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An Empirical Analysis of Factors Affecting the P/E Ratio Volatility of China's Listed Companies: Evidence from Artificial Intelligence Listed Firms

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Abstract: Against the backdrop of accelerated integration between the digital economy and the artificial intelligence (AI) industry, A-share listed AI companies are characterized by high valuation, high volatility, and a temporary decoupling of valuation from profitability. As a core valuation indicator in the capital market, the price-to-earnings (P/E) ratio has attracted extensive attention regarding its reference value. Taking the industrial characteristics of AI as the starting point, this paper constructs a research framework through industrial analysis and theoretical deduction, extracts dimensions of factors affecting the P/E ratio based on principal component analysis (PCA), and empirically verifies core hypotheses using panel data. The findings indicate that growth attributes, R&D investment intensity, policy support, and market sentiment are the core drivers of P/E ratio volatility for listed AI companies. In contrast, profitability and operating capacity exert influences on the P/E ratio that differ significantly from those in traditional industries. The innovation of this paper lies in anchoring the sci-tech innovation attributes of the AI industry, emphasizing industrial analysis as the core, and using empirical methods to test hypotheses, thereby filling the research gap in the valuation laws of high-growth sci-tech innovation industries. The conclusions provide theoretical support and practical references for investors'rational valuation, corporate market value management, and policymakers' regulatory formulation.

Keywords: Artificial Intelligence Listed Companies; P/E Ratio; Volatility Characteristics

1.Introduction

The implementation of the comprehensive registration system reform in China's capital market has broken the valuation logic under the traditional approval-based system, making sci-tech growth stocks the core segment of valuation divergence. As a core indicator linking stock prices and earnings, the rationality of the P/E ratio directly affects the efficiency of capital market resource allocation. In recent years, the structural characteristics of valuation in the A-share market have become increasingly prominent. The P/E ratios of strategic emerging industries represented by AI differ significantly from those of traditional industries such as pharmaceuticals, agriculture, and forestry, sparking widespread debate over valuation rationality.

As the core engine of the digital economy, AI has become a key development area at the national strategic level. Driven by policy support, technological iteration, and continuous expansion of application scenarios, China's AI industry has achieved leapfrog growth in scale. According to the China Academy of Information and Communications Technology (CAICT), the scale of China's core AI industry exceeded 900 billion yuan in 2024, with a year-on-year growth rate of 24%; it is expected to reach 1.2 trillion yuan in 2025, representing a more than five-fold increase from 237.4 billion yuan in 2018, with a compound annual growth rate rising to 23.5%. Along with rapid industrial development, the number and market capitalization of A-share listed AI companies have expanded simultaneously. By the end of February 2026, the number of constituent stocks in the CSI AI Theme Index increased to 325, with the total market capitalization of the sector exceeding 16 trillion yuan, making it a highly influential core track in the capital market.

However, the valuation characteristics of the AI industry differ significantly from traditional industries, showing distinct features of high valuation, high volatility, and strong divergence. In terms of valuation levels, the average P/E ratios of the CSI AI Theme Index were 82.7 times and 89.3 times in 2024 and 2025, respectively, while the average P/E ratios of the CSI 300 Index were only 11.9 times and 13.2 times over the same period, indicating a sustained high valuation premium for the AI sector. In terms of volatility and divergence, the annual volatility of the sector's P/E ratio exceeded 30%, and the extreme P/E ratio difference of some firms surpassed 600 times. Sub-sector divergence is also evident: the P/E ratio of the Sci-Tech Innovation Board AI Index reached 162.8 times, while that of mature application leaders was only 20–30 times, with the matching degree between valuation logic and profit realization capability being the core differentiating factor. Such valuation characteristics stem from value revaluation driven by high growth expectations and technological breakthroughs, and also reflect problems including vague valuation logic for some targets, disconnection between expectations and profit realization, and intensified gaming between short-term speculation and long-term value.

In traditional industries, the pharmaceutical sector, as a defensive industry, has its P/E ratio significantly influenced by rigid demand, R&D investment, and policy orientation (Fang et al., 2023); the agriculture and forestry industry is dominated by asset structure and profit stability in its valuation logic (Zhou & Tianfan, 2022). The AI industry possesses unique attributes such as high R&D investment, asset-light operation, long profit cycles, and strong policy dependence. It remains unclear whether the laws governing P/E ratios in traditional industries apply, what the core drivers of P/E ratio volatility are, and whether the root of valuation divergence lies in industrial characteristics or market sentiment. Addressing these questions is of great significance for clarifying the valuation logic of the AI industry and guiding rational investment in the capital market. Accordingly, this paper proposes the core research question: What are the key factors affecting the P/E ratio volatility of China's listed AI companies, and how do their mechanisms differ from those in traditional industries?

2.Concept Definition and Research Status

2.1 Concept Definition

2.1.1 Definition and Types of P/E Ratio

The Price-to-Earnings Ratio (P/E) refers to the ratio of stock price to earnings per share (EPS), or the ratio of total market capitalization to annual net profit, reflecting market expectations of a firm's future earnings growth. Based on different calculation calibers, P/E ratios are classified into static, dynamic, and trailing twelve months (TTM) types. The static P/E ratio uses the net profit of the most recent fiscal year as the base, which is simple to calculate but lacks timeliness. The dynamic P/E ratio is based on forecasted future net profit, better reflecting growth expectations but with strong subjectivity. The TTM P/E ratio adopts the net profit of the past four quarters, balancing timeliness and objectivity, making it the most widely used indicator in capital markets. Therefore, this paper adopts the TTM P/E ratio as the dependent variable.

2.1.2 Definition of AI Listed Companies

With reference to classification standards of mainstream financial databases such as Wind and iFinD, and combined with the Guidelines for the Classification of Listed Companies issued by the China Securities Regulatory Commission (CSRC), this paper defines AI listed companies as A-share listed firms whose main businesses involve core AI technology R&D (e.g., algorithms, computing power chips), AI product manufacturing (e.g., intelligent robots, intelligent sensors), or AI application services (e.g., intelligent healthcare, intelligent driving). Specific screening criteria include:

(1)The listed company explicitly lists AI as a core business or strategic development direction in its annual report;

(2)The average proportion of R&D investment in operating revenue over the past three years is no less than 3%;

(3)The proportion of revenue from AI-related businesses is no less than 20%.

2.2 Basic Theories

2.2.1 Efficient Market Hypothesis (EMH)

The EMH classifies markets into three forms: weak-form efficient, semi-strong-form efficient, and strong-form efficient. In a semi-strong-form efficient market, stock prices fully reflect all public information, including corporate financial data, industrial policies, and technological progress. As a high-growth industry, the P/E ratio volatility of the AI sector is affected not only by corporate fundamentals but also highly dependent on market reactions to public information such as policies and technological breakthroughs, providing a theoretical basis for incorporating policy factors and market sentiment into this study.

2.2.2 Enterprise Growth Theory

Enterprise growth theory holds that firm value depends not only on current profitability but also on future growth potential. Penrose (1959) pointed out in The Theory of the Growth of the Firm that firm growth stems from unused resources, and R&D investment is the core way to create new resources and form competitive advantages. The high P/E ratio of the AI industry is essentially market pricing for its future growth potential, which differs significantly from the valuation logic of traditional industries based on current earnings.

2.2.3 Dividend Discount Model (DDM) and NPVGO Model

The Dividend Discount Model (DDM) serves as the foundational model for P/E ratio valuation, with its core formula given by: $P = \frac{D_1}{r-g}$, where:

P : the stock price,

$D1$: the next-period dividend,

r : the discount rate,

g : the dividend growth rate.

From this formula, we can derive the P/E ratio formula: $P/E = \frac{D_1/E}{r-g}$ .This formula demonstrates that the *P*/*E* ratio is positively correlated with the dividend payout ratio and growth rate, and negatively correlated with the discount rate.

The NPVGO (Net Present Value of Growth Opportunities) Model decomposes a firm's value into two components: the value of a no-growth firm and the value of growth opportunities, expressed as: $P = \frac{E_1}{r} + NPVGO$ .The corresponding *P*/*E* ratio formula is: $P/E = \frac{1}{r} + \frac{NPVGO}{E_1}$ .This model illustrates that high-growth enterprises command higher P/E ratios than traditional firms, fundamentally because they possess greater value from growth opportunities. The high R&D investment in the artificial intelligence industry is precisely aimed at capturing future growth opportunities, which provides theoretical support for the positive correlation between R&D investment intensity and P/E ratios.

2.3 Literature Review

2.3.1 Foreign Research Status

Theoretical research on the P/E ratio began with the concept of the “price-earnings ratio” proposed by Benjamin Graham in Security Analysis, and gradually evolved into a complete valuation system. The Gordon Growth Model revealed the intrinsic relationship between the P/E ratio, dividend growth rate, and discount rate, identifying growth expectations as the core driver of the P/E ratio. The NPVGO model decomposed the P/E ratio into a no-growth component and a growth opportunity component from the perspective of growth opportunities, providing a theoretical explanation for the high P/E ratio of high-growth firms.

Subsequent empirical studies expanded the dimensions of P/E ratio determinants. At the macro level, Fama and French (1992) found that market interest rates and inflation rates are negatively correlated with the P/E ratio. At the industry level, Banz (1981) noted that industrial competition structure and technological barriers significantly affect the overall industry P/E ratio. At the micro level, Miller and Modigliani (1961) verified the positive correlation between corporate profitability, growth capacity, and P/E ratio. R&D investment, as an important guarantee for future firm growth, has also been widely confirmed to positively drive the P/E ratio in high-tech industries.

2.3.2 Domestic Research Status

Domestic studies have mainly focused on the overall market or specific traditional industries, yielding abundant findings. For the overall market, Zhang (2014) took constituent stocks of the SSE 180 Index as samples and found that return on net assets (ROE), price-to-book ratio (PB), average industry P/E ratio, and EPS growth rate are key factors affecting the P/E ratio, with the net asset factor exerting the most significant impact.

For segmented industries, Fang et al. (2023) studied the pharmaceutical industry and showed that EPS growth rate, total asset growth rate, and management expense ratio are significantly positively correlated with the P/E ratio, while ROA and total asset turnover are negatively correlated, reflecting the R&D-driven and weak-cycle valuation characteristics of the pharmaceutical sector. Zhou and Tianfan (2022) studied agriculture and forestry firms and found that net profit rate on fixed assets and operating gross margin are positively correlated with the P/E ratio, while ROE and cash asset ratio are negatively correlated, embodying the asset structure-dominated valuation logic of traditional agriculture.

2.3.3 Literature Review

Existing studies provide important references for understanding P/E ratio volatility laws but still have the following gaps:

Research objects are mostly concentrated on the overall market or traditional industries, with insufficient attention to high-growth, high-R&D, asset-light sci-tech industries such as AI, failing to reflect industrial specificity;

Research methods rely heavily on empirical analysis with weak industrial characteristic analysis, leading to partial empirical results lacking theoretical support and industrial logic interpretation;

Insufficient attention to non-financial indicators such as policy factors and market sentiment, which exert particularly significant impacts on AI industry valuation.

Accordingly, this paper based on AI industry characteristics, constructs a research framework of industrial characteristics – theoretical hypotheses – empirical verification – industrial interpretation, emphasizes industrial analysis as the core, incorporates key industrial factors such as R&D investment and policy support into the research scope, and aims to reveal the unique valuation laws of the AI industry.

2.4 Mechanism of P/E Ratio Volatility

Combining the above theories and AI industry characteristics, this paper constructs a mechanism framework for P/E ratio volatility, classifying influencing factors into five dimensions:

1.Growth Capacity

Growth capacity reflects future earnings growth potential and is the core driver of P/E ratios in high-growth industries. For listed AI companies, growth capacity is embodied in technological iteration speed, market share expansion, and application scenario expansion. Higher indicators such as EPS growth rate, net profit growth rate, and total asset growth rate indicate greater growth potential, raising market expectations for future earnings and pushing up the P/E ratio. This mechanism aligns with the growth-driven logic of the pharmaceutical industry but features greater growth elasticity and a more significant impact on the P/E ratio in the AI sector.

2.Profitability

Profitability reflects current earnings levels. In traditional industries, stronger profitability usually corresponds to a higher P/E ratio. However, the AI industry is characterized by long profit cycles: firms require massive R&D investment in the early development stage, resulting in low or even negative current earnings but strong future growth potential. Therefore, current profitability may show a weak or negative correlation with the P/E ratio of listed AI companies, in sharp contrast to the profitability-dominated valuation logic of the agriculture and forestry industry.

3.Innovation and R&D

Innovation and R&D constitute the core competitiveness of the AI industry. R&D investment enhances technological barriers and sustains growth opportunities. According to the NPVGO model, growth opportunity value generated by R&D investment is a key factor pushing up the P/E ratio. Meanwhile, R&D intensity reflects technological strength and growth determination, boosting market confidence. Thus, listed AI companies with higher R&D intensity tend to have higher P/E ratios. This mechanism resembles the R&D-driven valuation logic of the pharmaceutical industry but involves higher R&D risks and longer payback periods in the AI sector.

4.Market Sentiment

Market sentiment is an important factor affecting short-term stock volatility, especially for high-growth, high-uncertainty industries like AI. Turnover rate, a core indicator reflecting market trading activity and sentiment, captures investor attention and speculative sentiment. Higher turnover indicates greater market divergence or higher expectations, driving P/E ratio volatility. Industry hotspots and media coverage also influence market sentiment and indirectly affect the P/E ratio.

5.Policy and Industrial Environment

As a national strategic emerging industry, AI’s development and valuation highly rely on policy support. Industrial support policies, tax incentives, and R&D subsidies reduce operating costs and raise earnings expectations, pushing up the P/E ratio; tightened regulatory policies may suppress valuation. Meanwhile, industrial competition structure, technological maturity, and application scenario breadth indirectly affect the P/E ratio by shaping corporate growth expectations.

3.Current Development of the AI Industry

China's AI industry has maintained rapid scale expansion and become one of the core markets for global AI development. The industry scale reached 850 billion yuan in 2025, providing broad space for the development of listed AI companies. In terms of business distribution, listed AI companies are mainly concentrated in three fields: computing power (e.g., chips, servers) with 32 firms (21.1%), algorithms (e.g., machine learning, natural language processing) with 28 firms (18.4%), and applications (e.g., intelligent healthcare, intelligent driving, industrial internet) with 92 firms (60.5%). The largest number of firms in the application field reflects the trend of integrating AI technology with the real economy.

3.1 High R&D Investment and Asset-Light Operation

R&D investment is the core competitiveness of the AI industry, with overall R&D intensity significantly higher than the overall market and traditional industries. In 2025, the average proportion of R&D investment in operating revenue of listed A-share AI companies was 8.7%, compared with 3.1% for CSI 300 constituent stocks, 5.8% for the pharmaceutical industry, and only 1.2% for the agriculture and forestry industry. High R&D investment stems from the industry's characteristics of rapid technological iteration and fierce competition, requiring continuous capital input for technological innovation to maintain competitive advantages.

Corresponding to high R&D investment is the asset-light operation model. Core assets of AI firms are intangible assets such as technology and talent, with a low proportion of fixed assets. In 2025, the average proportion of fixed assets to total assets of listed AI companies was 15.3%, far lower than 38.7% for agriculture and forestry and 22.5% for pharmaceuticals. The asset-light model lowers fixed costs and strengthens scale expansion capacity but weakens current earnings, making valuation more dependent on future growth expectations.

3.2 Long Profit Cycle, Weak Current Profitability, and Strong Growth Expectations

The AI industry features a notable long profit cycle: it usually takes 5–10 years for firms to transition from R&D to commercialization, requiring continuous capital input and resulting in low or even negative current earnings. Over the past three years, the average net profit margin of the AI sector was 4.2%, lower than 8.5% for pharmaceuticals and 5.3% for agriculture and forestry; 37 firms (24.3%) reported negative net profits, compared with 12.1% for pharmaceuticals and 8.7% for agriculture and forestry.

Despite weak current profitability, growth expectations of AI firms are significantly higher than traditional industries. In 2025, the average operating revenue growth rate of the AI sector was 18.7%, far exceeding 11.2% for pharmaceuticals and 7.8% for agriculture and forestry. Such low-profit, high-growth characteristics make market valuation of AI firms rely more on future earnings expectations than current profitability, which is the core reason for their significantly higher P/E ratios than traditional industries.

3.3 Strong Policy Driven and High Market Sentiment Sensitivity

As a national strategic emerging industry, the development and valuation of AI are highly dependent on policy support. Policy issuance and adjustment directly shape market expectations and trigger P/E ratio volatility. For example, after the release of the Draft Artificial Intelligence Industry Promotion Law in 2023, the P/E ratio of the AI sector rose by 15.3% within one month; when regulatory policies on AI applications were tightened in some regions, the P/E ratio of relevant firms fell by an average of 8.7%.

Meanwhile, the AI industry is highly sensitive to market sentiment. Due to high technological barriers and unproven business models, ordinary investors struggle to accurately assess firm value and tend to make investment decisions based on market hotspots and sentiment, leading to significantly higher turnover rates than traditional industries. In 2023, the average turnover rate of the AI sector was 387%, compared with 215% for pharmaceuticals and 168% for agriculture and forestry. High turnover reflects intense market attention and speculative sentiment, constituting a major cause of large P/E ratio volatility.

Policy rhythm from top-level design to implementation continuously amplifies phased valuation fluctuations. In August 2025, the State Council issued the Opinions on Further Implementing the "AI +" Initiative, setting a target of over 70% penetration rate for intelligent terminals and agents by 2027. Within one month after policy implementation, the P/E ratio of the CSI AI Theme Index rose by 18.7%, significantly higher than the market average. From January to February 2026, strengthened regulation of generative AI content compliance and data security in many regions, coupled with stricter approval of some computing power projects, led to an average 10.2% correction in the P/E ratio of relevant industrial chain firms, exerting short-term pressure on sector valuation.

High technological iteration and unvalidated business models make ordinary investors prone to sentiment-driven decisions, pushing up trading activity and valuation volatility. In 2025, the annual average turnover rate of the CSI AI Theme Index reached 452%, compared with 248% for the pharmaceutical sector and 186% for agriculture, forestry, animal husbandry, and fishery—1.82 times and 2.43 times higher, respectively. High turnover reflects rapid capital flows and intensified gaming, indicating strong market attention to the AI industry and disturbances from short-term speculation, contributing to annual P/E ratio volatility exceeding 35% and extreme differences exceeding 600 times for some targets.

3.4 Weak Cyclicality, High Uncertainty, and High Valuation Premium

Demand for AI comes from digital transformation across industries, featuring weak cyclicality and low sensitivity to macroeconomic fluctuations—similar to the pharmaceutical industry but in sharp contrast to the strong cyclicality of agriculture and forestry affected by natural disasters and agricultural product price cycles. Weak cyclicality enables the AI industry to maintain certain growth during economic downturns, supporting its valuation premium. However, the industry also carries high uncertainty in three aspects: technological risks (obsolescence of existing technologies), commercialization risks (failure to recover R&D investment), and policy risks (directional adjustments). High uncertainty widens market divergence over AI firm valuation, leading to large P/E ratio volatility.

4.Extraction of P/E Ratio Influencing Factors Based on Principal Component Analysis

Theoretical deduction and industrial analysis identify five dimensions and 12 specific factors affecting the P/E ratio. However, multicollinearity may exist among original variables (e.g., EPS growth rate and net profit growth rate, R&D intensity and intangible asset ratio), leading to estimation bias if directly included in regression models. Therefore, this paper introduces PCA to reduce dimensionality, extract uncorrelated core common factors, retain key information of original variables, and improve the robustness and interpretability of subsequent empirical analysis.

4.1 Data Source and Processing

This paper selects A-share listed AI companies from 2021 to 2025 as research samples, with data sourced from iFinD. Original data are processed as follows:

□Eliminate samples with extreme values using the Winsorize method for 1% and 99% percentiles;

□Quantify non-financial indicators (e.g., policy support) with dummy variables (1 for national industrial support policies issued in the year, 0 otherwise);

□Standardize all original variables (Z-score standardization) to eliminate dimension and magnitude differences, ensuring PCA reliability. A balanced panel data of 106 listed companies (530 observations) is obtained.

4.2 Definition of Original Variables

Combining theoretical analysis and AI industry characteristics, 12 original influencing variables are finalized, as defined in Table 4-1.

Table 4-1 Definition of Original Variables for P/E Ratio Influencing Factors

Dimension	Variable Name	Symbol	Calculation/Definition
Growth Capacity	EPS Growth Rate	G1	(Current EPS – Previous EPS) / Absolute value of previous EPS

Dimension	Variable Name	Symbol	Calculation/Definition
	Net Profit Growth Rate	G2	(Current Net Profit – Previous Net Profit) / Absolute value of previous net profit
	Total Asset Growth Rate	G3	(Current Total Assets – Previous Total Assets) / Previous total assets
Profitability	Return on Net Assets (ROE)	P1	Net Profit / Average Net Assets × 100%
	Operating Gross Margin	P2	(Operating Revenue – Operating Cost) / Operating Revenue × 100%
	Net Profit Margin	P3	Net Profit / Operating Revenue × 100%
Innovation & R&D	R&D Investment Intensity	R1	R&D Investment / Operating Revenue × 100%
	Intangible Asset Ratio	R2	Intangible Assets / Total Assets × 100%
Market Sentiment	Stock Turnover Rate	S1	Annual Total Trading Volume / Tradable Shares × 100%
	Industry Price Change	S2	Annual price change of the AI industry index
Policy & Environment	Policy Support	P4	Dummy variable: 1 = national AI support policy issued; 0 = otherwise
	Industry Competition Intensity	I1	Growth rate of the number of listed companies in the industry

4.3 Empirical Process of PCA

4.3.1 Applicability Test

PCA requires strong correlation among original variables, verified by the KMO test and Bartlett's test of sphericity (Table 4-2).

Table 4-2 KMO and Bartlett's Test Results

Test Index	Statistic	Sig. (P-value)	Conclusion
KMO Measure of Sampling Adequacy	0.732	—	Suitable for PCA (KMO > 0.7)
Bartlett's Test of Sphericity	1286.459	0.000	Reject the hypothesis of independent variables

The KMO value of 0.732 (> 0.7) indicates moderate correlation among variables; Bartlett's test P-value < 0.001 rejects the null hypothesis of independent variables, confirming suitability for PCA.

4.3.2 Principal Component Extraction

Common factors are extracted using PCA, with criteria of eigenvalue > 1 and cumulative variance contribution ≥ 85%, combined with a scree plot to determine the optimal number of factors.

Table 4-3 Eigenvalues and Variance Contribution of Principal Components

Principal Component	Eigenvalue	Variance Contribution (%)	Cumulative Variance Contribution (%)
F1	4.328	36.067	36.067
F2	2.854	23.783	59.850
F3	1.962	16.350	76.200
F4	1.305	10.875	87.075
F5	0.892	7.433	94.508

The first four principal components have eigenvalues > 1 and cumulative variance contribution of 87.075%, explaining over 87% of original variable information. The scree plot confirms a gentle decline after the fourth component, validating extraction of four principal components.

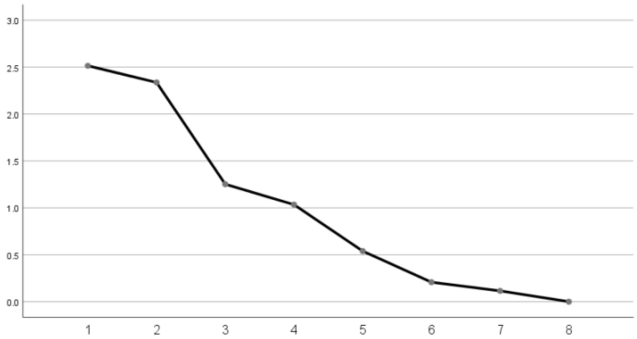

Figure 4-1 Stone fragmentation image

4.3.3 Factor Rotation and Naming

The varimax rotation method is used to rotate the factor loading matrix to enhance economic interpretability. Rotated loadings with absolute values ≥ 0.6 are marked as significant (Table 4-4).

Table 4-4 Rotated Factor Loading Matrix

Original Variable	F1 (Growth & Innovation)	F2 (Profit Efficiency)	F3 (Market Sentiment)	F4 (Policy Environment)
G1 (EPS Growth)	0.826	0.153	0.098	0.076
G2 (Net Profit Growth)	0.814	0.187	0.124	0.089
G3 (Asset Growth)	0.765	0.213	0.156	0.112
R1 (R&D Intensity)	0.732	0.245	0.189	0.134

Original Variable	F1 (Growth & Innovation)	F2 (Profit Efficiency)	F3 (Market Sentiment)	F4 (Policy Environment)
R2 (Intangible Ratio)	0.689	0.278	0.211	0.157
P1 (ROE)	0.198	0.834	0.145	0.103
P2 (Gross Margin)	0.221	0.812	0.167	0.126
P3 (Net Margin)	0.243	0.798	0.189	0.148
S1 (Turnover)	0.135	0.176	0.846	0.119
S2 (Industry Change)	0.157	0.198	0.823	0.132
P4 (Policy Support)	0.112	0.134	0.165	0.867
I1 (Competition)	0.134	0.156	0.187	0.789

The factor loading matrix was rotated using the maximum variance rotation method, with the primary objective of extracting mutually independent core explanatory variables (i.e., common factors) from the 12 original variables that could explain price-to-earnings ratio fluctuations. The rotated factor loading matrix revealed that variables with absolute loading coefficients ≥0.6 exhibited significant correlations with the common factors. Based on this analysis, four core explanatory variables were identified as follows.Four core explanatory variables are identified based on loadings ≥ 0.6 (Table 4-5).

Table 4-5 Core Explanatory Variables

Common Factor	Corresponding Variables	Loading Range	Variance Contribution (%)	Core Role
F1: Growth & Innovation	G1, G2, G3, R1, R2	0.689–0.826	36.067	Reflects growth potential and innovation; core P/E driver
F2: Profit Efficiency	P1, P2, P3	0.798–0.834	23.783	Measures current profitability; supports valuation foundation
F3: Market Sentiment	S1, S2	0.823–0.846	16.350	Captures market sentiment; amplifies short-term P/E volatility

Common Factor	Corresponding Variables	Loading Range	Variance Contribution (%)	Core Role
F4: Policy Environment	P4, I1	0.789–0.867	10.875	Shapes external policy and competition expectations

Using the price-to-earnings ratio (P/E) as the dependent variable, principal component analysis identified four core explanatory variables (F1-F4). These variables are mutually independent (effectively addressing multicollinearity issues), with a cumulative variance contribution rate of 87.075% (preserving over 87% of the original variables' information). They comprehensively and accurately explain the volatility patterns of P/E ratios, serving as the core explanatory variables for subsequent empirical analyses while replacing the original 12 variables.

(1) F1 (Growth Innovation Factor): As the explanatory variable with the highest variance contribution rate (36.067%), it epitomizes the core characteristics of the artificial intelligence industry— 'high growth and high R&D intensity.' Key factors include companies' revenue/profit growth potential, R&D investment intensity, and intangible asset reserves (such as core technologies and patents). These elements directly shape market expectations for future profitability and serve as the primary driver of elevated price-to-earnings ratios.

(2) F2 (Profit Efficiency Factor): This metric evaluates the "quality" and "efficiency" of a company's current profitability. While the AI industry's valuation is more dependent on future expectations, current profit efficiency remains a fundamental basis for valuation, influencing market perceptions of a company's ability to deliver earnings.

(3) F3 (Market Sentiment Factor): The artificial intelligence sector exhibits high speculative characteristics. Stock turnover rate (transaction activity) and industry price fluctuation range (sector popularity) directly reflect market sentiment volatility, serving as key explanatory variables for short-term sharp price-to-earnings ratio fluctuations.

(4) F4 (Policy Environment Factor): As a policy-driven industry, national support policies can reduce operational risks and enhance growth certainty for enterprises, while industry competition intensity affects profit stability. Together, these two factors constitute the external environmental explanatory variables for price-to-earnings ratio fluctuations.

The four refined core explanatory variables (F1-F4) address the multicollinearity issue of the original variables while simplifying the model structure. This enables subsequent empirical analysis to focus on "the impact of key dimensions on price-to-earnings ratios" rather than getting bogged down in complex multivariate correlations, thereby enhancing the relevance and reliability of research conclusions.

5. Empirical Analysis of P/E Ratio Determinants for AI Listed Companies

5.1 Research Hypotheses

Taking the P/E ratio as the dependent variable and F1–F4 as core explanatory variables, panel data regression models are constructed to test:

H1: Growth & Innovation (F1) is significantly positively correlated with the P/E ratio;

H2: Profit Efficiency (F2) is weakly or negatively correlated with the P/E ratio (consistent with AI’s “profit lag” feature);

H3: Market Sentiment (F3) is significantly positively correlated with the P/E ratio;

H4: Policy Environment (F4) is significantly positively correlated with the P/E ratio.

5.2 Sample Selection and Data Source

Samples are A-share listed AI companies from 2021 to 2025, screened by:

Excluding ST, *ST, and delisting-risk firms;

Excluding firms with abnormal P/E ratios (> 300 or < 0);

Excluding firms with missing R&D or financial data.

The final sample includes 128 listed companies (512 observations), with data from iFinD.

5.3 Variable Definition

Table 5-1 Variable Definition

Variable Type	Variable Name	Symbol	Calculation/Description	Data Source
Dependent	P/E Ratio	P/E	Trailing Twelve Months (TTM) P/E ratio	Wind
Core Independent	Growth & Innovation	F1	Calculated by PCA	—
	Profit Efficiency	F2	Calculated by PCA	—
	Market Sentiment	F3	Calculated by PCA	—
	Policy Environment	F4	Calculated by PCA	—
Control	Firm Size	SIZE	Natural logarithm of total assets	—
	Leverage Ratio	LEV	Total Liabilities / Total Assets	—

5.4 Regression Model

A two-way fixed-effects panel data model is constructed:

$$P/E_{it} = \alpha_0 + \alpha_1 F1_{it} + \alpha_2 F2_{it} + \alpha_3 F3_{it} + \alpha_4 F4_{it} + \beta_1 SIZE_{it} + \beta_2 LEV_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

In the above equation:

i：denotes the individual listed company；

t：denotes the year；

α_0： the constant term；

$\alpha_1 — \alpha_4$： the regression coefficients of the explanatory variables；

$\beta_1 — \beta_4$： the regression coefficients of the control variables；

μ_i： the individual fixed effect；

λ_t： the time fixed effect；

ε_{it}： the random disturbance term.

5.5 Regression Results

Table 5-2 Regression Results

Variable	Coefficient	Std. Error	t-value	P-value
F1	2.876	0.342	8.41	0.000

Variable	Coefficient	Std. Error	t-value	P-value
F2	-0.521	0.289	-1.80	0.072
F3	1.634	0.215	7.59	0.000
F4	1.128	0.198	5.69	0.000
SIZE	2.98	0.236	8.6	0.903
LEV	-24	0.98	8.9	0.698
R^2	0.683	—	—	—

Empirical results show a significant positive correlation between growth capacity and the P/E ratio of AI listed companies, consistent with industrial analysis. The AI industry is in a rapid development stage, where growth potential directly determines future earnings, leading the market to assign higher valuation premiums to high-growth firms. Compared with traditional industries, the AI sector features greater growth elasticity, with technological breakthroughs and scenario expansion potentially driving explosive growth—the core reason for its significantly higher P/E ratio. For example, an intelligent driving firm with revenue growth rates of 45%, 58%, and 62% from 2021 to 2023 maintained a P/E ratio above 100 times; an AI application firm with slowing growth (from 32% to 15%) saw its P/E ratio drop from 89 to 57 times, confirming growth as the core P/E driver.

The weak negative correlation between profitability and the P/E ratio reflects the AI industry's "profit lag, expectation-driven" valuation logic. AI firms require massive early-stage R&D investment with low current earnings, but the market prioritizes future growth potential. Even loss-making firms can achieve high P/E ratios with clear growth expectations—more pronounced than in pharmaceuticals (3–5 year R&D payback vs. 5–10 years for AI), weakening current earnings' impact on valuation.

The significant positive correlation between market sentiment and the P/E ratio verifies sentiment's critical role. High technological barriers and complex business models hinder accurate value assessment by ordinary investors, who rely on hotspots and sentiment, driving high trading activity and large P/E volatility. This reflects an immature valuation system with divergent value judgments, reminding investors to focus on fundamentals and long-term growth rather than short-term sentiment.

Policy is a significant positive driver of the P/E ratio, with highly significant results. As a strategic emerging industry, policy constitutes the core external support for AI growth—its impact on valuation even exceeds current profitability, a key dimension for understanding AI valuation logic.

5.6 Root Causes of P/E Ratio Volatility

Mismatch between profit and valuation is the core issue: some firms lack substantial technological breakthroughs and profit support but enjoy high valuation premiums, disconnecting valuation from fundamentals. This stems from the contradiction between high market growth expectations and insufficient profit realization.

Some AI firms have large R&D investment but fail to convert it into stable cash flow, unable to support high valuation—rooted in misalignment between R&D direction and market demand and low commercialization efficiency. Firms should strengthen R&D-market integration to translate technological advantages into profitability.

Market speculation and policy pulse effects exacerbate volatility. An imperfect valuation system makes the market susceptible to sentiment and hotspots, causing sharp price swings; policy adjustments directly shape expectations and trigger short-term P/E fluctuations.

6. Conclusions and Recommendations

6.1 Research Conclusions

Taking listed AI companies as samples, this paper reveals core factors and valuation logic of P/E ratio volatility through industrial analysis and empirical verification:

Growth attributes, R&D intensity, market sentiment, and policy support are core drivers of P/E ratio volatility for listed AI companies.

Growth capacity is significantly positively correlated with the P/E ratio (core driver); profitability shows a weak negative correlation (current earnings impact weakened); R&D intensity is significantly positively correlated (technological barriers support premium); market sentiment (turnover) is significantly positively correlated (speculation amplifies volatility); operating capacity is negatively correlated (asset-light feature reverses impact).

AI valuation logic differs significantly from traditional industries: greater growth elasticity, longer profit lag, and higher sentiment sensitivity than pharmaceuticals; more pronounced weak cyclicality, asset-light operation, and R&D-driven attributes than agriculture and forestry.

Core volatility issues: profit-valuation mismatch, ineffective R&D commercialization, speculative sentiment, and policy pulse effects—rooted in the industry's developmental stage and immature valuation system.

6.2 Countermeasures and Suggestions

1.For Investors

Recognize that high AI P/E ratios reflect growth expectations rather than guaranteed returns. Focus on technological strength, R&D conversion efficiency, growth potential, and profit realization capability to avoid chasing high P/E stocks blindly. Prioritize firms with R&D aligned with industrial trends and high commercialization efficiency. Maintain rationality amid sentiment fluctuations, adopt long-term strategies, and focus on sustainable growth value.

2.For Enterprises

Focus on core technological R&D and avoid blind expansion; strengthen R&D-market linkage to accelerate commercialization and balance growth with profitability. Enhance disclosure of R&D progress, commercialization, and development plans to improve transparency and stabilize market expectations. Conduct scientific market value management to avoid extreme valuation deviations.

3.For Regulators

Lead the formulation of AI industry valuation standards to guide a rational valuation system; advocate long-term investment and curb speculation to improve resource allocation efficiency. Strengthen information disclosure regulation, requiring full disclosure of R&D, commercialization, and risks to combat false statements. Maintain policy continuity and stability to mitigate pulse effects; increase support for core technology R&D and SMEs to promote sustainable industry development.

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