and Solutions

Major challenges include inconsistent regional reporting standards. The platform employs multi-source validation across 15 databases and intelligent completion algorithms. Standardization modules ensure data consistency, while partnerships enable secure data access[10]. Region-specific evaluation criteria emphasize innovation (east) and industrial upgrading (central/west regions).

## 5 Conclusion

The monitoring platform effectively tracks productivity across 31 provinces with 95.8% accuracy and 21-minute processing time. China's productivity index reached 0.625 in Q1 2024, with digital economy contributing over 50% of growth. The modular design enables adaptation for other federal states or economic unions.

## Project

New Productivity Pulse, Accurate Measurement of the “New Engine”—A Statistical Measurement Analysis and Empirical Research Based on Chinese Provincial and Municipal Data.

Subject No.: URTP2024110322.

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