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**-RESEARCH ARTICLE-**

# MANAGERIAL DECISIONS AND FUND PERFORMANCE: INSIGHTS INTO THE ROLE OF FINANCIAL TECHNOLOGY

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## —Abstract—

Mutual fund managers operate under substantial pressure to enhance fund returns, and their strategic choices are assumed to align with determinants of persistent superior performance. This research investigates the determinants influencing managerial decision processes and evaluates their effects on fund outcomes, with a specific focus on the role of financial technology utilisation and market uncertainty. Data were collected through a structured survey administered to 141 equity fund managers in Tunisia, while fund performance metrics were derived from historical records covering January 2020 to September 2023. The methodological approach integrates principal component analysis to extract behavioural and technological decision dimensions, followed by regression analysis employing adjusted Sharpe and LPM Treynor ratios to assess performance dynamics before and after the COVID-19 period. The empirical findings demonstrate that herding tendencies exert a negative and statistically significant impact on fund outcomes, with more pronounced detrimental effects under turbulent market conditions. Conversely, managerial experience and professional training exhibit a positive contribution to performance, with their influence strengthening during crisis periods. Furthermore, the implementation of FinTech solutions, such as artificial intelligence, machine learning applications, robo-advisory systems, and digital investment platforms, significantly enhances fund performance during and after the crisis, highlighting their importance in facilitating real time financial assessment, risk control, and informed strategic decision making. In contrast, financial incentive structures do not display a statistically meaningful association with performance indicators. Overall, the results emphasise the importance of managerial human capital and FinTech integration in strengthening fund outcomes and provide

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practical implications for fund management organisations, investors, and regulatory authorities within emerging market contexts.

**Keywords:** Mutual Funds; FinTech; Managers' Practices; Emerging Markets; Performance; Asset Management; Remuneration Scheme.

## INTRODUCTION

The increasing presence of market participants across both developed and emerging economies has intensified competitive pressures within the mutual fund industry. Over recent decades, mutual fund total net assets have expanded substantially, reaching USD 33.6 trillion in the United States, USD 21.5 trillion in Europe, USD 9.7 trillion in the Asia-Pacific region, and USD 4 trillion in other regions. Mutual funds accounted for approximately 20 percent of global capital market assets in 2010, increasing to 27 percent by 2023 (report, 2024). In the Tunisian context, Exchange Market reports document a continuous rise in the number of funds and assets under management, with the collective investment industry exceeding five billion dinars in assets during the first half of 2023 for the first time since 2011.

Simultaneously, the rapid expansion of financial technologies (FinTech), including artificial intelligence, machine learning, digital financial platforms, and robo-advisory services, has reshaped financial intermediation processes and managerial decision frameworks (Amnas et al., 2024; Pahsa, 2024; You et al., 2023). From the investor perspective, FinTech has embedded mutual fund investment into everyday financial activities (Baker & Dellaert, 2018; Gaspar & Oliveira, 2024; Jung et al., 2018). Enhanced technological access now enables investors to examine and purchase diverse mutual fund products through mobile applications and online platforms (You et al., 2023; Kasemharuethaisuk & Samanchuen, 2023). From the supply side, fund managers, irrespective of organisational size or market prominence, can utilise financial technologies to broaden investor outreach, perform advanced asset evaluations using AI and ML tools, and enhance investor accessibility and financial literacy through robo-advisory platforms (Begenau et al., 2018; D'Acunto et al., 2019;Bonelli and Liu, 2024).

Within this highly competitive setting, fund managers, whose remuneration is often linked to total assets under management, compete intensely to attract capital inflows and increase annual compensation (Chevalier & Ellison, 1997; Sirri & Tufano, 1998). Moreover, financial data providers and investment publications frequently publish semi-annual rankings that compare managers based on relative performance against benchmarks or peers. These rankings generate strategic behavioural incentives. Managers with strong interim performance may adopt risk-averse strategies to preserve their position, whereas those lagging behind may increase portfolio risk or pursue unconventional strategies to improve end-of-period rankings, particularly during adverse market conditions (Li et al.,2022). Such tournament-like dynamics can substantially affect portfolio risk-taking decisions and, consequently, mutual fund performance outcomes (Elton et al., 2012).

Although prior research has extensively analysed quantitative determinants of fund performance, such as fund-specific attributes, managerial traits, and macroeconomic factors (Babbar & Sehgal, 2018; Cuthbertson et al., 2016; Golec, 1996; Graham et al., 2020; Singh & Tandon, 2021), limited empirical evidence exists regarding the influence of managerial practices in emerging markets, primarily due to data limitations. While several studies have investigated the effects of FinTech on retail investor behaviour (Abdullah et al., 2018; Srivastav et al., 2024), research on its implications for asset management and emerging equity fund performance remains scarce. This gap motivates an examination of how managerial attributes and practices affect fund performance during and after the pandemic, particularly under increasing FinTech integration. Accordingly, this study analyses managerial practices and professional characteristics to determine key drivers of fund performance in the presence of FinTech advancements. The findings provide valuable insights for fund managers, investors, and regulators by demonstrating how managerial practices, professional attributes, and FinTech adoption jointly influence fund performance, thereby informing investment strategies, regulatory policies, and future financial technology research.

This paper is structured into three main sections. The first section reviews the literature on determinants of managerial decision-making and their effects on fund performance. The second section outlines the research methodology. The final section presents and discusses the empirical results, followed by a conclusion that summarises the key findings, acknowledges study limitations, and proposes directions for future research.

## LITERATURE REVIEW

### Theoretical Support

The qualitative characteristics of fund managers, particularly their investment approaches and decision-making mechanisms, are increasingly acknowledged as key determinants of mutual fund performance (Minahan, 2006; Prather et al., 2004). These attributes can be interpreted through human capital theory and cognitive processes theory, while agency-related issues may further affect performance outcomes. The attractiveness of mutual funds largely stems from managerial expertise (Berk et al., 2017), and managerial decisions can be evaluated through professional attributes and behavioural tendencies. Human capital plays a central role in influencing fund outcomes, especially in an industry characterised by frequent managerial turnover (Asal, 2016; Golec, 1996). Empirical evidence suggests that replacing poorly performing managers can enhance fund results (Khorana, 1996). Academic qualifications, institutional reputation, and professional certifications such as CFA and

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MBA credentials significantly affect performance (Andreu & Puetz, 2017; Chevalier & Ellison, 1999; Golec, 1996), with graduates from elite institutions benefiting from broader professional networks and superior career opportunities.

Managerial experience also represents an important determinant (Golec, 1996; Porter & Trifts, 2014), although its impact is complex. Experience can improve judgement and strategic decisions (Rachmawati et al., 2020), yet older managers may exhibit greater conservatism and risk aversion, potentially reducing performance (Naidenova et al., 2015). Conversely, younger managers, who are more exposed to contemporary financial theories and technologies, often demonstrate higher adaptability and motivation (Chevalier & Ellison, 1999; Golec, 1996). Evidence regarding the optimal size of management teams remains inconclusive (Bliss et al., 2008; Golec, 1996). Behavioural biases also play a significant role in shaping managerial decisions (Hirshleifer, 2001). Prior empirical research documents biases including anchoring (Kaustia et al., 2008), overconfidence (Eshraghi & Taffler, 2012), loss aversion (Alevy et al., 2007), and the disposition effect (Wulfmeyer, 2016), which can systematically lead managers away from fully rational investment behaviour.

Agency relationships, particularly those arising from information asymmetry and conflicts of interest, further influence managerial actions (Charreaux, 2000). Compensation schemes and career-related concerns are key determinants of managerial behaviour. Performance-based remuneration can attract high-quality managers, enhance fund outcomes, and increase investor inflows (Chevalier & Ellison, 1997; Elton et al., 2001; Hu et al., 2011), while career concerns motivate managers to maintain strong performance to secure their professional positions (Khorana, 1996). Information asymmetry may encourage managers to engage in portfolio manipulation practices, such as window dressing, or to increase risk exposure to improve returns (Agarwal et al., 2014; Chen & Pennacchi, 2009; Khorana, 1996; Marques et al., 2020). However, empirical evidence also indicates that compensation structures do not necessarily induce excessive risk-taking behaviour ( Chevalier& Ellison,1997; Luo et al., 2023).

## Manager's Practices during Crisis Period

The COVID-19 pandemic generated simultaneous shocks to demand and supply, severely disrupting major economies and triggering substantial declines in financial markets. These effects were intensified by widespread credit rating downgrades, which limited fund access to high-quality issuers ( Fang & Parida, 2022). Despite these disruptions, evidence indicates that active portfolio management provided advantages during the crisis, as actively managed funds demonstrated superior performance (Chevalier & Ellison, 1999; Golec, 1996), reinforcing the view that active management tends to outperform during economic downturns (De Souza & Lynch, 2012).

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Rizvi et al. (2020) documented shifts in investment styles from high-risk to low-risk assets during the pandemic using fund-level returns and panel regression techniques. Mirza et al. (2020) further reported that fund managers engaged in volatility timing strategies, employing time-series models and risk-adjusted performance indicators. Santi and Zwinkels (2023) provided evidence of persistent herding behaviour among US equity fund managers, who adopted style-based feedback trading strategies that increased exposure to previously successful investment styles. Using detailed holdings and return data combined with panel regressions and robustness tests, they showed that herding behaviour was largely unrelated to fundamentals and more prevalent among smaller firms, likely reflecting higher levels of information asymmetry. Increased market uncertainty was also found to intensify herding tendencies (Di Guilmi et al., 2014). Ling et al. (2022) identified liquidity, portfolio diversification, historical risk-adjusted performance, and incentive structures as key determinants of fund resilience, while noting that prestigious educational backgrounds alone did not ensure superior outcomes. Their panel regression analysis revealed that managers with both elite education and finance-related degrees achieved stronger performance, whereas those holding advanced industry certifications exhibited weaker results, potentially due to excessive risk aversion. In a related study, Boise et al. (2023) reported that Prime Institutional and Prime Retail fund managers increased daily liquidity buffers in anticipation of investor redemptions, based on high-frequency flow and trading data analysed using time-series methodologies.

## Fintech Adoption in Asset Management Decisions

The incorporation of financial technology (FinTech) within the asset management sector has fundamentally altered how mutual fund managers conduct operations and formulate investment decisions. As financial markets undergo rapid digital transformation, managers increasingly rely on FinTech applications, including artificial intelligence (AI), machine learning (ML), robo-advisory systems, digital financial platforms, and big data analytics, to improve analytical capabilities, portfolio allocation, and interactions with investors. FinTech innovations, particularly AI and ML, allow managers to analyse large volumes of financial information in real time, thereby improving the precision and timeliness of investment decisions. AI- and ML-driven decision support systems (DSS) have become integral to digital finance, assisting in risk evaluation and strategic portfolio planning (Pahsa, 2024). These technologies support predictive analytics, sentiment evaluation, and portfolio stress-testing through Generative AI applications. Wealth management firms are increasingly embedding GenAI into operational processes, reshaping investment product development and communication practices, with compliance-ready AI systems expected to broaden adoption among mid-sized asset managers by 2025 (Yang & Lee, 2024).

Robo-advisory technologies automate portfolio construction and monitoring, enabling managers to concentrate on strategic decision-making while ensuring consistent advisory services. These tools also enhance financial inclusion by expanding access to formal financial services, with trust, service quality, and security identified as primary adoption determinants (Amnas et al., 2024). Additionally, big data techniques and advanced analytics improve asset selection processes and portfolio diversification efficiency (Arner et al., 2017). Digital financial platforms further increase market accessibility and operational efficiency in mutual fund markets, reducing asset clustering and encouraging underperforming managers to adopt diversification strategies to attract investor inflows (You et al., 2023). Behavioural finance tools integrated within FinTech systems enable real-time strategic adjustments, which are particularly valuable during periods of heightened market volatility, such as the COVID-19 crisis (Gomber et al., 2018). Nevertheless, FinTech implementation introduces cybersecurity threats, intensified competition from technology-driven firms, and regulatory challenges, including requirements for AI transparency and governance adjustments due to disruptive technologies such as blockchain and AI (Forum, 2025; Secinaro et al., 2025; Zetzsche, 2017).

Although the literature has extensively examined managerial characteristics, behavioural biases, and FinTech adoption, these factors are typically analysed separately. This study extends existing research by integrating managerial behaviour, professional human capital, and FinTech utilisation within a unified empirical framework, and by evaluating their combined influence on fund performance across both stable and crisis periods in an emerging market setting. Based on this framework, the following research hypotheses are developed.

**H1:** *Fund managers demonstrate style transition across different market conditions.*
**H2:** *Fund managers herding behaviour weaken fund performance.*
**H3:** *Manager's professional characteristics affect positively the fund performance.*
**H3a:** *Manager's experience affects positively the fund performance.*
**H3b:** *Fund performance is a positive function of the manager's educational level.*
**H4:** *Fund performance is positively associated with the manager's financial incentive.*
**H5:** *Fintech play a pivotal role in enhancing fund performance.*

## METHODOLOGY

This section analyses the decision-making behaviour of Tunisian mutual fund managers using evidence obtained from a dedicated survey. The objective is to determine the principal determinants shaping managerial decisions and to evaluate their implications for fund performance, with particular emphasis on the influence of FinTech adoption in asset management and the effects of market volatility. The empirical investigation is based on multiple data sources. The main dataset is derived from the questionnaire

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detailed in the survey methodology section, with an illustrative sample included for transparency. In addition, fund performance information is collected from the Tunisian Stock Exchange and official fund-specific online disclosures.

## Survey Design

The questionnaire was designed following an extensive literature review and informed by insights obtained from preliminary exploratory interviews. It collected information on managerial practices across five dimensions: criteria for asset selection, sources of information used in investment decisions, management style, approaches to fund performance evaluation, and professional and demographic characteristics. Each dimension was further decomposed into detailed subcomponents. Participants evaluated the relevance of these factors using a five-point Likert-type scale ranging from 1 (not important) to 5 (extremely important), consistent with the CoxIii (1980) and Krosnick (1999), who highlighted the reliability benefits of clearly labelled scale points. Survey reliability was assessed using Cronbach's Alpha, with a value of 0.70 considered acceptable according to Nunnally and Bernstein (1994), whereas Malhotra (2002) suggested that values below 0.60 indicate inadequate reliability. The survey covered 141 fund managers representing 17 asset management firms, which is a smaller sample compared to Demarchi and Thomas (1997), who analysed 36 firms. To improve the representativeness of the data, multiple managers from each fund management team were included. As an illustration, the Table 1 summarises the principal items used to measure FinTech adoption as a determinant of managerial investment decisions.

In line with established methodological approaches in survey-based research in finance and management, Likert-scale responses from conceptually related items were aggregated to create composite indicators of FinTech adoption, thereby improving measurement reliability and interpretability (Hair, 2019). In this study, responses related to FinTech usage were examined by calculating the mean percentage distribution for each Likert response category across thematically linked items, allowing each FinTech application to be treated as an integrated construct rather than a collection of independent features. As the individual indicators, such as real-time financial analytics, risk evaluation, and market trend identification, represent complementary aspects of the same technological function, aggregation minimises item-specific variability and yields a more stable and interpretable representation of perceived importance.

## Table 1: Fintech Adoption Measurement

| Artificial Intelligence (AI) | Machine Learning (ML) | Robo-Advisors | Financial Platforms | Big Data Analytics |
|---|---|---|---|---|
| Q1. How important are AI tools for the following fund activities within your management company?<br>• Financial Analysis of Large Volumes of Financial Data in Real Time<br>• Improving Risk Assessment<br>• Predicting Market Trends<br>Q2. How important are the following AI applications for your fund?<br>• News and Financial Statement Analysis (NLP) *(e.g., Text-Mining Algorithms, Sentiment Scoring Models)*<br>• AI-Based Portfolio Optimization *(e.g., AI-Enhanced Mean–Variance Optimization, Heuristic Optimization Algorithms)*<br>• Credit and Counterparty Risk Assessment *(e.g., Classification Models, Risk Scoring Algorithms)*<br>• Market Trend Detection *(e.g., Pattern Recognition Models, Time-Series AI Algorithms)* | Q3. How important are machine learning tools for the following fund activities within your management company?<br>• Financial Analysis of Large Volumes of Financial Data in Real Time<br>• Improving Risk Assessment Predicting market trends<br>Q4. How important are the following ML techniques for your fund?<br>• Regression and Classification Models<br>• Neural Networks / Deep Learning<br>• Clustering for Asset Segmentation<br>• Algorithmic Trading Models<br>Q5. How important are the following data sources for ML models in your fund?<br>• Historical Market Data (Prices, Returns)<br>• Macroeconomic Indicators (GDP, Inflation, Interest Rates)<br>• Firm-Level Financial Statements<br>• Regional/Market Data | Q6. How important is the use of robo-advisory solutions in your fund(s)?<br>Q7. How important are the following functions supported by robo-advisors?<br>• Automated Asset Allocation<br>• Portfolio Rebalancing<br>• Risk Profiling of Investors<br>• Investment Recommendations<br>• Promoting Financial Inclusion | Q8. How important are digital platforms in your fund for the following purposes?<br>• Enhancing Accessibility and Attracting Potential Investors<br>• Providing Real-Time Feedback on Investor Actions and Preferences<br>Q9. How important are the following digital financial platforms for your fund?<br>• Electronic Trading Platforms (Local or International)<br>• Portfolio Management Systems (PMS)<br>• Risk Management and Compliance Platforms<br>• Client Reporting and Disclosure Platforms<br>Q10. How important is the sourcing of these platforms (local vs. international) for your fund? | Q11. How important is the use of big data analytics in your fund(s)?<br>Q12. How important is big data analytics in your fund for the following investment strategies?<br>• Asset Selection<br>• Market Timing<br>• Portfolio Diversification<br>Q13. How important are the following technologies to support big-data analytics in your fund?<br>• Cloud-Based Solutions<br>• Data Visualization and Reporting Tools<br>• External Analytics Providers<br>• In-House Data Systems |

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## Table 1(continued): Fintech Adoption Measurement

| |
|---|
| Q14. How important are the following factors as limitations to the use of FinTech tools in your fund?<br>• High Implementation Cost<br>• Data Availability and Quality<br>• Regulatory Constraints<br>• Lack of Technical Expertise |

**Note:** All adoption-related FinTech measurement questions in this study were assessed using a 5-point Likert scale ranging from 'Extremely important' to 'Not important.

## Table 2: General Sample Characteristics

| Company Nature | Breakdown of Managers | % Out of the Sample | Assets Under Management in Million TDN | Funds Under Management | Management Players | | Clientele Types | |
|---|---|---|---|---|---|---|---|---|
| | | | | | Manager (Average Number) | Financial Analyst (Average Number) | Retail Clients | Institutional Clients |
| **Subsidiary Bank** | 6 | 35% | 389.063 | 32 | 82 (3) | 37 (2) | 72.16% | 27.84% |
| **Independent Management Company** | 11 | 65% | 243.837 | 42 | 59 (2) | 24 (1) | 67.98% | 32.02% |
| **Total** | 17 | 100% | 632.900 | 74 | 141 | 51 | - | - |

**Note:** This table summarizes the main characteristics of management companies based on ownership structure, fund size, clientele types and key management players, (dated September-2023).

By combining responses across items and deriving category-wise distributions, the ordinal nature of the Likert data is retained while facilitating meaningful comparisons among different FinTech tools. Moreover, incorporating multiple indicators for each FinTech dimension strengthens internal consistency and measurement robustness, as related questions served as cross-validation mechanisms, ensuring that the aggregated metrics capture coherent managerial assessments rather than isolated subjective views. For risk-adjusted performance evaluation, monthly net asset values (NAVs), Tunindex, Tunindex20, and 13-week Tunisian Treasury Bill yields were obtained to compute excess market and fund returns. The empirical sample comprised 74 Tunisian equity funds over the period from January 2020 to September 2023. Considering the severe financial disruptions associated with the COVID-19 pandemic, fund performance was assessed during and after the crisis period. The analysis utilised the adjusted Sharpe and LPM-Treynor ratios, which are widely applied in both academic research and professional investment practice.

## General Sample Characteristics

The description of sample characteristics aims to contextualise the empirical setting of the study. Specifically, this section outlines key organisational and structural attributes of the management companies, including ownership configuration, where Tunisian asset management firms are predominantly affiliated with banking institutions or operate as independent entities. It also reports fund size indicators, measured by total assets under management and the number of funds under supervision, as well as the composition of the client base and the number of principal managerial stakeholders involved in fund operations.

As illustrated in Table 2 (excluding liquidated funds), the majority of fund managers are employed by independent management firms, representing 65 percent of the sample, whereas 35 percent work for bank-affiliated subsidiaries. Subsidiary banks oversee the largest average fund size, amounting to 389.063 million dinars, while independent firms manage relatively smaller funds, averaging 243.837 million dinars. Regarding fund distribution, subsidiary banks are responsible for 32 of the 74 equity funds, managing larger asset pools compared with the 42 funds administered by independent companies. These bank-linked management firms also maintain the largest staff numbers, likely reflecting the scale of their operations and the greater number of funds under their control. It is noteworthy that financial analysts are occasionally underrepresented, as several managers simultaneously perform analyst duties. In terms of client composition, retail investors constitute the bulk of the clientele, accounting for 72.16 percent in subsidiary banks and 67.98 percent in independent management companies.

# EMPIRICAL RESULTS

This section reports the empirical findings, starting with an overview of the fund management procedures, and subsequently examining managerial practices and their effects on fund performance both during and following the COVID-19 pandemic.

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## Description of the Fund Management Process

Managerial practices are characterised using three groups of variables: investment goals and asset selection strategies, approaches to management style, and the determinants guiding managerial decisions, which encompass investment criteria, professional attributes, and compensation structures.

## Analysis of Investment Objectives

Among the surveyed professionals, 40.4% report maintaining a long-term investment horizon exceeding three years. A medium-term horizon of two to three years is indicated by 30.8% of managers, while 28.8% follow a one-year investment plan. Only 30.8% of managers consider client type to be irrelevant to their investment horizon, whereas the remaining 69.2% acknowledge that their strategies are largely shaped by investment horizons, which tend to be longer for institutional clients. The average annual turnover for the sampled funds is 74.09% of assets under management, with observed rates ranging from 5% to 400%. Nevertheless, 10% of managers' report difficulty in accurately calculating the turnover of their portfolios. Regarding performance measurement periods, 59.6% of managers prefer intervals shorter than one year. With respect to benchmark selection, the findings reveal that 78.8% of managers use TUNINDEX20 for performance comparison. Furthermore, 34.2% of respondents indicate that their primary objective is to outperform a benchmark, 13.5% adopt a passive management approach, and 52.3% employ benchmarks mainly for informational purposes, without directly linking them to performance targets.

## Asset Selection and Management Style

The findings indicate that 82.7% of managers prioritise core corporate information when selecting stocks, while 16.3% rely on index inclusion, and only 1% adopt a sector-based selection approach. Within these strategies, 53.2% of managers focus on undervalued equities with potential for capital appreciation, 22.9% target companies with stable earnings, and 7.6% pursue emerging opportunities. Fund management styles were examined through asset selection approaches and the use of contractual benchmarks. Active management is the most prevalent, representing 50% of the sample. A more detailed classification of styles reveals that 42.2% follow a "stock picking value" approach, 21.1% adopt "stock picking growth," 9.6% engage in index management, 7.6% apply a general "stock picking" strategy, and 5.7% use other active management techniques. Notably, 23.1% of managers reported altering their management style, with a particular shift toward "stock picking growth," which increased from 3.8% to 15.4%.

## Factors Influencing Managers' Decisions: Investing Criteria, Professional Characteristics and Remuneration System

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The study first aims to determine the investment-related factors that guide managerial decision-making. Subsequently, it investigates fund managers' professional attributes and compensation arrangements as critical components influencing their decision processes.

**Table 3: Descriptive Statistics on Investment Factors**

| Investment Factors | Extremely Important % | Important % | Somewhat Important % | Little Important % | Not Important % |
|---|---|---|---|---|---|
| **Asset-Specific Factors** | | | | | |
| Recent Decline in Return | 3.8 | 44.2 | 38.5 | 13.5 | 0 |
| Recent Increase in Return | 3.8 | 48.1 | 36.5 | 9.6 | 1.9 |
| Recent Price Decrease | 25 | 30.8 | 36.5 | 7.7 | 0 |
| Recent Price Increase | 23.1 | 30.8 | 42.3 | 0 | 3.8 |
| Recent Increase in Volatility | 15.4 | 30.8 | 38.4 | 13.5 | 1.9 |
| Recent Decrease in Volatility | 5.8 | 46.2 | 46.2 | 1.9 | 0 |
| Analyst Recommendation | 30.8 | 30.8 | 19.2 | 5.8 | 0 |
| Fundamental Information | 50 | 30.8 | 19.2 | 0% | 0 |
| Sector Specific Information | 7.7 | 34.6 | 48.1 | 9.6 | 0 |
| Macroeconomic Information | 3.8 | 13.5 | 51.9 | 25 | 5.7 |
| Other Managers' Comments | 0 | 5.8 | 25 | 26.9 | 42.3 |
| Other Managers' Positions | 0 | 9.6 | 21.1 | 32.7 | 36.5 |
| **Management Factors** | | | | | |
| **Management Constraints** | | | | | |
| Institutional Constraints | 32.7 | 36.5 | 15.4 | 13.5 | 1.9 |
| Asset Purchase or Redemption | 34.6 | 28.8 | 26.8% | 5.8 | 3.8 |
| Tracking Error (Relatively to the Previously Fixed Risk) | 7.7 | 25 | 30.8 | 25 | 11.5 |
| Index Replication | 28.8 | 23.1 | 30.8 | 13.5 | 3.8 |
| Lack of Entry and Exit Rights | 17.3 | 17.3 | 48.1 | 17.3 | 0 |
| **Management through FinTech** | | | | | |
| **AI & ML:** Financial analysis of large volumes of financial data in real time, better risk assessment and predicting market trends | 85 | 13 | 2 | 0 | 0 |
| **Robo-Advisors:** Investment advice delivery; promoting financial inclusion | 77 | 21 | 1 | 1 | 0 |
| **Big Data Analytics:** Asset selection, market timing, and portfolio diversification strategies | 66 | 22 | 12 | 0 | 0 |
| **Digital Platforms:** Enhancing accessibility: Attracting potential investors; real-time feedback on investor actions and preferences | 88 | 12 | 0 | 0 | 0 |

**Note:** The investment factors are divided into subcategories: asset-specific factors and management factors.

## Investment Factors

Table 3 presents the descriptive statistics corresponding to the two categories of investment criteria analysed in the study.

SPSS was employed to conduct a principal component analysis (PCA) on all variables. The analysis revealed that the variable "increase in volatility" needed to be excluded, as its communalities fell below the 0.5 threshold. Following this removal, a subsequent factor analysis was performed. The Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test yielded significant results, confirming the dataset's suitability for factor extraction. Initially, four factors were suggested based on eigenvalues, but only those explaining between 50% and 60% of the total variance were retained. Consequently, the first three factors were preserved, accounting for 60.495% of the variance. Figure 1 depicts these three principal components.

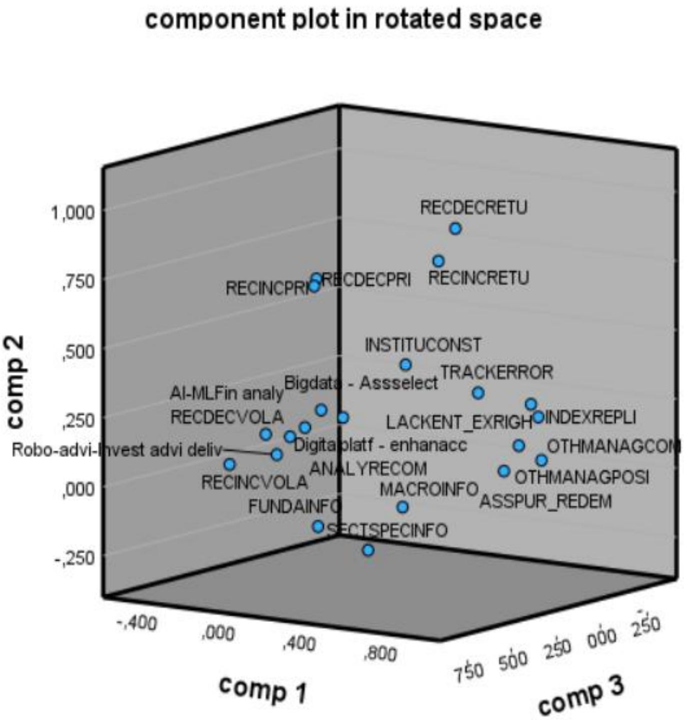


**Figure 1:** Principal Components of Manager's Practices

The first principal component is labelled Herding Behaviour (HB) and is primarily driven by factors such as index replication, the influence of peers' remarks, and their portfolio positions. This component captures managerial constraints arising from predefined objectives, asset redemptions, index tracking requirements, and restrictions on entry and exit. The second component is defined as the Manager's Instantaneous Reaction to Changes in Prices and Returns (IRPR), with particularly strong loadings from recent fluctuations in prices and returns. The third component, exhibiting higher contributions from fundamental data, analyst recommendations, and technological tools such as artificial intelligence, machine learning, robo-advisors, and digital platforms, is interpreted as FinTech Integration in Fund Management (FinTechFM). The internal reliability of these three dimensions was evaluated using Cronbach's alpha, with all factors exceeding the 0.70 threshold, demonstrating a high level of measurement consistency (Hair, 2010).

**Professional Characteristics and Remuneration System**

A second PCA was carried out on variables representing both managerial characteristics and the compensation framework. The analysis included manager-specific variables such as age, tenure within the organisation, experience in fund management, educational level, possession of specialised diplomas, performance-linked remuneration, and compensation tied to the growth of assets under management. The Bartlett and KMO tests were both significant, confirming the suitability of the dataset for factor extraction. Additionally, the communalities of all variables exceeded 0.5, indicating satisfactory representation in the factor model. To determine the number of components to retain, each component's contribution to the total explained variance was carefully assessed to establish its relative importance.

As illustrated in Figure 2, the extracted factors are interpreted as follows: portfolio management experience, the manager's financial incentives, and the manager's level of professional training.

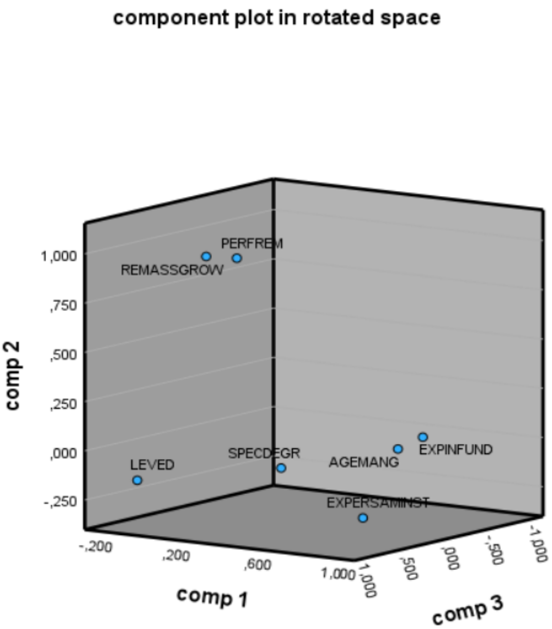


**Figure 2:** Principal Components of Manager's Professional Traits

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## Manager Practices and Fund Performance During and After the COVID-19 Outbreak

As previously discussed, the relationship between managerial practices and fund performance is well documented. This study, however, posits that the integration of FinTech is likely to reinforce this link. Supporting this perspective, prior evidence indicates that FinTech has substantially transformed asset management, influencing both decision-making processes and performance outcomes (Amnas et al., 2024; You et al., 2023). The research was carried out in two phases. In the first phase, the performance of Tunisian equity funds was assessed using fund returns, the adjusted Sharpe ratio, and the LPM-Treynor ratio, benchmarked against TUNINDEX20 and TUNINDEX during and following the COVID-19 pandemic (Grinblatt & Titman, 1994). In the second phase, the managerial decision-making factors identified in the study were employed to explain variations in fund performance.

## Performance Measurement of Mutual Funds

Pedersen and Rudholm-Alfvin (2003) suggest that an effective performance measure should account for market conditions, industry characteristics, asset classes, and investor preferences. Accordingly, given the elevated volatility during this period, the study utilises two risk-adjusted performance metrics suitable for higher-order moments. The first of these is the adjusted Sharpe ratio, as proposed by Pézier and White (2006), defined as follows:

$$AS_p = S_P\left(1 + \frac{s_k}{6} \times S_p - \left(\frac{k_r - 3}{24}\right)\right) \times S_p^{\,2} \tag{1}$$

Where, $S_p$ is Sharpe ratio for fund p, $s_k$ represents skewness, and $k_r$ is kurtosis.

Next, the LPM-Treynor ratio is calculated using the lower partial moment capital asset pricing model (LPM-CAPM) developed by Bawa and Lindenberg (1977). The LPM-Treynor ratio (LPM-TR) is expressed as follows:

$$TR_P - LPM = \frac{R_p - R_f}{\beta_P^{LPM_2}} \tag{2}$$

$R_p$ = Average Return on the Fund

$Rm$ Market Return

$R_f$ = Risk-Free Rate

$\beta_p^{LPM_2}$ = Fund Beta

As presented in Table 4, the overall sample of Tunisian funds exhibited negative risk-adjusted performance both during and after the pandemic. This pattern holds whether risk is measured as total risk using the adjusted Sharpe ratio or as systematic risk via the LPM-Treynor ratio. Nevertheless, a modest improvement in risk-adjusted returns is observed during the COVID-19 period, which appears to be driven by the outperformance of the equity funds subsample.

Specifically, within Tunisian equity portfolio management, equity funds achieved the highest average returns, recording 3.6% during the COVID-19 crisis and 0.54% in the post-pandemic period. In contrast, preventive funds registered the lowest performance, with average returns of -0.13% during the crisis and 0.27% afterwards. This outcome is partly attributable to the strong showing of the growth investment style during the crisis, as evidenced by a shift in investment approaches that primarily benefited the "stock picking growth" strategy, which increased from 3.8% to 15.4%.

## Managers' Practices and Funds' Performance

To evaluate the influence of managerial decision-making factors on fund performance, factor scores were initially computed. Subsequently, the mean scores were calculated for all managers overseeing the same fund. These average factor scores were then used as explanatory variables in regressions on fund performance. The regression outcomes are presented in Table 5. As anticipated, portfolio management experience, commonly recognised as a critical factor in fund manager selection, emerged as the most significant predictor of fund performance, with the largest beta coefficients ($.288 \leq \beta \leq .341$) observed for both risk-adjusted measures and the two benchmarks, supporting the acceptance of H3a. Concerning manager training, notable differences were observed across the study periods. In the post-COVID-19 phase, a manager's professional training had a positive effect on fund performance, particularly for the adjusted Sharpe ratio, leading to the acceptance of H3b. These results highlight the essential role of continuous professional development for fund managers, especially in light of rapid FinTechFM advancements in asset management. The analysis further indicated that HB exerted a negative impact on Tunisian fund performance, consistent with the acceptance of H2. Certain managers increased exposure to previously successful growth investment styles, contributing to underperformance and reinforcing H1. Additionally, FinTechFM adoption demonstrated a significant positive influence on fund performance during and after the COVID-19 crisis, supporting H5. Conversely, managers' IRPR was negatively associated with performance during the crisis period. Finally, no statistically significant relationship was detected between managers' financial incentives and fund outcomes, resulting in the rejection of H4.

## Table 4: Performance Evaluation of Equity Fund Subsamples

| **Study Period** | **January 2020-August 2021 (During Pandemic Period)** | | | | | **September 2021-September 2023 (Post-Pandemic Period)** | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Fund Group** | Number of Funds (2023) | Average Return | $AS_p$ | $\frac{TR_P - LPM}{\beta_P - LPM}$ TUNINDEX20 | $\frac{TR_P - LPM}{\beta_P - LPM}$ TUNINDEX | Average Return | $AS_p$ | $\frac{TR_P - LPM}{\beta_P - LPM}$ TUNINDEX20 | $\frac{TR_P - LPM}{\beta_P - LPM}$ TUNINDEX |
| Equity Funds (Assets Saving Account) | 17 | 0.03604 | -0.04320 | 0.16700<br>0.34945 | 0.14545<br>0.37159 | 0.00543 | -2.07938 | -0.16507<br>0.33657 | -0.22008<br>0.25244 |
| Dynamic Funds | 31 | 0.00020 | -2.62561 | -0.24941<br>0.24375 | -0.26818<br>0.21096 | 0.00420 | -2.54630 | -0.19069<br>0.29782 | -0.29376<br>0.19333 |
| Balanced Funds | 11 | -0.00132 | -2.92355 | -0.27861<br>0.24893 | -0.27837<br>0.24939 | 0.00382 | -2.85960 | -0.28831<br>0.19829 | -0.34347<br>0.16644 |
| Preventive Funds | 15 | -0.00137 | -4.26730 | -0.31613<br>0.18674 | -0.31713<br>0.18674 | 0.00270 | -4.12930 | -0.78093<br>0.07464 | -0.58075<br>0.10037 |
| Full Sample | 74 | 0.00917 | -2.46492 | -0.14428 | -0.15956 | 0.00404 | -2.70365 | -0.35625 | -0.35952 |
| **Benchmarks** | | | | | | | | | |
| $AS_{TUNINDEX}$ | -2.01855 | | | | | -0.31511 | | | |
| $AS_{\text{TUNINDEX20}}$ | -1.73908 | | | | | -1.22905 | | | |
| $T_{TUN} - LPM$ | -0.06038 | | | | | -0.04012 | | | |
| $T_{TUN20} - LPM$ | -0.06097 | | | | | -0.04843 | | | |
| Average Return TUNINDEX | 0.00061 | | | | | 0.02087 | | | |
| Average Return TUNINDEX20 | 0.00003 | | | | | 0.01256 | | | |

**Note:** Average return, Adjusted Sharpe ratios ( $AS_p$ ) and LPM-Treynor ( $\frac{TR_P - LPM}{\beta_P - LPM}$ ) ratios computed for equity, dynamic, balanced, preventive, and full samples.

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## Table 5: Linear Regression of Funds' Performance on Managers' Decision Factors

| **Manager's Traits** | $AS_{P_{Tunindex20}}$ | $AS_{P_{Tunindex}}$ | $TR_P - LPM_{Tunindex20}$ | $TR_P - LPM_{Tunindex}$ |
|---|---|---|---|---|
| **During COVID-19 Period** | | | | |
| Experience in Managing Portfolios | 0.322** | 0.302* | 0.341*** | 0.314* |
| Manager's Financial Incentive | -0.063 | -0.078 | -0.004 | -0.099 |
| Manager's Level of Training | 0.206** | 0.199** | 0.278** | 0.275*** |
| Manager Herding Behaviour-HB | -0.285* | -0.530 | -0.162** | -0.353** |
| IRPR | -0.278** | 0.219 | -0.393* | -0.423*** |
| FinTech-FM | 0.363 | 0.222 | 0.333 | 0.289 |
| $R^2$<br>$F$ | 0.508<br>112.617 | 0.485<br>97.142 | 0.444<br>57.42 | 0.451<br>86.13 |
| **Post- COVID-19 Period** | | | | |
| Experience in Managing Portfolios | 0.291** | 0.288* | 0.327* | 0.312* |
| Manager's Financial Incentive | -0.156 | -0.128 | 0.146 | 0.101 |
| Manager's Level of Training | 0.176** | 0.174*** | 0.216 | 0.175 |
| Manager Herding Behaviour-HB | -0.125* | -0.230 | -0.142** | -0.153** |
| IRPR | 0.236 | 0.215 | 0.303 | 0.421 |
| FinTech-FM | 0.473* | 0.320** | 0.522** | 0.479** |
| $R^2$<br>$F$ | 0.478<br>112.617 | 0.465<br>97.142 | 0.412<br>57.42 | 0.456<br>86.13 |
| * p < 0,05; ** P < 0,01; *** P < 0,001 | | | | |

**Notes:** This table presents the estimation results from the regression of fund performance on managers' decision factors before and during the pandemic. The selected factors are listed in the first column, while the two performance indicators are displayed in the first row for each chosen benchmark. The probabilities associated with the applied tests are shown in parentheses for each statistic. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

## DISCUSSION

This study investigates the determinants of managerial decision-making and their influence on fund performance, with particular emphasis on FinTechFM adoption and periods of market volatility in the Tunisian context. Building on prior research regarding fund manager behaviour, the analysis identifies key drivers such as investment objectives, asset selection strategies, and management styles. The findings indicate that managerial decisions are influenced by client characteristics, with institutional investors associated with longer investment horizons. Managers tend to favour shorter performance evaluation periods, typically under one year, reflecting an active management approach that responds to prevailing market trends. Market indices are predominantly employed as benchmarks for performance assessment rather than as direct guides for investment choices (Lin et al., 2023).

Principal component analysis reveals three principal dimensions shaping managerial behaviour: HB, IRPR, and FinTechFM adoption. While descriptive statistics indicate that 69.2% of managers' report rarely considering other managers' positions, the factor analysis uncovers the presence of HB, which tends to drive managers toward higher-risk investment styles, contrasting with findings reported by Rizvi et al. (2020). The analysis further underscores the significance of managerial attributes, including experience, training, and financial incentives, corroborating previous studies that highlight the role of professional qualifications in investment decision-making (Andreu & Puetz, 2017; Chevalier & Ellison, 1999; Golec, 1996; Lin et al. 2023) These behavioural and professional factors are subsequently linked to fund performance.

Risk-adjusted performance analysis, based on the adjusted Sharpe and LPM-Treynor ratios, shows that most fund categories recorded negative returns during the post-COVID period, underperforming the market, with the deterioration most severe during the crisis. Equity funds represent an exception, demonstrating relatively stronger performance both during and after the pandemic. This resilience appears driven by a long-term investment strategy targeting reputable, financially robust firms with growth potential. Overall, the results do not support the notion that active management consistently outperforms during economic downturns, aligning with previous evidence (Golec, 1996; Fang et al., 2025).

Regression analyses confirm that managerial experience exerts a positive and statistically significant impact on fund performance, with effect sizes increasing during the pandemic (β ranging from 0.302 to 0.341). Managerial education and training also positively influence performance, particularly in periods of heightened market uncertainty. These findings suggest that experienced and well-trained managers are better equipped to navigate turbulent conditions, partly due to their reliance on FinTechFM tools for interpreting complex data, evaluating evolving market conditions, and executing timely strategic adjustments. This interpretation aligns with prior studies emphasising the importance of managerial tenure and human capital efficiency in sustaining performance and resilience under extreme stress (Anuar et al., 2025; Mirza et al., 2020; Porter & Trifts,

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2014; Rachmawati et al., 2020; Yarovaya et al., 2021).

Conversely, HB negatively affects fund performance, with more pronounced impacts during crisis periods, as reflected by higher beta coefficients. Similarly, IRPR is negatively associated with performance during the pandemic, indicating that heightened uncertainty may prompt managers to rely on non-fundamental information sources, thereby reinforcing herding tendencies. These findings corroborate the evidence of Di Guilmi et al. (2014) and Santi and Zwinkels (2023), supporting broader conclusions that intentional style herding is substantial and persistent in mutual fund markets, particularly following periods of high volatility. Finally, FinTechFM adoption—including AI, ML, robo-advisors, and digital platforms—demonstrates a positive and statistically significant effect on fund performance both during and after the COVID-19 crisis. These technologies enhance real-time financial analysis, improve risk assessment and market forecasting, facilitate the provision of personalised investment advice, and boost investor engagement by increasing accessibility and enabling immediate feedback on investor behaviour (Amnas et al., 2024; Gomber et al., 2018; Pahsa, 2024; Wang, 2023; You et al., 2023; Zetzsche, 2017). Contrary to initial expectations, financial incentives show no significant association with fund performance, potentially due to sample size constraints or the specific structure of remuneration systems in the Tunisian market (Ma et al., 2016).

## CONCLUSION

This study investigates the factors shaping managerial decision-making and their impact on fund performance, with particular emphasis on FinTechFM adoption and market volatility. The findings indicate that managerial experience, advanced professional training, and the strategic application of FinTechFM tools play a critical role in enhancing fund outcomes, particularly during periods of heightened market turbulence such as the COVID-19 crisis. Conversely, HB is identified as a performance-detracting factor, while financial incentives exhibit no significant direct effect on fund results. The analysis further underscores the influence of regulatory frameworks, liquidity considerations, and client characteristics in guiding investment strategies. Although the study is situated within the Tunisian context, these insights are applicable to other emerging markets that share similar technological infrastructures and regulatory environments. The dynamic interplay between managerial practices, FinTechFM adoption, and fund performance highlights mechanisms likely to be present in comparable financial systems, offering a practical perspective for understanding technology-driven asset management beyond Tunisia. While the study relies on cross-sectional survey data, the relative stability of managerial roles during the examined period mitigates potential biases. Ethical standards were rigorously maintained, including informed consent, protection of participant anonymity, and exclusive use of responses for research purposes. Overall, the results emphasise the increasing importance of managerial expertise and FinTechFM integration in achieving superior fund performance, providing actionable guidance for asset managers, regulators, and investors. Future research could employ longitudinal methodologies to monitor managerial behaviour and fund performance over extended

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periods, examine FinTechFM adoption across a wider range of emerging and developed markets, and investigate additional behavioural factors such as risk appetite, decision-making approaches, and cultural influences.

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