



# Active versus Passive Investment in the Artificial Intelligence Field: A Comparative Case Study of Funds

Runhe Yue, Ruowen Wang, Yu Yang\*, and Jie Ren

Tianjin College, University of Science and Technology Beijing, Baodi, Tianjin, 301830, China

\*yangy012@126.com

**Abstract.** The wave of artificial intelligence (AI) is sweeping the globe, transforming production and lifestyles with unprecedented speed, breadth, and depth. Its rapid development worldwide has made it a crucial force driving high-quality economic growth and social change. According to predictions by International Data Corporation (IDC), AI is set to become the core of the global technology industry in the coming years, fueling innovation and development across all sectors. An increasing number of investors seek exposure to the AI field, primarily through actively managed funds and passive funds. This paper compares representative active and passive funds within the AI domain and concludes that passive ETFs demonstrate superior risk-adjusted returns.

**Keywords:** Artificial Intelligence; Investment Strategy; Actively Managed Funds; Passive Index Funds; Performance Comparison

## 1 Introduction

Artificial intelligence, as the core driver of a new round of technological revolution and industrial transformation, has become a key area for global capital markets. In the A-share market, investment themes related to the AI industry chain remain highly active, giving rise to a variety of thematic investment fund products. For ordinary investors looking to participate in AI investment, two main paths are available: actively managed thematic funds that rely on fund managers' stock selection and timing, or passive index funds such as ETFs that track AI-related indices to capture market-average returns[4].

This paper employs a comparative case study method, selecting two representative AI thematic funds—Guoxin Guozheng Xinrui Fund A (001068) and ChinaAMC AI ETF (515070)—as research subjects. It comprehensively compares their risk-return metrics, portfolio structures, and operational costs from January 1, 2021, to December 20, 2025, to empirically examine the actual performance of these two investment strategies in this field, thereby providing a reference for informed investor decision-making.

## 2 Literature Review

Following the rapid development of China's public fund industry, comparative studies on the performance of active versus passive funds have increased. Most research focusing on the entire market finds that, over the long term, the majority of actively managed funds struggle to consistently outperform market benchmarks, and their higher management fees erode final returns (An Zhongwen,2025)[3]. Research on thematic or sector funds, particularly in growth-oriented sectors like technology and healthcare, shows divergent conclusions. Some studies suggest that in sectors with rising industry sentiment and high information asymmetry, skilled active fund managers can achieve significant alpha through selective stock picking (Zhang Xueyan., 2025)[2].

Existing research on the specific AI investment theme mostly focuses on industry chain analysis or performance evaluation of single funds. There is a lack of case studies that directly and meticulously compare active and passive investment strategies within the same thematic arena(Ding Ning,2025)[1]. The marginal contribution of this paper lies in focusing on the high-growth AI sector and conducting a rigorous case comparison to quantitatively evaluate the effectiveness of the two investment paths across multiple dimensions, thereby filling a gap in this niche research area[6].

## 3 Research Design

### 3.1 Research Methodology and Sample Selection

The core research method of this paper is the comparative case study[9]. To ensure the representativeness and comparability of the selected funds, the sample selection is based on the following criteria:

(1)Representativeness: Both selected funds enjoy high market recognition and substantial asset size, managed by leading fund companies, ensuring significant assets under management and market attention. (2)Data Completeness: The selected active fund was established on April 15, 2015, providing a long history and sufficient data for full-cycle analysis[7]. (3)Thematic Focus: The investment scope of both funds is concentrated on the AI-related field, ensuring thematic purity[8].

### 3.2 Evaluation Indicator System

To scientifically and systematically evaluate the strengths and weaknesses of the two investment strategies, namely active management and passive tracking, it is necessary to establish a multi-dimensional and comprehensive evaluation framework. Based on this, this paper constructs the following evaluation system by integrating five core dimensions: return performance, risk level, risk-adjusted return ratio, portfolio characteristics, and operational costs.

- (1) Return Metric: Annualized Return.
- (2) Risk Metrics: Annualized Volatility, Maximum Drawdown.
- (3) Risk-Adjusted Return Metric: Sharpe Ratio.

(4) Portfolio Characteristics: Concentration of Top Ten Holdings, Industry Distribution.

(5) Cost Metric: Combined Management Fee and Custody Fee.

### 3.3 Basic Information of Sample Funds

The core basic information of the two sample funds is shown in Table 1, and the differences in their key attributes directly affect the implementation logic and operational efficiency of investment strategies.

**Table 1.** Basic Information of Sample Funds (as of December 20, 2025)

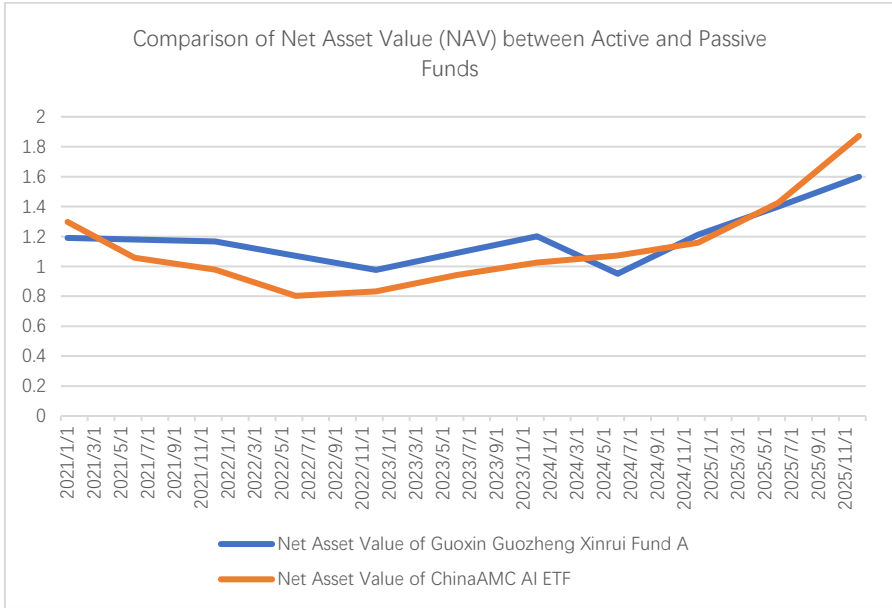
Item	Guoxin Guozheng Xinrui Fund A (001068)	ChinaAMC AI ETF (515070)
Fund Type	Actively Managed Equity Fund	Passive Index ETF
Inception Date	April 15, 2015	December 9, 2019
Latest AUM	117 million CNY	9.096 billion CNY
Management Fee	1.20%	0.50%
Custody Fee	0.2%	0.10%
Tracking Target	Not Applicable	CSI Artificial Intelligence Theme Index (930713)

## 4 Empirical Analysis

### 4.1 Comparison of Return and Risk Characteristics

We first compare the overall performance of the two funds during the study period. To intuitively present the differences in the return performance of the two funds during the research period, we first conduct an overall comparison based on the net asset value (NAV) trends and the data of key time points, as illustrated in Figure 1.

As shown in the Figure 1, throughout the research period, the NAV of Guoxin Guozheng Xinrui Fund A exhibited greater volatility compared to the ChinaAMC AI ETF.



**Fig. 1.** The Net Asset Value (NAV) trend of Guoxin Guozheng Xinrui Fund A.

To further quantitatively compare the risk-return performance of the two funds, this paper constructs a core indicator system including annualized return, annualized volatility, and Sharpe ratio based on the complete data during the research period, with the specific calculation results shown in Table 2.

**Table 2.** Risk-Return Metrics Comparison (January 1, 2021 – December 20, 2025)

Fund	Annual-ized Re- turn	Annual-ized Vol- atility	Sharpe Ratio	Maximum Draw- down	Com- bined Fee (p.a.)
Guoxin Guozheng Xinrui A	26.9%	36.85%	0.51	43.98%	1.55%
ChinaAMC AI ETF	62.19%	43.8%	1.45	45.6%	0.62%

The formulas used for Table 2 are as follows:

Annualized Return:

$$R_{annual} = (1 + R_{total})^{1/T} - 1 \tag{1}$$

Annualized Volatility:

$$\sigma_{annual} = STDEV.P (R_t) \times \sqrt{252} \quad (2)$$

Sharpe Ratio:

$$SR = (R_{annual} - R_f) / \sigma_{annual} \quad (3)$$

Maximum Drawdown:

$$MDD = \min_{t \in (0, T)} \left( \frac{NAV_{t - \max_{s \in (0, t)} NAV_s}}{\max_{s \in (0, t)} NAV_s} \right) \quad (4)$$

Quantitative analysis from Table 2 reveals:

(1) The annualized return of the actively managed fund is lower than that of the passive fund.[4] This is primarily attributed to two factors: Actively managed funds typically have higher fees than passive funds. Passive funds simply replicate an index, resulting in lower management costs, while active funds require fund managers and teams for research, stock selection, and trading, leading to higher fees. [5] As shown in the table, the fee for Guoxin Guozheng Xinrui A is approximately 1% higher than that of the ChinaAMC AI ETF. Over the long term, compounded, this fee differential erodes a significant portion of returns.

(2) The Sharpe Ratio of the actively managed fund is lower than that of the passive fund, indicating that the passive fund's excess return outweighs the additional risk it bears, offering higher cost-effectiveness. Although the ChinaAMC AI ETF exhibits higher volatility, implying greater fluctuation risk, its corresponding return is also significantly higher.

## 4.2 Comparison of Portfolio Structures

The composition of the investment portfolio directly reflects the core differences between the two strategies. Taking the holdings data from the Q3 2025 report as an example, this paper conducts an analysis, as shown in Table 3.

From Table 3, we observe:

(1) The actively managed fund exhibits flexible sector allocation, concentrating or dispersing investments based on market trends. In contrast, the passive fund maintains a fixed sector allocation, strictly replicating the industry weights of the index constituents.

(2) There is low overlap in the top holdings between this active fund and the passive fund, highlighting the distinct strategy of the active manager. Furthermore, the active fund heavily concentrates on the Information Transmission, Software & IT Services sector, leading to higher sector-specific risk.

(3) The top ten holdings of the active fund account for 82.92% of the portfolio, indicating a higher concentration compared to the passive fund (71.94%). This reflects the fund manager's conviction in stock selection but may also increase idiosyncratic (single-stock) risk.

**Table 3.** Comparison of Top Ten Holdings (as of September 30, 2025)

Rank	GuoxinGuozhengXinrui Fund A	Weight	ChinaAMC AI ETF	Weight
1	AsiaInfo Security	9.69%	Sunwave	11.83%
2	Foxit Software	9.68%	Zhongji Innolight	11.71%
3	ZWSOFT	8.91%	Cambricon	9.02%
4	Suochen Tech	8.70%	Montage Tech	5.78%
5	Kingsoft Office	8.40%	Sugon	5.68%
6	ArcSoft	7.87%	iFLYTEK	4.23%
7	Sansec Technology	5.65%	OmniVision	4.20%
8	Jingwei Hengrun	2.96%	Hikvision	3.80%
9	StarRing Tech	2.66%	Inspur Information	2.50%
10	UCloud	2.39%	Kingsoft Office	2.39%
Top10 Concentration	82.92%		71.94%	
Primary Industry Distribution	Information Transmission, Software & IT Services		Manufacturing, Information Transmission, Software & IT Services	

## 5 Conclusion

### 5.1 Research Findings

Through a comparative case analysis of Guoxin Guozheng Xinrui Fund A (active) and ChinaAMC AI ETF (passive), this paper concludes the following:

Market data from January 2021 to December 2025, based on the analysis of these two cases, indicates that in the technology sector characterized by frequent technological updates and an undetermined competitive landscape, passive exchange-traded funds tracking the corresponding thematic index demonstrate superior performance in terms of risk-adjusted return metrics (Sharpe Ratio). This outcome stems from three core advantages of passive index products: their operational and management fees are significantly lower than those of actively managed funds, and lower costs directly enhance investors' net returns; passive ETFs construct a diversified portfolio based on core constituents across the entire industry chain—their top ten holdings concentration (71.94%) is much lower than that of the active fund Guoxin Guozheng Xinrui A (82.92%)—effectively mitigating portfolio impact from individual company volatility or specific stock risks; the index investment model strictly follows index compilation rules for constituent selection and weight adjustment, ensuring high strategy transparency and avoiding potential issues inherent in active management, such as subjective judgment errors or style drift by the fund manager.

While actively managed funds may demonstrate the potential to capture alpha during certain cyclical upturns within the technology sector, they exhibit greater return volatility, higher maximum drawdowns, and significantly higher subscription/redemption and management fees. Consequently, their long-term comprehensive return capability, as shown in this case comparison, falls short of the passive index investment strategy. The active management model struggles to consistently capture rapidly evolving investment opportunities in the tech field, whereas index-based products, with their coverage of core constituents across the entire industry chain, are better aligned with the developmental dynamics of this sector.

## 5.2 Practical Recommendations

### 1. For the majority of ordinary investors

If an investor is optimistic about the future development of the AI sector, has a lower risk tolerance, and seeks a hands-off approach, passive index funds are recommended. This is primarily because passive funds track an index, eliminating the need for constant market monitoring or timing decisions—regular investments according to a plan suffice. By holding the index constituents, passive funds dilute the impact of any single stock. If an investor is concerned about high volatility, adopting a dollar-cost averaging strategy can smooth out costs over time, and extending the investment horizon is advisable. Furthermore, the lower fees of passive products mean that the cost difference will amplify the disparity in returns over the long term due to compounding.

### 2. For professional or high-risk-tolerant investors

These individuals typically possess industry research capabilities, enabling them to identify trends and high-quality stocks within the AI field. Actively managed funds are more suitable for them, but careful selection of fund managers or management companies with strong research capabilities is crucial. While actively managed funds carry

higher risk, this can be mitigated through portfolio diversification and flexible adjustment of holdings. Their management fees are usually higher than those of passive funds. Actively managed funds also have their own advantages: the AI sector encompasses numerous sub-industries with rapid technological iteration, and active management can more precisely capture technological breakthroughs and policy tailwinds (e.g., the localization of AI chips, the commercialization of application scenarios).

### **3. For asset allocators**

If they possess industry analysis capabilities, they might prioritize actively managed funds but must rigorously evaluate the fund manager's technology background and historical performance. If they prioritize efficiency or require a tool-based allocation, passive funds offer better cost-effectiveness. Utilizing both strategies in synergy, aiming to capture alpha while controlling risk, can be the optimal solution for the AI sector. High-risk-tolerance investors could allocate 70%-80% to active funds as the core, complemented by 20%-30% in specialized sector ETFs to capture beta returns. Dynamic adjustments should be made based on the stage of the industry cycle. For example, overweight active funds during periods of technological breakthrough (e.g., the release of GPT-5) and increase allocation to index products during periods of earnings realization (e.g., better-than-expected financial reports from optical module manufacturers).

### **5.3 Research Limitations and Future Prospects**

This study has certain limitations. First, it only compares one actively managed fund and one passive fund, involving a limited sample size. The generalizability of the conclusions requires validation through an expanded sample. Second, the research period covers a specific market cycle, and results may vary across different phases. Future research could broaden the sample scope to include more AI-themed funds and employ longer study periods. Additionally, tools such as the Brinson attribution model could be introduced to conduct a more granular decomposition of the sources of active funds' excess returns (e.g., asset allocation, stock selection, sector timing).

## **Acknowledgments**

The authors gratefully acknowledge the IoT Laboratory of Tianjin College, University of Science and Technology Beijing, for technical support and resources. China Council for the Promotion of International Trade (CCPIT) Commercial Industry Committee 2025 Accounting Research Project: Research on the Construction of Digital Resources for Financial Analysis Courses Empowered by Artificial Intelligence, Project No.: KJKY002.

The 8th University-Level Undergraduate Education Teaching Reform & Research Project of Tianjin College, Univ. of Sci. & Technol. Beijing.: "Practice and Exploration of Interdisciplinary Integration from Digital-Intelligent Empowerment Perspective". Project No.: tyjy2025021.

China Electronic Labor Association (Ceal) 2024 "Industry-Education Integration & University-Enterprise Cooperation" Education Reform & Development Research Topic. "Research on Digital Literacy Cultivation of Applied Undergraduates Under 'New Engineering + AI' Background". Project No.: Ceal2024092.

2025 Annual Research Project of the "14th Five-Year Plan" National Business Education Research Program of the China Council for the Promotion of International Trade (CCPIT) Commercial Industry Committee: Research on the Exploration and Application of the "AI + Education" Model Reform under the Background of New Business Education, Project No.: SKJYKT-2505142.

The Key Talents Cultivation Program of Tianjin College, University of Science and Technology Beijing, Project No.: TYGG2024J06.

## References

1. Ding Ning. Research on Performance Evaluation of Artificial Intelligence Themed Funds [D]. Shanghai Normal University, 2025.
2. Zhang Xueyan. Research on Optimization of Investment Strategies for Artificial Intelligence Themed Funds [D]. Shenyang University of Technology, 2025.
3. An Zhongwen. Funds Heavily Invested in AI Theme See "Distinct Landscape" [N]. Securities Times, 2025-08-25(A06).
4. Ren, J., Yang, Y., Zhang, Y., et al. Application of Artificial Intelligence-Driven Big Data Financial Analysis in Enterprise Financial Management[J]. Times Economic & Trade, 2025, 22(12): 59-61.
5. Fu, W., Ren, J., Yang, Y. Common Characteristics and Enlightenments of Government Performance Auditing in Major English-Speaking Countries[J]. Social Scientist, 2021, (08): 108-112.
6. Hong X ,Mao J ,Zhuang Z . The local influence of fund management company shareholders on fund investment decisions and performance [J]. Emerging Markets Review, 2026, 71 101428-101428.
7. Majumdar P ,Giri C B . Investment decisions in blockchain and big data information services for mitigating greenwashing in closed-loop supply chains: a tripartite evolutionary game model [J]. Applied Soft Computing, 2026, 188 114439-114439.
8. Kulkarni S M ,Patil P K ,Pramod D . The role of robo-advisors in behavioural finance, shaping investment decisions [J]. Cogent Economics & Finance, 2025, 13 (1).
9. azirani A ,Bhattacharjee T . The impact of time constraints on new venture investment decisions: an experimental study [J]. Venture Capital, 2026, 28 (1): 93-117.

**Open Access** This chapter is licensed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (<http://creativecommons.org/licenses/by-nc/4.0/>), which permits any noncommercial use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.

