Performance of AI Powered Mutual Fund: A case study of Tata QUANT Fund

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Abstract: *As quant trading continues to reshape India's mutual funds landscape, it's crucial for investors and fund managers to adapt to new paradigms and stay informed about industry trends. This study is undertaken as a systematic investigation into the performance of the first AI-powered mutual fund in India, Tata QUANT fund. Moreover, this study offers a critical analysis of the theoretical foundation for AI-driven portfolio management, incorporating ideas from the literature on behavioural economics and finance. This research provides important insights into the constraints and usefulness of AI-driven funds in a developing economy environment by addressing concerns about the marginal predictive capability of AI approaches and their ability to achieve optimal trade-offs amidst transaction costs. Though there have been many funds based on quantitative algorithms, Tata QUANT is the only fund that is on AI and it has a performance history of only three years. It is seen from the analysis that though the quant funds have been performing quite well, the Tata Quant has not been able to beat the market yet. The fund has high volatility with poor risk adjusted return. But as the legal and regulatory landscape is opening up to the AI, it is expected that even this fund will perform in the long run. To conclude, quant funds definitely have a great future when technology as well as Indian capital markets develop and mature.*

Keywords: *Quantitative trading, mutual funds, AI-powered, Tata QUANT fund, performance analysis, theoretical framework, behavioural economics, predictive capability, transaction costs, volatility, risk-adjusted return.*

Introduction

The efficient market hypothesis (EMH) proposed by Fama (1995)[1]postulates a scenario in which asset prices would be difficult to predict as they will behave like a random walk. Neither the direction nor the magnitude of market movements will render themselves suitable for prediction, if EMH operates perfectly. However,recent inroads into the field of Artificial Intelligence (AI) have opened the field to new possibilities. The application of Machine Learning (ML) has allowed the portfolio management to be more AI driven. Several funds have come up with the objective of capitalising on these techniques to do better portfolio management.

"The Modern Portfolio Theory as proposed by Markowitz (1952)[2], focuses on the portfolio diversification by selecting the securities based on their covariance relationships[3]. Accordingly, the Mean-Variance optimised Portfolio is chosen by allocation of resources to a series of different asset classes in a particular investment period [4]. Many tools have been developed with the objective of improving the optimization and allocation process of portfolios. One such method is quadratic programming, that uses conventional mathematical techniques to optimise [5]. "On the other hand, ML algorithms based on AI can outperform humans and, therefore, be faster for taking decisions. Algorithmic trading is widely applied to optimize and automate order submissions and executions but only after a portfolio choice is made [7]." AI, in sharp contrast, makes decisions in the earlier stages of portfolio choices. Moreover, AI-powered funds use proprietary techniques to perform *real-time* prediction and greatly enhance the flexibility and timeliness of traditional quantitative funds [6]. However, the use of AI based techniques have been questioned for their limited marginal predictive power. The concern arises from the trading frequency and associated transaction costs. It has been documented that actively-managed mutual funds are not able to beat the market after transaction costs and expenses are accounted for [8]. As AI continuously optimizes portfolios, whether AI-powered funds can achieve the superior risk adjusted returns remains to be investigated. "

"US has the distinction of launching the first ever AI powered mutual fund called AIEQ in 2017. The actively managed public fund used machine learning technologies to pick stocks that had the highest possibility of capital appreciation in the next 12 months. The AIEQ became one of the most popular funds in 2017 by raising more than $70 million within a few weeks of its launch.Some, like the $54 billion Pangora Asset Management Quant Fund, even use natural language processing (NLP) to keep tabs on traders to predict upcoming market trends."

"India joined the trend with Tata Mutual Funds launching its first AI-driven QUANT fund based on the BSE 200 index. Instead of having fund managers analyse market trends to pick the best stocks, a combination of rule-based algorithms picks the winners and losers. In a developing economy like the Indian markets, that can sometimes be unpredictable, there is bound to be a lot of scepticism regardingsuch strategy. The value of human intervention, that comes with its own set of advantages like experience, the ability to understand complex problems and instincts, cannot be undermined and could prove to be a panacea."

""This study is undertaken as a systematic investigation into the performance of the first AI-powered mutual fund in India, Tata QUANT fund. The rest of the paper is organized as follows. In addition to this introduction, a brief theoretical framework on the subject describedalong with the review of literature is presented in Section 2;the overview of quantitative funds in India is presented in section3; the data about Tata QUANT is organised in section 4; the discussion surrounding the research is available in Section 5; and, finally, the conclusions can be found in Section 6."

Research Methodology

The study's methodology uses a quantitative technique to look into the Tata QUANT Fund's performance in a methodical manner. This is the first AI-powered mutual fund in India. The process of collecting data involves obtaining numerical information from reputable sources such as financial databases, industry journals, official reports, and portfolio composition, sector allocation, performance measures, and net asset value (NAV) of the fund. In addition to conducting a comparative analysis with traditional mutual funds in India, the research uses a thorough sampling strategy and takes into account the Tata

QUANT Fund's entire historical performance since its founding. The analysis focuses on active management strategies and is benchmarked against similar indices. Throughout the study process, ethical considerations are made to ensure confidentiality and integrity in the management and interpretation of data.

Theoretical framework and review of literature

Behavioural economists in finance persuasively contend, based on psychological literature, that people have a variety of information-processing biases that have a substantial impact on their investing decisions. People may, for instance, exhibit confirmation bias, which is the propensity to perceive new information in a way that confirms preexisting ideas,underreact or overreact to new information, or allow their early experiences to have an undue influence on their behaviour (a phenomena known as imprinting). These biases have the ability to affect securities prices because a significant portion of investors probably share them. In other words, prices may consistently stray from what is justified by basic economic principles."

As a result, these prejudices produce a lucrative investing opportunity that takes advantage of the systematic mispricing of securities. Artificial intelligence has the ability to detect mispricing of securities as a result of other investors' biassed trading decisions, as well as account for the effects of these biases on a portfolio manager's prospective investment decisions.

Trillions of dollars have been invested in actively managed funds by US investors. Retail investors had $8.34 trillion in assets invested in actively managed funds and $8.53 trillion in index mutual funds as of March 31, 2022, according to Morningstar [11]. For active asset managers, achieving alpha or outperforming the benchmark is the ultimate goal. Even in declining markets, active managers have found it difficult to beat the indices in the majority of asset classes [12]. According to research, the low performance of active managers can be attributed to the fact that competition, particularly from new funds, increases as the sector expands. In a larger and more competitive industry, it is more difficult to excel [13].

Asset managers are increasingly using machine learning and artificial intelligence (AI) in their pursuit of alpha. (ML). AI's ability to find fresh alpha in at least three ways outside of conventional quantitative investment methodologies is what makes it so appealing to investors [14].

While artificial intelligence (AI) encompasses a wide range of methodologies that have been created over time, the majority of contemporary attention in AI has been focused on machine learning (ML), which is by far the most widely used AI methodology to date. The goal of machine learning (ML) is to gradually modify the parameters of statistical, probabilistic, and other computational models using data. In essence, it automates one or more information processing steps.

These days, most machine learning (ML) applications in asset management and even in finance in general rely on a few key techniques, such as artificial neural networks (ANNs), cluster analysis, decision trees and random forests, evolutionary (genetic) algorithms, least absolute shrinkage and selection operator (LASSO), support vector machines (SVMs), and natural language processing (NLP), even though there is a long list of techniques that can achieve this automation. When compared to ordinary least squares regression, elastic nets, LASSO regressions, random forests, and gradient boosted regression trees, ANNs have been found to perform the best among AI techniques available for return prediction [16].Even though AI techniques are frequently used to optimise and automate order submissions and executions, portfolio decisions must first be made [22, 23]. AI, on the other hand, takes decisions early in the portfolio selection process. Additionally, AI-powered funds significantly improve the flexibility and timeliness of conventional quantitative funds by utilising patented techniques to perform real-time prediction [6].

AI is supposed to be more reasonable since it learns to maximise the predicted result and become more efficient [24]. Since the number of qualified fund managers is drastically declining and nearly nonexistent in the new millennium, the performance of human managed mutual funds has been declining [25, 26]. As a result, the investment community longs for financial gains from cutting-edge technological advancements [27, 28].

But there are also clear drawbacks to AI-powered funds. The first is on the potential incremental contribution from AI techniques as well as the accomplishments of the current finance literature. Whether deep learning can anticipate pricing kernels and the cross-section of stock returns more accurately than "traditional" linear factor models or features is the subject of a significant number of recent publications [29, 30, 31]. While encouraging, the current progress is by no means a breakthrough. "All (machine learning) methods agree on the same set of dominant predictive signals, a set that includes variations on momentum, liquidity, and volatility," according to Gu et al. [16] among them. It seems that the marginal predictive potential of AI approaches is limited.

The frequency of trade and related transaction costs are the second area of concern. After transaction costs and expenses are subtracted, actively-managed mutual funds perform worse than the market, as numerous prior studies have clearly shown [32]. Further research is necessary to determine whether AI-powered funds can achieve the best possible trade-off between return and turnover, as AI is always optimising portfolios.

There is a noticeable void in the literature about the performance evaluation of AI-powered mutual funds, especially in the context of developing economies like India, despite the growing adoption of AI-powered methodologies in portfolio management. While the literature on artificial intelligence (AI) and machine learning in finance is expanding, few studies explicitly examine how well AI-driven funds perform in terms of producing greater risk-adjusted returns. Concerns about the AI methods' marginal predictive power and their capacity to strike the best possible balance between return and turnover while taking transaction costs into account also need to be addressed.

To close the gap in the literature and offer important insights into the advantages and difficulties of AI-driven portfolio management in the context of a developing economy, this study attempts to methodically examine the risk-adjusted performance, predictive abilities, turnover efficiency, and market adaptation of Tata QUANT Fund, the first AI-powered mutual fund in India. In order to investigate this hypothesis, the study looks at the possibility that, in the Indian market, the risk-adjusted performance of Tata QUANT Fund will surpass typical mutual funds statistically significantly, demonstrating the efficacy of AI-driven portfolio management.

Harnessing AI to Manage Portfolios

Artificial intelligence (AI) provides a big edge when it comes to making investing decisions since it can quickly examine large amounts of data that human analysts would miss. AI algorithms can evaluate a variety of data sets, including financial statements, news articles, and social media sentiment, and use their capacity to spot patterns and trends to find signals and forecast a company's future success. Consequently, this can help investors reduce risk, make better-informed decisions, and optimise their investment portfolios [17].

Portfolio optimisation

Artificial intelligence (AI) has the ability to generate more precise return and risk predictions than alternative techniques, which can be integrated into conventional frameworks for portfolio development. In contrast to portfolios created using conventional linear methodologies, AI techniques can offer alternative approaches to portfolio development that result in more accurate portfolio weights and optimised portfolios with superior out-of-sample performance. Despite the paucity of empirical data, academics and practitioners appear to be becoming more interested in this area. It is possible to train artificial neural networks (ANNs) to make asset allocation decisions under complicated restrictions, which are frequently difficult to incorporate into the mean-variance paradigm. A neural network, for instance, is capable of choosing portfolios based on a learning criterion that, when subject to value-at-risk limitations, maximises returns [18]. Complex multi-objective optimisation issues can also be resolved by ANNs.

Algorithmic Trading

Three significant developments have led to an increase in the use of algorithmic trading in asset management [18]. First, there have been fundamental changes to the way financial markets function as a result of advances in computing power, data science, and telecommunication. Second, advances in quantitative finance and machine learning have given computers the means to perform insightful financial analysis faster and more effectively than humans. Third, the size, speed, and complexity of financial markets, along with the variety of new structural products available, have made it harder, if not impossible, for humans to keep track of the markets and make real-time trading decisions. In contrast, complex artificial intelligence techniques like neural network analysis (ANNs) can be used almost instantly [20]".

Trade management

By actively learning from actual market microstructure data, AI techniques make trade execution modelling easier by identifying the best execution tactics. AI-based methods have the benefit of using data to calculate market effect costs, price changes, and liquidity rather than normative assumptions. As a result, they are able to adjust as new information becomes available and market conditions shift. But these models are sometimes hard to understand and train, particularly for huge portfolios that stand to gain the most from lower transaction costs. Furthermore, there is a chance that methods of systematic execution could trigger a systemic event that impacts the entire market [21].

Overview of AI Funds in India

AI based trading also referred to as Quant trading, involves using mathematical and statistical models for making investment decisions. The adoption of quant trading in mutual funds in India has increased significantly, transforming the investment landscape. Quant trading provides opportunities for enhanced returns, but it also poses risks related to model accuracy and overfitting. In India, major fund houses like HDFC, SBI, and ICICI Prudential, Tata, Nippon, DSP, AXIS are integrating quant trading to optimize fund performance. The overview of these funds is presented in Table 1.

Table 1: Snapshot of Quant Funds in India

BASIS OF COMPARISON	***"DSP Quant Fund"***	***"ICICI Prudential Quant Fund "***	***"Nippon Quant Fund"***	***"Quant Quantamental Fund"***	***Tata Quant Fund***	***Axis Quant Fund***
Fund House	DSP Mutual Fund	"ICICI Prudential Mutual Fund"	"Nippon India Mutual Fund"	"Quant Mutual Fund"	"Tata Mutual Fund"	"Axis Mutual Fund"
Benchmark	"S&P BSE 200 Total Return Index"	"S&P BSE 200 Total Return Index"	"NIFTY 50 Index"	"NIFTY 200 Total Return Index"	"S&P BSE 200 Total Return Index"	"S&P BSE 200 Total Return Index"
"Launch Date"	Jun 10, 2019	Dec 11, 2020	Jan 01, 2013	Apr 27, 2021	Jan 22, 2020	Jun 30, 2021
AUM in Crores	1370 Cr	65 Cr	35 Cr	1602.5	43 Cr	1305 Cr

CAGR	15.20%	22%	11.80%	32.47%	2.30%	8.70%
"Expense ratio"	0.55% as on Jan 31, 2024	1.23% for Regular plan as on Feb 12, 2024	0.51% for Direct plan as on Feb 05, 2024	2.06% for Regular plan as on Feb 08, 2024	2.39% for Regular plan as on Feb 11, 2024	2.2% for Regular plan as on Feb 14, 2024.
Exit Load	0%	1% if redeemed within 3 months	0.25% if redeemed within 1 month	1%, if redeemed within 15 days	"For units in excess of 12% of the investment,1 % will be charged for redemption within 365 Days"	"For units in excess of 10% of the investment,1 % will be charged for redemption within 365 days"
Risk-o-meter	Very High	Very High	Very High	Very High	Very High	Very High
Return Since Launch	15.47%	22.11%	14.42%	31.35%	7.52%	16.97%

Source: economic times.indiatimes.com

Tata Quant- A case Study

Tata Mutual Funds decided to use artificial intelligence (AI) and machines learning (ML) to beat the market by removing human bias from portfolio construction and selection choices.

Though the impact of human biases on performance of fund is difficult to quantify, it is believed that by systematic elimination of judgements which are not completely objective can lead to superior returns. "With this belief in focus, Tata introduced India's first mutual fund to offer an AI-driven investment strategy. Even though the fund may not know how to react to a situation like an unexpected war, for normal events like policy changes, budget declarations and earnings, the model is geared to predict how the market will react and figure out how to beat it. It relies on data from the past 22 years to forecast how the market will move and the model has been tested since 2011".

The Tata Quant fund's investment goal is to provide medium- to long-term capital growth through the selection of equity and equity-related securities using a quantitative model (Quant Model). The fund builds a diverse portfolio of equities and equity-linked securities across market capitalization and industries in an attempt to meet this investing goal."

The goal of the quant model-based factor strategy is to maximise the advantages of both rule-based and active systematic investing by reducing the impact of human emotions and biases on decision-making, fostering more discipline, and utilising machine computation capacity for operational efficiency. The investment strategy of this fund is to reduce net long equity exposure or identify hedge positions (partial or complete) using unique in-house Quant Models for optimal factor-based portfolio design and to improve performance consistency."

Portfolio Positioning and Construction

The Quant Model is programmed to use parameters that cover stocks selection, Return on Equity, capital employed, Earnings, income distribution cum capital withdrawal and leverage including macroeconomic parameters related to GDP, inflation, Interest rates, Currency, commodity, etc. and finally index movement. "

The fund has 80.36% investment in domestic equities of which 50.32% is in Large Cap stocks, 9% is in Mid Cap stocks, 0.4% in Small Cap stocks. The fund has 16.8% investment in Debt, of which, 0.04% is in Low-Risk securities. The remaining assets are held in Cash. The overall composition of portfolio is depicted in figure 1 and the holding analysis is depicted in figure 2.

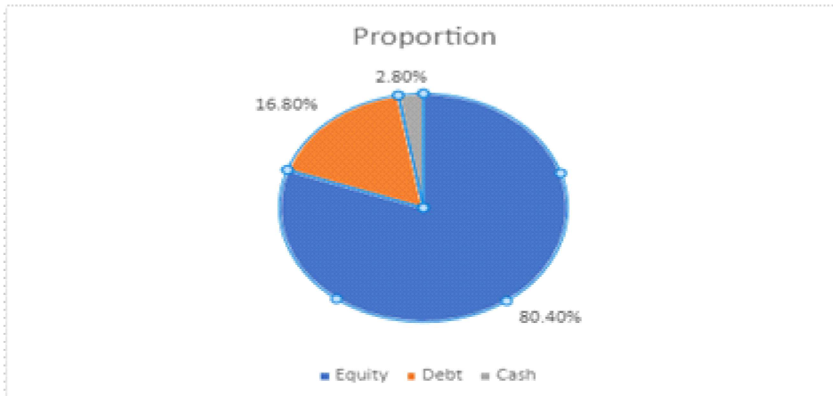

Figure 1: Portfolio Distribution of Tata Quant Fund

Figure 2: Holding Analysis of Tata Quant Fund

The Sector wise distribution of the equity portfolio of Tata Quant is depicted in figure 3. It is seen that the highest allocation is done to the financial sector followed by the technology sector.

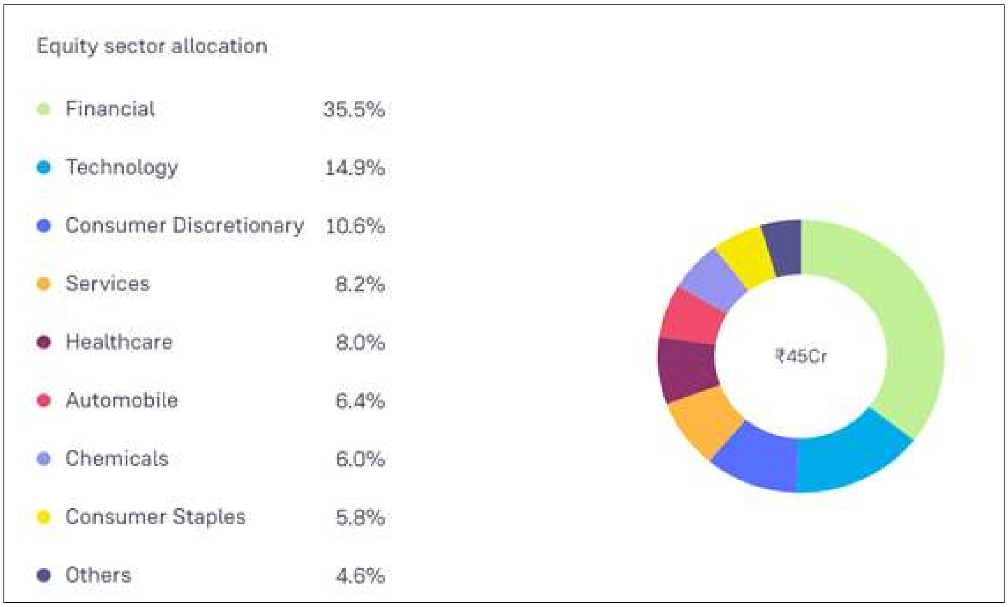

Figure 3: Equity Sector Allocation of Tata Quant Fund

Performance Analysis

The performance of the fund is depicted in Table 2. The third column depicts the value of an investment of Rs.10,000/- for various periods, whereas the fourth column calculates the absolute returns over the corresponding periods."

Table 2: Performance of Tata Quant Fund

Tata Quant Fund -RETURNS (NAV as on 31st January, 2024)						
Period Invested for	Rs10000 Invested on	Latest Value	Absolute Returns	Annualised Returns	Category Average	Rank within Category
1 Week	24-Jan-24	10013.8	0.14%	-	1.96%	150/167
1 Month	29-Dec-23	9714.5	-2.85%	-	3.35%	161/166
3 Month	31-Oct-23	10888.4	8.88%	-	19.29%	152/159
6 Month	31-Jul-23	11169.7	11.70%	-	18.85%	114/147
YTD	1-Jan-24	9715.5	-2.84%	-	3.35%	161/166
1 Year	31-Jan-23	12778.9	27.79%	27.79%	39.39%	107/138
2 Year	31-Jan-22	12909.2	29.09%	13.62%	18.95%	92/128
3 Year	29-Jan-21	14630.3	46.30%	13.50%	23.68%	107/117
Since Inception	27-Jan-20	13269.2	32.69%	7.30%	17.63%	160/168

A comparison of the annualised returns of the fund with the category averages over the 1-year, 3-year and the 5-year period reveal that the fund has been performing below average and accordingly ranked quite low in its category. However, the performance of the fund as a monthly Systematic Investment Plan(SIP) looks quite promising as illustrated in Table 3. It is quite evident that an investor choosing the path of SIP to invest in the fund is able to get an annualised return of 27.68% for the latest completed year. This has been quite an improvement as compared to the previous years.

Table 3: SIP performance of Tata Quant Fund

Tata Quant Fund - SIP RETURNS (NAV as on 31st January, 2024)					
Period Invested for	Rs1000 SIP Started on	Investments	Latest Value	Absolute Returns	Annualised Returns
1 Year	31-Jan-23	12000	13740.2	14.50%	27.68%
2 Year	31-Jan-22	24000	29357.2	22.32%	20.61%
3 Year	29-Jan-21	36000	44861.03	24.61%	14.78%

The fund performance has also been compared with its benchmark index S&P BSE 200 TRI , Nifty 50 and other players in the industry, the results of which are presented in Table 4. It is seen that the fund has been able to beat the general market index Nifty 50, but has performed poorly compared with its own benchmark index. A comparison of the fund with the best in category and worst in category reveal that the fund ranks quite low. The return generated by the fund does not satisfy the need of the investor as it is below market but the risk assumed by the fund is very high.

Table 4: Comparative performance of Return of Tata Quant Fund

Tata Quant Fund - Comparative Performance								
Category	1M	3 M	6 M	YTD	1Y	2Y	3Y	5Y
This Fund	-2.86%	8.88%	11.70%	-2.86%	27.79%	13.62%	13.50%	0.00%
Nifty 50	-0.03%	13.87%	9.98%	-0.03%	23.01%	11.93%	16.77%	14.93%
Benchmark S&P BSE 200 TRI	1.36%	17.14%	14.72%	1.36%	30.76%	15.64%	20.60%	17.83%
Category Average	3.35%	19.29%	18.85%	3.35%	39.39%	18.95%	23.68%	19.49%
Category Rank	161/166	152/159	114/147	161/166	107/138	92/128	107/117	0/0
Best in Category	18.15%	50.83%	61.77%	18.15%	99.89%	45.28%	50.81%	34.41%
Worst in Category	-6.09%	1.68%	-11.20%	-6.09%	-12.27%	-8.79%	-9.74%	2.27%

The risk comparison of the fund with the category averages are illustrated in table 5. The data used for computing these ratios are the daily returns of the last three years.

Table 5: Comparative performance of Risk of Tata Quant Fund

Tata Quant Fund - Risk Ratios (as on 31 January 2024)					
Risk Criteria	**Standard Deviation**	**Beta**	**Sharpe Ratio**	**Treynor Ratio**	**Jensen Alpha**
Tata Quant	14.4	0.88	0.48	0.08	-4.55
Category Avg.	15.08	0.85	0.99	0.18	2.9

It is evident from the table 5 that the fund has high volatility as compared to the industry average but has a very low risk adjusted return as seen from the Sharpe's ratio and the Treynor's ratio. Also the performance of the fund manager as measured by the Jensen's alpha is disappointing at -4.55%. The fund is not able to match even the market returns.

Discussion

Quant funds are a kind of mutual fund in which algorithmic trading, artificial intelligence (AI), and other techniques are used to carry out investing and portfolio construction with as little human (fund managers) interaction as possible. Hence, quant funds largely remove the possibility of human error, which includes emotional and other behavioural biases that can arise throughout the investing process. Typically, rule-based investing strategies are employed by quant funds. These funds forecast future share prices and make investments based on a range of techniques, including cutting-edge and well-established financial models, algorithms, machine learning, artificial intelligence, Big Data, etc. Fund managers create these guidelines after taking a thorough technical and fundamental study into account.

However, because these funds will update on their own, the fund manager is involved on a daily basis once the regulations are established. Fund managers, however, keep an eye on the model and adjust it slightly as needed. To anticipate the future price, the models essentially seek for patterns in historical data and factors such trading value, volume, volatility, beta, yield, liquidity, momentum, alpha, correlation, covariance, and other multifactor models. Even while quant funds are free of fund management bias, each fund keeps its model "proprietary" and does not make it publicly available, making the process of choosing stocks opaque.

Furthermore, there isn't a long enough performance history for these funds to be evaluated in terms of efficiency and performance. Thus, investors with conservative or moderate risk tolerance should ideally stay away from these quant funds. As a diversification tactic, ambitious investors can think about allocating a tiny portion of their whole portfolio to quant funds.

Limitations of the study

Due to its reliance on historical data, possible data flaws, and the breadth of its comparative research, the study is vulnerable to several constraints. Despite efforts to gather accurate data, inconsistencies or missing data points may compromise the analysis's robustness. Furthermore, the results of the study might only apply to the Tata QUANT Fund and its operational setting, which would restrict their applicability to other AI-driven mutual funds or to other areas of the world. The study's validity is further challenged by methodological limitations, such as the possibility of overfitting models and biases in data interpretation. The performance of the fund may also be impacted by unanticipated occurrences or modifications to the market, which are outside the purview of historical data analysis. These restrictions highlight the necessity of interpreting data cautiously and taking into account larger market variables that go beyond the purview of the study.

Scope for further research

The study's conclusions provide opportunities for more investigation in a number of fields. First off, further research on the efficiency and performance of various AI models and algorithms used by mutual funds might be conducted in the future, especially considering how AI-driven portfolio management in the financial sector is developing. Examining how particular AI methods, such deep learning or natural language processing, affect risk management and portfolio optimization could yield insightful information for investors and fund managers. Furthermore, a deeper understanding of the sustainability and profitability of AI-powered funds would result from performing longitudinal studies to evaluate their long-term performance and flexibility in changing market situations. Additionally, examining how investor sentiment and regulatory frameworks affect the uptake and performance of AI-driven strategies in various market environments may provide insightful information for industry players and regulators. Lastly, investigating the possible trade-offs and synergies between integrating AI with conventional investing strategies may open the door to future breakthroughs in portfolio management.

Conclusion

The concept of quant funds is new in India and each fund has its own rules. Investors should understand each fund model and assess the benchmark for its performance comparison before investing. Quant funds base their stock selection purely on quantitative data; thus they might miss out action in the stock market owing to qualitative information such as efficiency of the board, business ethics and other intangible factors which are hard to quantify. To ensure openness and investor protection, the Securities and Exchange Board of India (SEBI) has enforced compliance with particular rules. Innovation in quant trading for Indian mutual funds appears to have a bright future thanks to developments in AI and machine learning. It is imperative that investors and fund managers adjust to new paradigms and remain up to date on industry developments as quant trading continues to transform the mutual fund environment in India. In conclusion, quant funds will undoubtedly have a bright future as long as technology and the Indian capital markets continue to advance and grow.

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