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# Three-Layer Framework for Service Industry Quality Assessment: Evidence from Shiyan City

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***Abstract.*** This study proposes a three-tier framework integrating VAE deep generative modeling, multi-method time series forecasting, and macro-environmental validation for service industry quality assessment in medium-sized cities. Applied to Shiyan City's 19 service industries, the framework achieved 0.7727 average quality scores and identified 14 positive-growth industries with 66.7% high-confidence predictions, providing systematic solutions for regional service industry development evaluation.

***Keywords:*** Service industry quality assessment, Variational Auto-Encoder, Time series forecasting, Medium-sized cities

## 1. Introduction

Assessment of service sector development quality and growth forecasting has become crucial for regional economic planning (Wu et al., 2024) [1]. China's service sector contributed 54.6% of GDP in 2023, yet significant regional variations exist in development quality. Medium-sized cities face unique challenges, with spatial complexity and multi-objective urban systems complicating policy formulation (Raimbault & Pumain, 2022) [2].

Existing research has methodological limitations: traditional econometric models fail to capture non-linear relationships; DEA techniques focus on static evaluations while ignoring dynamics (Mariz et al., 2018) [3]; machine learning applications remain fragmented (Ogrizović et al., 2024) [4]. Key gaps include: lack of integrated frameworks combining assessment with forecasting, limited deep learning applications, and insufficient macro-micro linkages.

This study proposes a three-layer framework: VAE-based quality assessment, integrated time series forecasting, and macroeconomic validation. Using 19 service industries in Shiyan City, we analyze 161 industry characteristics and 23 macro variables.

Main innovations include: integrating deep generative modeling with forecasting methods; novel VAE application in service quality assessment; and developing robust multi-method forecasting systems for systematic service industry analysis in medium-sized cities.

## 2. Methods

### 2.1. Research framework design

This study constructs a three-tier progressive analytical framework based on the internal logic of services development: services development = f(Endogenous development capacity, historical development trends, external macro-environment).

The first tier conducts development quality assessment through VAE, the second tier forecasts trends based on the quality assessment results, and the third tier validates the reasonableness of the forecasts through the macro-environment and provides policy recommendations.

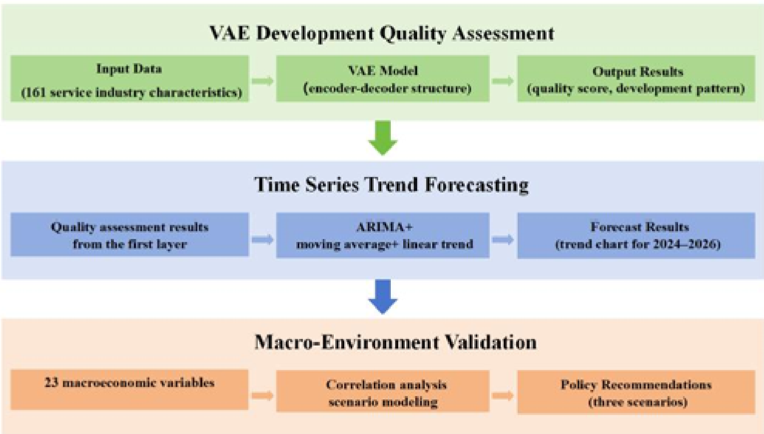


Figure 1. Three-tier progressive analysis framework

### 2.2. Data collection and preprocessing

This study utilizes data from 2018-2024 Shiyan City Statistical Yearbook and Monthly Reports, covering service industry development from 2017-2023. The dataset comprises 13 basic financial indicators (enterprises, assets, revenue, profit, taxes) and 59 engineered features; macroeconomic variables including GDP, population, income, and consumption indicators; and 47 growth rate and structural derivatives.

Data preprocessing employed stratified cleaning using Python tools. An intelligent keyword-based algorithm separated mixed data types, followed by differentiated imputation for missing values through time series interpolation and business logic validation. Feature engineering constructed four systems: development trend features, relative performance indicators, volatility measures, and early warning systems. Post-processing achieved 100% data completeness, providing high-quality inputs for deep learning models.

### 2.3. VAE quality assessment model

Variational Auto-Encoder (VAE) uses an encoder-decoder symmetric architecture to realize unsupervised quality assessment(Kingma & Welling, 2014) [5]. The encoder compresses the high-dimensional input data layer-by-layer into a low-dimensional potential space, capturing the core feature distribution of the data; the decoder reconstructs the potential representation layer-by-layer back to the original dimension. The model is trained by a combined loss function that minimizes the reconstruction error and KL scatter to ensure the regularity of the latent space and the accuracy of the reconstruction. The quality assessment mechanism is based on the reconstruction error: the

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smaller the reconstruction error, the higher the quality of the sample and the less it deviates from the normal pattern.

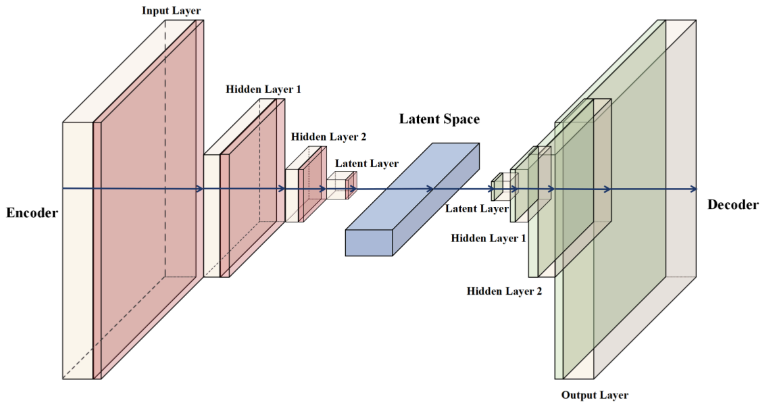


Figure 2. VAE model architecture diagram

## 3. Model development

### 3.1. VAE quality assessment model

This study constructs a hierarchical VAE architecture with an encoder-decoder symmetric structure. The service industry layer is set with potential dimension 12 and intermediate layer dimension 128; the wholesale and retail industry layer is adjusted to potential dimension 10 and intermediate layer dimension 96.The model uses Adam optimizer (Kingma & Ba, 2015) [6] and early stopping mechanism.

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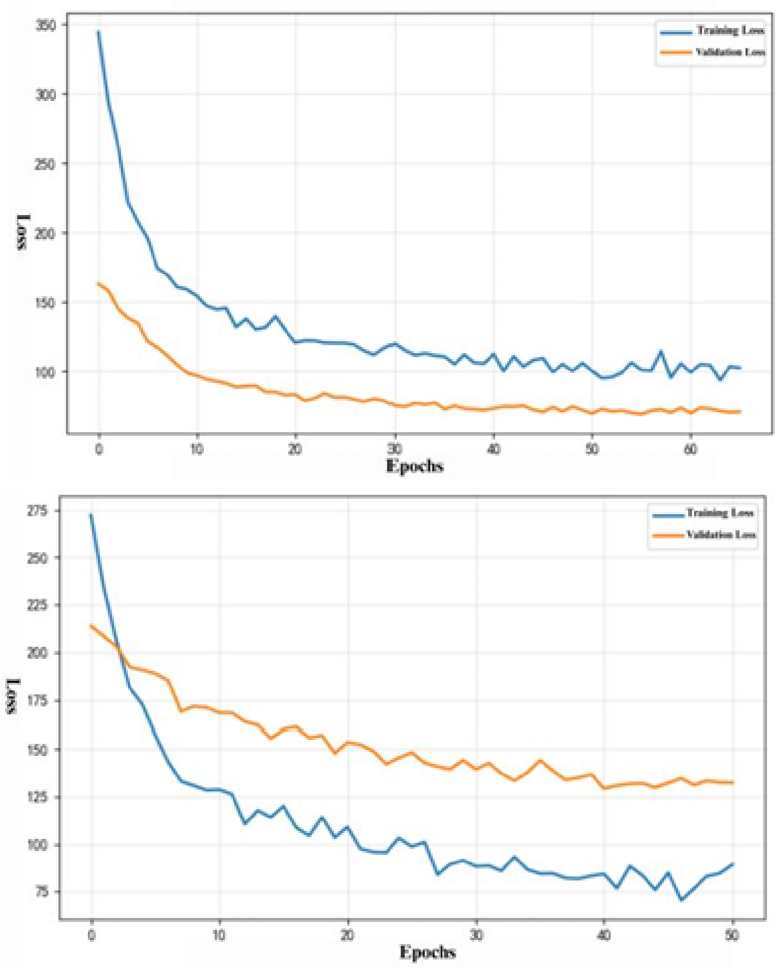


(1) Wholesale and retail curve (2) Services loss curve
Figure 3. VAE training loss curve

The VAE loss function consists of a reconstruction loss and a KL scattering loss: $L = L\_recon + \beta \cdot L\_KL$ where the reconstruction loss is: $L\_recon = E[||x - \hat{x}||^2]$, and the KL scattering loss is: $L\_KL = -1/2 \sum(1 + log\,\sigma^2 - \mu^2 - \sigma^2)$

The quality score is calculated based on the reconstruction error: $qualityscore = 1/(1 + reconstructionerror)$ ,ensuring that the score is in the (0,1) interval. A 95% quantile threshold is used for anomaly detection, and the quality grade is categorized as excellent, good, fair, or poor.

### 3.2. Time series forecast

This study constructs a multi-method fusion time series forecasting framework (Hyndman & Athanasopoulos, 2018) [7]with three core methods: linear trend analysis, growth rate modeling, and moving average. Linear trend forecasting establishes relationship $y\_i = \alpha + \beta x\_i + \varepsilon\_i$ , with least squares parameter estimation and $R^2$, fit assessment for trending series. The growth rate model uses weighted average strate $\hat{g} = 0.3 \times g\_all + 0.7 \times g\_recent$ emphasizing recent trends with stability indicator $stability = 1/(1 + \sigma\_q)$ Moving average forecasting adopts 3-period

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window $MA\_i = 1/3 \sum(i = 0\ to\ 2)\ y\_(i-1)$ , to extract trend information by smoothing fluctuations.

A dynamic method selection mechanism automatically chooses optimal prediction models based on dataset performance, using weighted fusion for multiple methods: $\hat{y}\_ensemble = \sum w\_i\,\hat{y}\_i$ where weight $w\_i = q\_i / \sum j\hat{}m\,q\_j$ derives from quality scores. To ensure practicality, an outlier detection mechanism identifies extreme predictions (growth rate > 500%) and applies reasonability constraints limiting growth rates to [-50%, 100%], effectively avoiding unrealistic results from data fluctuations.

### 3.3. Macro-environmental validation

The macro-environment validation layer implements a MacroValidationAnalyzer class as the core validation engine with three key modules. The correlation analysis utilizes Pearson correlation coefficients to quantify associations between macroeconomic variables and service indicators, systematically categorizing macro variables into GDP, population, income, consumption, and structural classes. The scenario simulation mechanism establishes optimistic, baseline, and cautious development scenarios, dynamically calculating adjustment coefficients based on industry sensitivity mapping. The policy impact quantification method generates consistency assessment levels through macro-support scoring, providing external validation for predictions and structured policy insights.

## 4. Results

### 4.1. Development quality assessment results

The VAE quality assessment model was evaluated on 129 service industry samples and 128 wholesale/retail subsector samples in Shiyan City, achieving good training convergence. Service industries averaged 0.7727 quality score, with 42.6% rated excellent and 50.4% good. Top performers are knowledge-intensive sectors: news/publishing(0.868), residential services(0.858), and education(0.843). Wholesale/retail averaged 0.7518 with solid overall development. Seven service industry anomalies were detected, primarily in technology-driven leapfrog development and unbalanced infrastructure services. Seven wholesale/retail anomalies reflected digital transformation shifts.

### 4.2. Trend projection results

Forecasts for 19 service industries in Shiyan City (2024-2026) were revised to cover 15 industries. Fourteen industries are projected to achieve positive growth, while only ecological protection and environmental governance is expected to decline by -37.9%. High-confidence forecasts (>0.6 confidence level) account for 66.7%.

Table 1. Forecasts of growth trends in the service sector (2024-2026)

| Growth Tier | Number of Industries | Growth Rate Range |
|---|---|---|
| High-Growth Tier | 11 | >20% |
| Steady Growth Tier | 2 | 0-20% |
| Risk-Watch Tier | 1 | <0% |

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Technology services show the highest growth potential, with software/IT and Internet services projected at 100% growth. Traditional sectors including education, business services, and road transportation also demonstrate strong momentum (>90% growth). High-confidence forecasts concentrate in stable industries like professional/technical services (0.810) and motor vehicle repair (0.755). With 67% of forecasts exceeding 0.6 confidence levels, the results provide a solid foundation for policy decisions.

### 4.3. Macro validation results

This study externally validates the forecasting results of the VAE-time series hybrid model through 23 core macro variables. Table 2 demonstrates the results of correlation strength analysis of the main macro factors.

Table 2. Strength of association analysis of macro factors

| Indicators | Key Macro Variables | Correlation Coefficient | Significance |
|---|---|---|---|
| Operating Revenue | Urbanization Rate | -0.891 | *** |
| Profit Margin | Wudang Mountain Tourism Consumption | +0.888 | *** |
| Number of Enterprises | Quarterly GDP Average | +0.938 | *** |
| Total Profit | Urbanization Rate | -0.844 | ** |

Note: *** denotes $p<0.01$, ** denotes $p<0.05$

The analysis found that: the quality of urbanization and the development of the service industry show a negative correlation ($r=-0.891$), reflecting the structural problem that the development of the service industry is lagging behind the rate of urbanization; the driving effect of tourism consumption is significant ($r=+0.888$), which verifies the validity of the strategy of the development of the "Tourism+" service industry. Macro support analysis shows that 80% of the high-growth predicted industries have received strong macro support (support > 0.5), verifying the reasonableness of the model predictions.

## 5. Conclusion

This study constructs a three-tier progressive analytical framework for service industry development quality assessment through VAE deep generative modeling, multi-method fusion time series forecasting, and macro-environmental validation. This approach introduces VAE into service industry quality assessment for the first time, effectively overcoming traditional econometric models' inability to capture nonlinear relationships.

The empirical results verify the framework's effectiveness. Shiyan's service industry shows good overall development quality with an average score of 0.7727. The prediction model identifies 14 positive growth industries with 66.7% high-confidence predictions, with 80% of high-growth predicted industries receiving strong macro support.

This study has limitations as the data scope is limited to a single city and VAE parameters are mainly experience-based. Future research will focus on framework popularization to different-sized cities for more scientific regional economic policymaking support.

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