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Robo-Advisor Performance and the Limits of Performance-Based Adoption Explanations

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Abstract

Robo-advisors offer low-cost automated investment services, but their reported investment outcomes do not by themselves explain who uses them. This paper compares ten selected U.S. robo-advisory accounts using a dated Condor Capital Robo Report extract. One-, three-, and five-year trailing results are summarized for total portfolio, equity-sleeve, fixed-income-sleeve, and risk-adjusted returns (Sharpe ratios). The accounts did not show uniformly weak reported outcomes. All ten fixed-income sleeves exceeded the displayed Bloomberg U.S. Aggregate Bond Index reference in the three- and five-year windows, whereas total and equity returns generally fell below the S&P 500 reference. These index comparisons are descriptive: portfolio allocations, risks, tax exposures, and fee conventions are not fully matched. Three-year Sharpe ratios were higher than five-year ratios in the supplied snapshot, but overlapping trailing windows do not establish a temporal decline. Most importantly, the data contain no investor-level adoption observations or direct performance-adoption relationship. The paper therefore does not claim to explain low adoption empirically. Instead, it positions reported performance alongside earlier work on investor trust, digital financial literacy, preferences for human advice, and provider incentives to outline propositions for future testing. The contribution is a bounded performance comparison and a clear separation of observed investment outcomes from conjectured adoption mechanisms.

Keywords

Robo-Advisors, Artificial Intelligence, Technology Adoption, Behavioral Finance, Retail Finance

1. Introduction

Professional investment management has traditionally been associated with high

costs and substantial financial barriers, making personalized portfolio management accessible primarily to wealthy investors. Many traditional financial advisors require minimum account balances of $25,000 or more, limiting access to professional investment advice for ordinary retail investors (Investopedia Team, 2025). Robo-advisors emerged as a response to these barriers by offering automated portfolio management at significantly lower costs. These digital platforms construct and manage investment portfolios according to users' financial goals, risk tolerance, and investment horizon, typically collected through an online questionnaire (Investopedia Team, 2025). Reher and Sokolinski (2024) further argued that robo-advisors improve access to professional wealth management by lowering traditional entry barriers, thereby expanding financial advisory services to previously underserved retail investors.

Unlike traditional financial advisory services, robo-advisors rely on algorithms based primarily on Modern Portfolio Theory to allocate assets among diversified portfolios composed largely of low-cost exchange-traded funds (ETFs). Portfolio rebalancing, tax-loss harvesting, and other investment management functions are performed automatically with minimal human intervention, enabling retail investors to access professional portfolio management at relatively low cost (Bromberg, 2025; Investopedia Team, 2025). More recently, robo-advisors have evolved beyond simple automated investment tools and are increasingly regarded as AI-enabled financial advisory systems embedded within broader technological, institutional, and regulatory environments. Their value therefore depends not only on portfolio performance but also on investor trust, digital competence, perceived security, and institutional design (Shetty et al., 2026).

Since the launch of Betterment and Wealthfront in 2008, the robo-advisory industry has expanded rapidly. Major financial institutions, including Vanguard, Fidelity, and Charles Schwab, now offer automated investment services alongside traditional wealth management products. Global assets managed by robo-advisors exceeded hundreds of billions of dollars, and the industry continues to experience rapid growth (Senteio & Hughes, 2024; Investopedia Team, 2025). Nevertheless, robo-advisors still account for only a small proportion of global assets under management, indicating that industry growth has not translated into widespread adoption among retail investors.

Existing robo-advisors vary considerably in their service models. Full-service platforms automatically construct and manage client portfolios, semi-automated platforms require investor approval before executing recommendations, while self-service platforms mainly provide investment information and portfolio suggestions (Au et al., 2021). Although management fees are generally far below those charged by traditional financial advisors, adoption remains surprisingly limited. Recent evidence suggests that only a small proportion of U.S. investors actively use robo-advisors, while many potential investors remain unfamiliar with the technology (Senteio & Hughes, 2024). These findings indicate that lower costs and technological accessibility alone are insufficient to encourage widespread adop-

tion.

For the purposes of this study, "low adoption" refers to limited current use among U.S. retail investors rather than to an absence of industry growth. A Qualtrics survey of 1577 U.S. consumers aged 18 - 76 found that only 1% of respondents with investments reported currently using a robo-advisor, even though 63% of respondents stated that they were at least open to using one (Evans, 2022). This contrast between expressed openness and reported current use provides a concrete user-level indicator of limited market penetration. Because the estimate was derived from a 2022 non-probability survey, it is not treated as a precise measure of the 2026 adoption rate. Instead, it establishes the empirical basis for examining why demonstrated technological and investment capabilities have not necessarily translated into widespread current use.

Previous studies have proposed several explanations for this adoption gap. One stream of research emphasizes investor trust. Cheng et al. (2019) found that trust in both the technology and the financial institution significantly influences adoption intentions, while firm reputation, service quality, and attitudes toward artificial intelligence also affect users' willingness to rely on algorithmic advice. Back et al. (2023) further demonstrated that social design elements embedded in robo-advisory interfaces can significantly influence investor confidence and investment decisions, suggesting that technology design itself shapes user acceptance beyond objective investment performance. Nourallah (2023) found that initial trust plays a decisive role during investors' first interactions with robo-advisors, indicating that early perceptions of algorithmic competence and transparency substantially influence adoption intentions. Similarly, Senteio and Hughes (2024) reported that many investors continue to prefer human financial advisors even when robo-advisors demonstrate comparable investment performance. Other studies highlight demographic and behavioral characteristics. Au et al. (2021) found that previous investment experience substantially increases the likelihood of adopting robo-advisory services, whereas age, education, and gender also influence adoption decisions. More recent research further suggests that subjective financial literacy and digital financial literacy positively influence robo-advisor adoption, whereas objective financial literacy alone does not necessarily encourage investors to use automated financial advice (Aristei & Gallo, 2025). Together, these findings indicate that adoption depends not only on financial knowledge but also on investor confidence, digital competence, and trust in financial technologies.

Although previous research has identified several behavioral and demographic determinants of robo-advisor adoption, relatively few studies have examined whether actual investment performance can explain the persistent gap between technological capability and market acceptance. Existing studies often investigate performance, investor trust, demographic characteristics, or institutional incentives separately. Consequently, the relationship between objective investment performance and the continued reluctance of retail investors to adopt robo-advisory services remains insufficiently understood. Luo et al. (2024) suggested that inves-

tors' willingness to adopt robo-advisors is shaped not only by expected financial outcomes but also by perceptions of fiduciary responsibility and advisory reliability.

To address this gap, this study examines what is referred to as the robo-advisor paradox—the coexistence of relatively strong investment performance and persistently low adoption among retail investors. Using independent performance data from ten leading robo-advisory platforms, this study evaluates portfolio performance across multiple investment horizons and interprets the findings within the broader literature on trust, digital financial literacy, investor behavior, and institutional incentives. Specifically, this study addresses the following research question:

RQ1. How do the selected U.S. robo-advisory portfolios perform across total portfolio returns, equity returns, fixed-income returns, and risk-adjusted returns over one-, three-, and five-year horizons?

RQ2. To what extent are the observed performance patterns consistent with a performance-based explanation of limited current robo-advisor use among U.S. retail investors, and what behavioral and institutional mechanisms identified in prior research provide plausible complementary explanations?

This paper makes three contributions. First, it provides a comprehensive comparative evaluation of ten major robo-advisory platforms using four widely accepted performance measures across three investment horizons. Second, it shows that the observed performance patterns are inconsistent with a simple explanation that attributes limited adoption solely to uniformly weak investment outcomes. Third, it develops a literature-informed interpretive framework that connects the observed performance evidence with behavioral and institutional mechanisms identified in prior research, thereby generating propositions for future empirical tests of robo-advisor adoption.

2. Methods

2.1. Research Design

This study uses a quantitative, descriptive comparison of secondary investment-performance data. It examines reported portfolio outcomes for selected robo-advisory accounts and considers the limits of interpreting those outcomes as an explanation for market adoption. Because investor use is not observed, the research does not estimate a performance-adoption relationship.

The analysis proceeds in two stages. First, selected robo-advisory accounts are compared on return and risk-adjusted measures using a common reporting snapshot. Second, the descriptive evidence is situated alongside previous work on investor trust, digital financial literacy, preferences for human advice, and provider incentives. The second stage provides an interpretive discussion, not a statistical or causal test of those mechanisms.

The empirical component of the study is limited to portfolio performance. It does not estimate adoption rates, model adoption intentions, or test a statistical

relationship between investment outcomes and investor adoption. Accordingly, the second stage of the analysis is interpretive rather than causal. Behavioral and institutional studies are used to identify plausible explanations for the contrast between observed portfolio performance and previously documented limited use, but these explanations are not treated as variables directly verified by the present dataset.

2.2. Data Source

The numerical observations were transcribed from the Condor Capital Wealth Management Robo Report performance tables identified in the author-supplied materials as updated to 31 March 2026 (Condor Capital Wealth Management, 2026b, 2026c). Condor maintains and monitors funded accounts at robo-advisory providers rather than relying exclusively on hypothetical portfolios. The analysis uses these reported account outcomes as a dated, observational snapshot; later changes to the live online tables are not part of the reported comparisons.

The accounts should not, however, be understood as experimentally identical portfolios. They may differ in target asset allocation, domestic and international exposure, fixed-income composition, duration, credit quality, cash holdings, advisory fees, fund expenses, tax treatment, and platform-specific risk classifications. Condor reports that returns are net of fees and that returns for periods longer than one year are annualized. The present study consequently treats the dataset as an observational cross-platform comparison rather than as a controlled experiment in which every platform manages the same portfolio.

2.3. Sample Selection

The purposive sample comprises ten U.S. robo-advisory accounts represented in the Condor report: Ally Invest Robo Portfolios, Betterment, Citi Wealth Builder, E*Trade Core Portfolios, Fidelity Go, Schwab Intelligent Portfolios, SigFig, SoFi Automated Investing, Vanguard Digital Advisor, and Wealthfront. The accounts were chosen for availability of the stated indicators and coverage of prominent commercial providers. They are not a random sample of U.S. robo-advisor products or of retail investors, and the findings should not be generalized to the entire industry.

2.4. Account Configuration and Comparability

Table 1 identifies the exact Condor account labels and the configuration fields documented in the source materials supplied for this revision. All ten observations were classified in Condor's approximately 60/40 allocation group; this grouping does not mean that their holdings or risks were identical. Information not documented for a tracked account is designated NR, not inferred from a provider's public marketing materials.

When Condor did not publicly disclose an exact initial funding amount, questionnaire response, tax status, or other account characteristic, the item was rec-

orded as "NR" rather than estimated. The selected observations were drawn from Condor's approximately 60/40 allocation group, but "approximately 60/40" does not imply identical holdings. Differences in international equity allocation, municipal-bond exposure, credit quality, bond duration, cash weight, and product expenses remain relevant when interpreting performance differences.

Table 1. Selected Condor accounts and documented configuration information.

Platform	Exact Condor account label	Risk designation	Advisory fee	Fund expense ratio	Cash allocation
Ally Invest Robo Portfolios	Ally Invest Robo Portfolios (9)	NR	NR	NR	NR
Betterment	Betterment (27)	NR	NR	NR	NR
Citi Wealth Builder	Citi Wealth Builder (40)	NR	NR	NR	NR
E*Trade Core Portfolios	E*Trade Core (21)	NR	NR	NR	NR
Fidelity Go	Fidelity Go (33)	NR	NR	NR	NR
Schwab Intelligent Portfolios	Schwab Intelligent Portfolios (5)	NR	NR	NR	NR
SigFig	SigFig (6)	NR	NR	NR	NR
SoFi Automated Investing	SoFi (17)	NR	NR	NR	NR
Vanguard Digital Advisor	Vanguard Digital Advisor (7)	NR	Combined fees capped at 0.20%	0.06%	0%
Wealthfront	Wealthfront (Risk 4.0; 2016) (44)	Risk 4.0	0.25% annually	0.04%	0%

Note. NR = not reported for the specific tracked account in the materials consulted. All ten accounts belong to Condor's approximately 60/40 allocation group. For the remaining accounts, the source materials did not establish a directly applicable fee, expense ratio, cash weight, risk designation, actual opening deposit, account type, or tax treatment. Product minimums are not the same as Condor's actual initial funding. Total portfolio returns are reported net of fees; equity and fixed-income sleeve returns are gross of fees; periods longer than one year are annualized. Fee and allocation details can change over time (Condor Capital Wealth Management, 2026a, 2026b, 2026c).

2.5. Performance Measures

Four reported indicators were examined: total portfolio return, equity-sleeve return, fixed-income-sleeve return, and the Sharpe ratio. Total return describes overall account performance; sleeve returns characterize reported returns on stocks and fixed income; and the Sharpe ratio summarizes excess return relative to reported volatility under the source's calculation conventions. These indicators offer complementary descriptions, but no single measure establishes portfolio quality independently of allocation, fees, risk, or an appropriately matched reference.

2.6. Benchmark Selection and Interpretation

Benchmark comparisons are descriptive. Condor's normalized-benchmark method adjusts reference weights for portfolio exposure and would provide a more allocation-sensitive basis for judging total returns (Condor Capital Wealth Management, n.d.). However, the figures reproduced here use the S&P 500 and the Bloomberg U.S. Aggregate Bond Index as broad, transparent market references; they do not report matched normalized-benchmark excess returns. Accordingly, the comparison is not used to estimate investment alpha or provider skill.

Second, equity-sleeve returns were compared with the S&P 500 as a transparent reference for U.S. large-cap equity performance. The S&P 500 is not a fully matched benchmark for every equity sleeve because robo-advisor portfolios may also hold international, emerging-market, small-cap, mid-cap, value, or sector-specific exposures. A return gap relative to the S&P 500 may therefore reflect differences in asset exposure rather than investment-management quality.

Third, fixed-income returns were compared with the Bloomberg U.S. Aggregate Bond Index as a broad reference for the U.S. investment-grade bond market. This index is not perfectly matched to portfolios containing municipal securities, high-yield bonds, international debt, short-duration instruments, or substantial cash allocations. Differences in duration, credit quality, tax status, and geographic allocation may explain part of the observed benchmark gap.

Accordingly, the S&P 500 and Bloomberg U.S. Aggregate Bond Index are used for descriptive context rather than as definitive tests of abnormal performance or algorithmic skill. Positive benchmark differences are described as higher returns than the selected reference index, not as investment alpha.

2.7. Analytical Framework

Figure 1 summarizes the sequence of data description and interpretation. Reported account returns and Sharpe ratios are first compared across selected platforms and horizons; interpretations from the technology-adoption literature are considered separately. The final contrast between performance and previously reported use is a research motivation rather than a causal inference from the current data.

2.8. Descriptive Statistical Analysis

For each indicator and horizon, cross-account mean, sample standard deviation (SD), minimum, maximum, range, and coefficient of variation (CV) were summarized for the ten selected accounts. The SD is calculated across accounts, not across repeated observations of each platform. Where the mean is positive, the descriptive CV is calculated as follows:

$$CV = (\text{sample SD} / \text{mean}) \times 100\%$$

The mean describes the selected accounts, whereas the SD and range describe their absolute cross-platform dispersion. CV compares the SD with the mean and becomes unstable when the mean is near zero; this qualification is particularly

important for five-year fixed-income returns. Cross-horizon comparisons describe overlapping trailing windows ending on the same reporting date, not a longitudinal trend in the same annual returns.

The analysis remains descriptive. These statistics summarize the selected accounts but do not test statistical significance, estimate population parameters, or establish causal differences among providers.

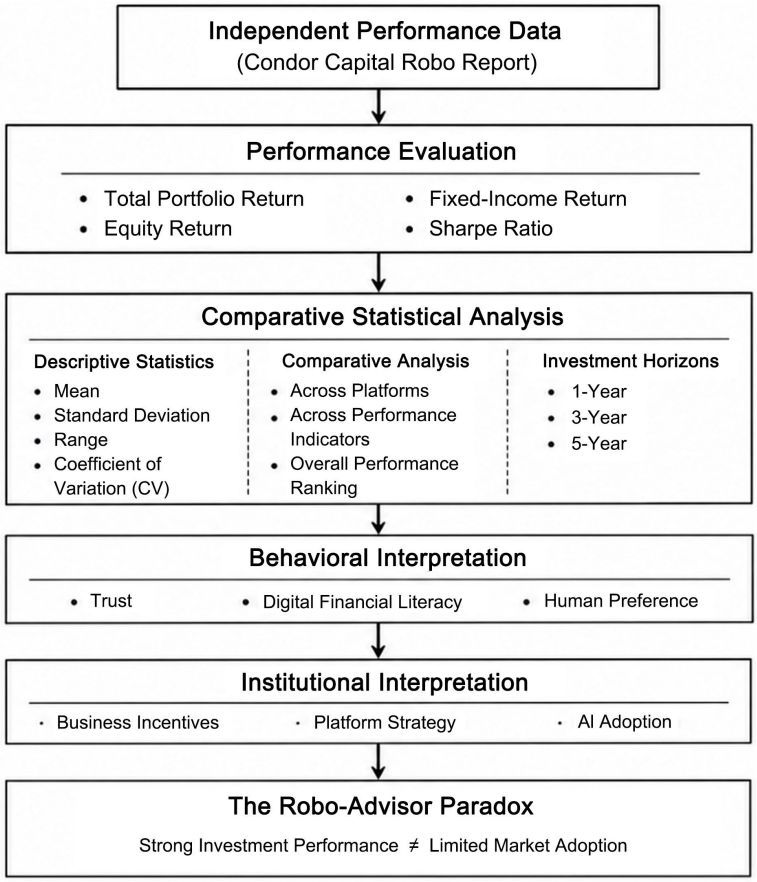


Figure 1. Analytical sequence used in this study. Behavioral and institutional explanations are interpretive, not empirically tested here.

2.9. Comparative Performance Analysis

Reported performance was compared across one-year, three-year annualized, and five-year annualized trailing windows. Four indicators were considered separately to avoid treating raw return and risk-adjusted return as interchangeable. Because all windows share an end date and overlap, their differences cannot by themselves establish how a platform's performance evolved through time. Provider rankings are descriptive: underlying portfolio composition, risk categories, fees, cash, and tax treatment are not experimentally standardized.

2.10. Descriptive Cross-Checks

The findings were cross-checked for direction and dispersion across reported in-

dicators, time horizons, and broad reference indices. These are descriptive triangulations within a common set of accounts, not independent replications, sensitivity tests based on alternative data, or causal robustness tests. Conclusions are limited accordingly.

2.11. Data Interpretation

The performance findings were interpreted in conjunction with prior research on behavioral finance, technology acceptance, artificial intelligence, and institutional conditions. This interpretive stage does not constitute an empirical test of adoption. The dataset contains no investor-level observations, platform-level adoption rates, or longitudinal measures linking changes in performance to changes in customer use.

The interpretive question is whether the selected accounts display uniformly weak reported outcomes, as a simple performance-deficiency account might presuppose. Observing some favorable return patterns does not test, disprove, or quantify performance-based adoption explanations. Prior research instead identifies possible behavioral and institutional variables for future designs that actually observe adoption.

3. Results

The results summarize the reported outcomes of the ten selected robo-advisory accounts across total returns, equity-sleeve returns, fixed-income-sleeve returns, and Sharpe ratios. One-year results and three- and five-year annualized results are compared as overlapping trailing-window summaries rather than independent investment periods.

Table 2. Cross-platform descriptive statistics for the ten selected accounts.

Performance indicator	Horizon	Mean	Sample SD	Minimum	Maximum	Range	CV
Total portfolio return (%)	1 year	14.94	1.21	12.26	16.60	4.34	8.10%
Total portfolio return (%)	3 years	11.30	0.57	10.47	12.49	2.02	5.00%
Total portfolio return (%)	5 years	6.00	0.61	5.22	6.86	1.64	10.09%
Equity return (%)	1 year	22.01	1.30	20.46	24.71	4.25	5.90%
Equity return (%)	3 years	16.52	0.92	15.64	18.61	2.97	5.57%
Equity return (%)	5 years	9.39	0.84	8.41	10.79	2.38	8.92%
Fixed-income return (%)	1 year	4.26	0.51	3.23	4.70	1.47	11.90%
Fixed-income return (%)	3 years	3.51	0.57	2.52	4.22	1.70	16.20%
Fixed-income return (%)	5 years	0.71	0.38	0.23	1.54	1.31	53.48%
Sharpe ratio	1 year	1.05	0.10	0.85	1.17	0.32	9.25%
Sharpe ratio	3 years	1.23	0.10	1.14	1.42	0.28	8.26%
Sharpe ratio	5 years	0.36	0.07	0.28	0.48	0.20	19.44%

Note. SD = cross-platform sample standard deviation; CV = SD / mean × 100%. Returns for periods longer than one year are annualized. Horizons are overlapping trailing windows with a common end date.

Table 2 shows that the selected platforms were most similar in their three-year total portfolio returns, which had a coefficient of variation of 5.00%. Three-year equity returns were also relatively concentrated, with a coefficient of variation of 5.57%. These results support the descriptive observation that medium-term total and equity returns differed only moderately across the ten accounts.

Relative dispersion was greater in fixed-income performance. The coefficients of variation were 11.90% for the one-year period and 16.20% for the three-year period. The five-year fixed-income coefficient of variation reached 53.48%, although this value should be interpreted cautiously because the cross-platform mean was only 0.71%. A relatively small absolute difference therefore produces a large percentage-based measure of dispersion.

Sharpe-ratio dispersion was moderate over the one- and three-year periods, with coefficients of variation of 9.25% and 8.26%, respectively. The five-year coefficient of variation increased to 19.44%, consistent with greater relative differentiation in long-term risk-adjusted outcomes.

3.1. Total Portfolio Returns

Figures 2-5 report total portfolio returns for the ten selected accounts in three trailing windows.

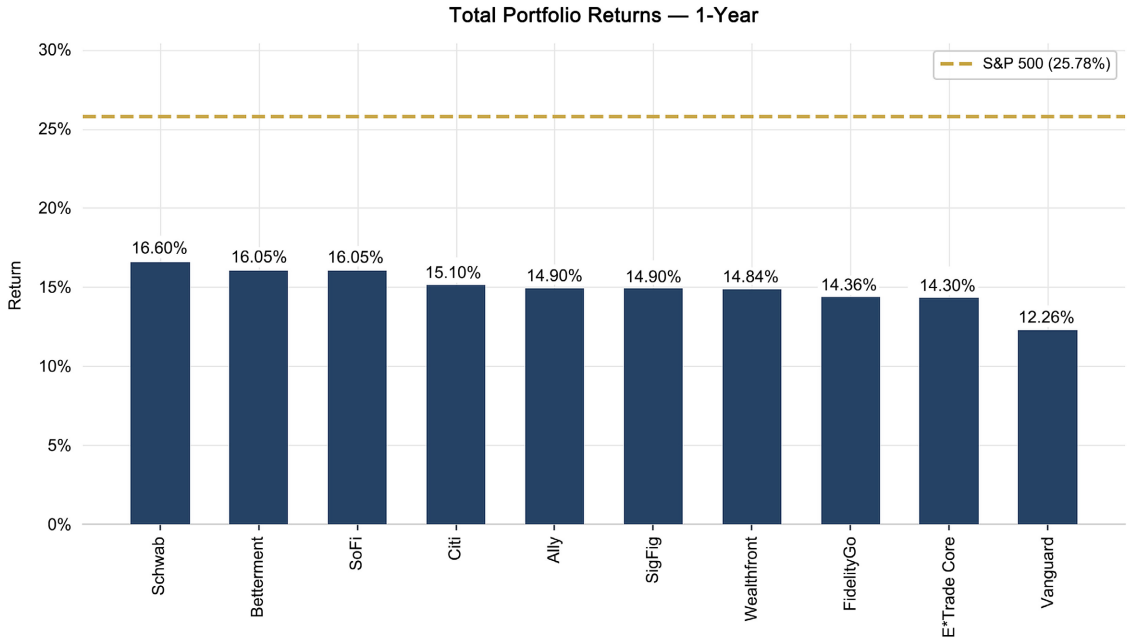


Figure 2. Total portfolio returns, 1-year.

During the one-year period, total portfolio returns ranged from 12.26% to 16.60%, indicating relatively modest performance differences among platforms despite noticeable ranking changes. Schwab Intelligent Portfolios achieved the highest return (16.60%), whereas Vanguard Digital Advisor recorded the lowest return (12.26%). Every total portfolio return was below the S&P 500 during the

one-year period. This comparison should not be interpreted as direct underperformance against a matched portfolio benchmark, because the S&P 500 represents U.S. large-cap equities, whereas the robo-advisor portfolios contained combinations of equities, fixed income, and cash. The return gap is therefore partly mechanical and reflects differences in asset-class exposure and risk rather than necessarily indicating inferior portfolio management.

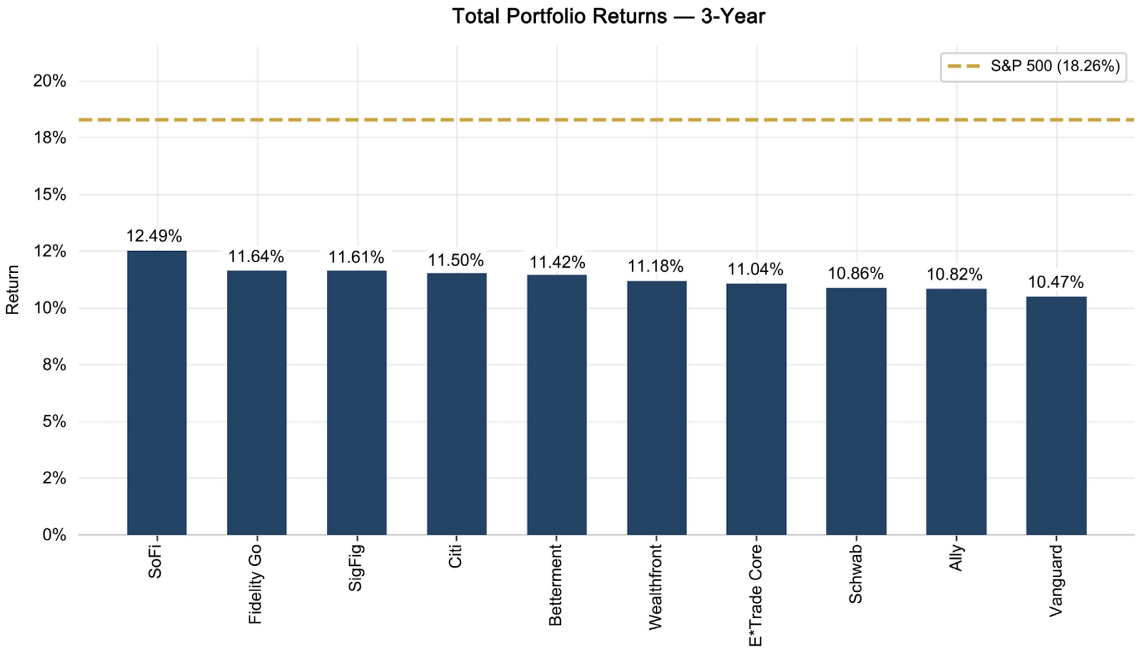


Figure 3. Total portfolio returns, 3-year annualized.

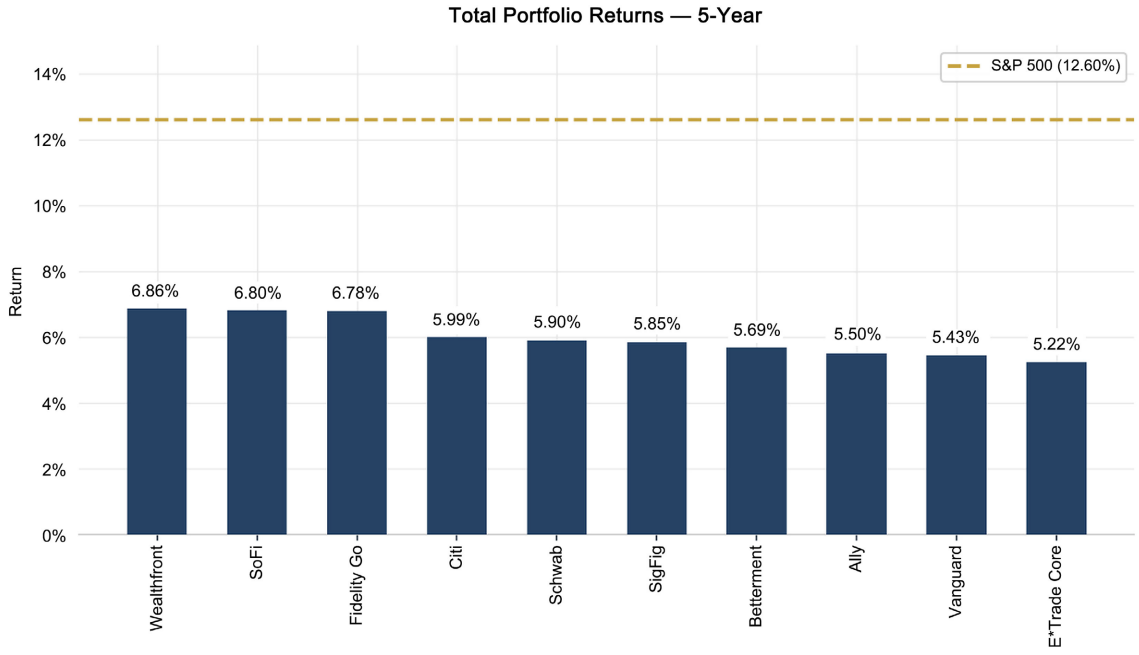


Figure 4. Total portfolio returns, 5-year annualized.

The 4.34-percentage-point range describes the dispersion among these selected accounts. It does not establish that platform choice has a small effect for investors holding different asset allocations, entering at different dates, or facing different fees.

In the three-year annualized window, returns ranged from 10.47% to 12.49%. SoFi recorded the highest value (12.49%), followed by Fidelity Go and SigFig. This cross-account spread was narrower than in the one-year window, while rankings differed between the two overlapping windows.

The smaller dispersion of the three-year annualized figures is a feature of this snapshot. It should not be interpreted as evidence that providers converged over time or that a longer holding period necessarily produces more reliable management performance.

Five-year annualized total returns ranged from 5.22% to 6.86%. Wealthfront recorded the highest value (6.86%) and E*Trade Core the lowest (5.22%). The selected five-year figures were below the corresponding three-year figures, and all were below the S&P 500 return shown in the supplied figures.

The one-, three-, and five-year windows cover different, overlapping market intervals. Although macroeconomic developments may have influenced the reported results, the data do not isolate those influences or establish why five-year averages differ from shorter-window averages.

	1-Year		3-Year		5-Year	
Portfolio	**Return**	**vs Bench**	**Return**	**vs Bench**	**Return**	**vs Bench**
Ally Invest Robo Portfolios	14.90%	**-10.88%**	10.82%	**-7.44%**	5.50%	**-7.10%**
Betterment	16.05%	**-9.73%**	11.42%	**-6.84%**	5.69%	**-6.91%**
Citi Wealth Builder	15.10%	**-10.68%**	11.50%	**-6.76%**	5.99%	**-6.61%**
E*Trade Core	14.30%	**-11.48%**	11.04%	**-7.22%**	5.22%	**-7.38%**
Fidelity Go	14.36%	**-11.42%**	11.64%	**-6.62%**	6.78%	**-5.82%**
Schwab Intelligent Portfolios	16.60%	**-9.18%**	10.86%	**-7.40%**	5.90%	**-6.70%**
SigFig	14.90%	**-10.88%**	11.61%	**-6.65%**	5.85%	**-6.75%**
SoFi	16.05%	**-9.73%**	12.49%	**-5.77%**	6.80%	**-5.80%**
Vanguard Digital Advisor	12.26%	**-13.52%**	10.47%	**-7.79%**	5.43%	**-7.17%**
Wealthfront (Risk 4.0 ; 2016)	14.84%	**-10.94%**	11.18%	**-7.08%**	6.86%	**-5.74%**
S&P 500 (benchmark)	**25.78%**	—	**18.26%**	—	**12.60%**	—

Figure 5. Total portfolio returns by platform (alphabetical).

Figure 5 displays the three return windows together. Relative ranks change across windows, and no one platform ranks first in each. These are cross-window comparisons for a common observation date rather than a time-series test of persistent provider performance.

Overall, the selected accounts showed relatively limited cross-platform variation in total portfolio returns, particularly over the three-year horizon. Their returns remained below the S&P 500 broad equity reference, although this comparison is not allocation-matched because the robo-advisor portfolios also contained fixed income and cash. The findings therefore provide descriptive evidence against characterizing the selected accounts as uniformly poor performers, but they do not directly test the relationship between portfolio performance and market adoption.

3.2. Equity Returns

Figures 6-9 report the equity-sleeve returns of the selected accounts. Separating the equity sleeve from the total account removes the arithmetic contribution of the bond and cash sleeves but does not equate risk, geographic exposure, capitalization, or investment style across providers.

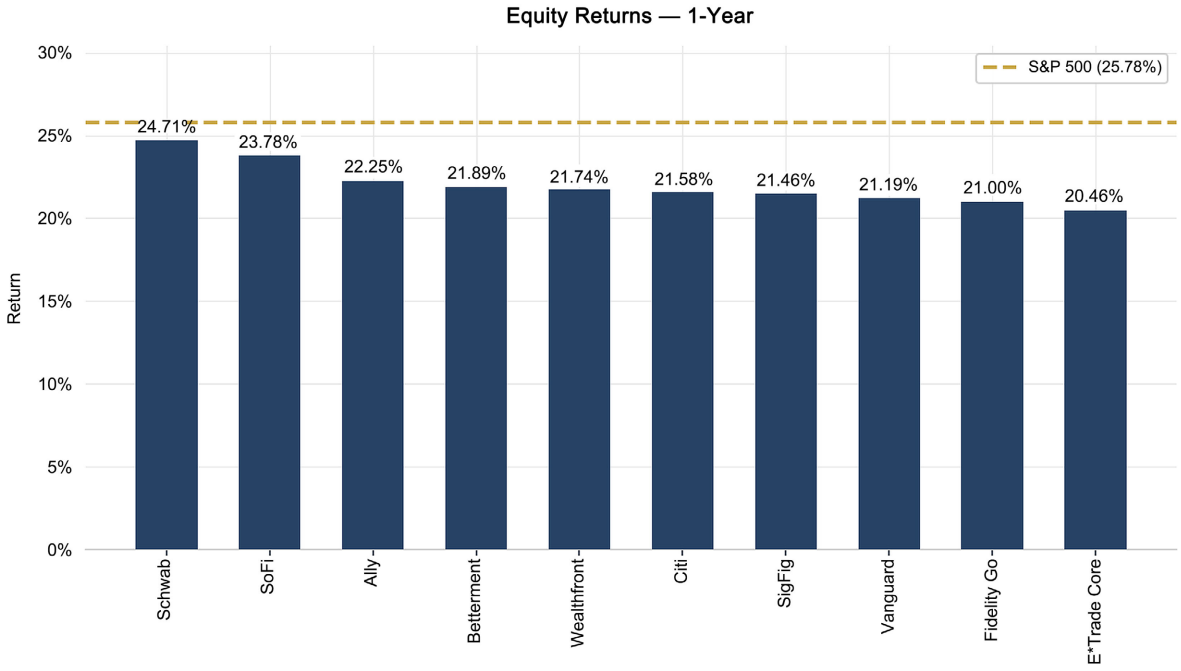


Figure 6. Equity returns, 1-year.

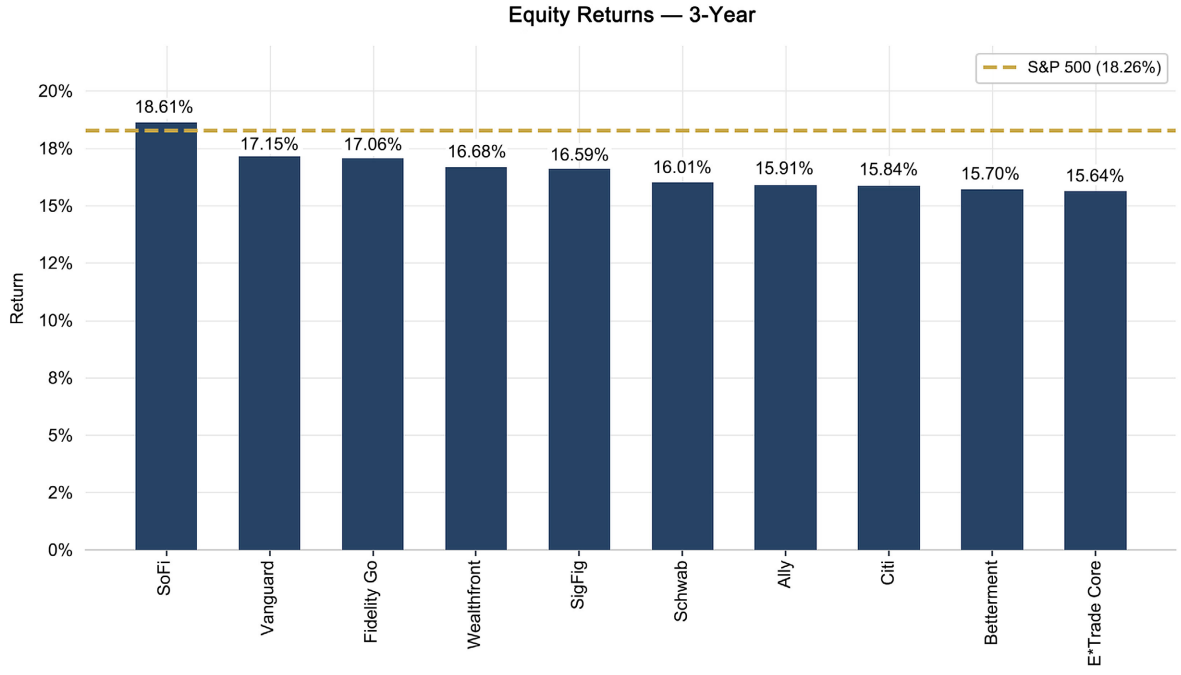


Figure 7. Equity returns, 3-year annualized.

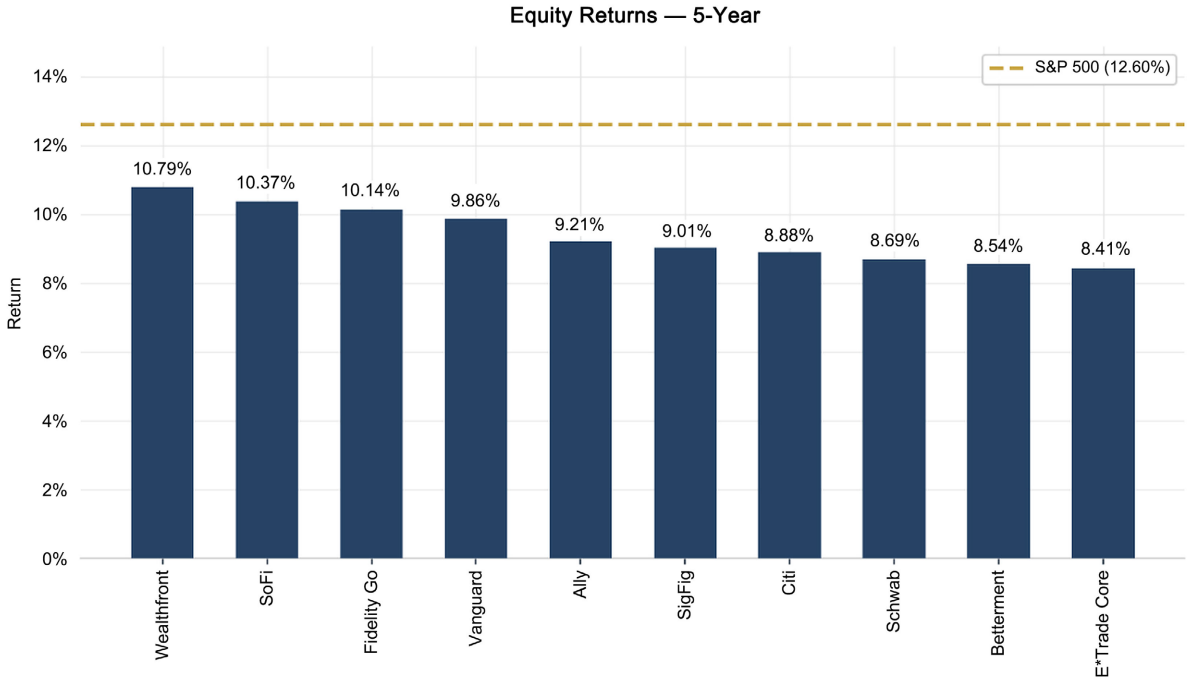


Figure 8. Equity returns, 5-year annualized.

During the one-year period, equity returns ranged from 20.46% to 24.71%, with Schwab Intelligent Portfolios achieving the highest return (24.71%) and E*Trade Core recording the lowest (20.46%). Compared with total portfolio returns, the variation among platforms remained relatively limited, with a spread of approximately four percentage points.

No selected equity sleeve exceeded the displayed one-year S&P 500 reference of 25.78%. Because the sleeves may hold securities outside U.S. large-cap equities, a smaller return than this reference is not a matched measure of tracking error or stock-selection skill.

Overall, one-year equity performance demonstrates that several equity sleeves produced returns relatively close to the S&P 500 reference. However, the comparison does not establish tracking effectiveness because the portfolios may contain international, small-cap, mid-cap, or style exposures not represented in the S&P 500.

Three-year annualized equity-sleeve returns ranged from 15.64% to 18.61%. SoFi reported the highest value (18.61%) and was the sole selected sleeve above the displayed S&P 500 reference for that window. This finding is a descriptive index comparison, not an estimate of benchmark-adjusted alpha.

Most other accounts reported three-year annualized equity returns near 16%-17%. The relatively small cross-account range does not establish convergence of investment strategies, because the three horizons are overlapping summaries rather than repeated measurements at different dates.

The equity results show some similarity in reported returns while leaving potentially important differences in international exposure, capitalization, and style

unmeasured.

Five-year annualized equity-sleeve returns ranged from 8.41% to 10.79%, below the corresponding three-year figures. Wealthfront recorded 10.79%, followed by SoFi (10.37%) and Fidelity Go (10.14%), while E*Trade Core reported 8.41%. These differences concern trailing-window averages, not a documented decline over successive calendar years.

The cross-account range remained moderate in this five-year window. No single selected platform led the equity returns for all three reported horizons.

Without annual account-level observations or matched allocations, the figures cannot distinguish market-wide influences from platform-specific investment decisions.

	1-Year		3-Year		5-Year	
Portfolio	**Return**	**vs Bench**	**Return**	**vs Bench**	**Return**	**vs Bench**
Ally Invest Robo Portfolios	22.25%	**-3.53%**	15.91%	**-2.35%**	9.21%	**-3.39%**
Betterment	21.89%	**-3.89%**	15.70%	**-2.56%**	8.54%	**-4.06%**
Citi Wealth Builder	21.58%	**-4.20%**	15.84%	**-2.42%**	8.88%	**-3.72%**
E*Trade Core	20.46%	**-5.32%**	15.64%	**-2.62%**	8.41%	**-4.19%**
Fidelity Go	21.00%	**-4.78%**	17.06%	**-1.20%**	10.14%	**-2.46%**
Schwab Intelligent Portfolios	24.71%	**-1.07%**	16.01%	**-2.25%**	8.69%	**-3.91%**
SigFig	21.46%	**-4.32%**	16.59%	**-1.67%**	9.01%	**-3.59%**
SoFi	23.78%	**-2.00%**	18.61%	**+0.35%**	10.37%	**-2.23%**
Vanguard Digital Advisor	21.19%	**-4.59%**	17.15%	**-1.11%**	9.86%	**-2.74%**
Wealthfront (Risk 4.0 ; 2016)	21.74%	**-4.04%**	16.68%	**-1.58%**	10.79%	**-1.81%**
S&P 500 (benchmark)	**25.78%**	—	**18.26%**	—	**12.60%**	—

Figure 9. Equity returns by platform (alphabetical).

Figure 9 summarizes equity returns across all investment horizons. Several general patterns emerge.

Equity-sleeve returns exceeded the corresponding total-portfolio returns in the displayed windows. Cross-platform return ranges were relatively small, but the data cannot determine whether strategies were equivalent or whether each sleeve effectively tracked its intended market exposure. The S&P 500 serves only as a broad reference.

Overall, the equity sleeves showed relatively modest cross-platform differences and generally produced returns below, but in several cases close to, the S&P 500 broad equity reference. Because the portfolios may differ in geographic, capitalization, and style exposures, these results do not establish equivalent investment strategies or tracking effectiveness. They indicate that the selected equity sleeves were not uniformly weak performers, while their implications for investor adoption remain interpretive rather than directly tested.

3.3. Fixed-Income Returns

Figures 10-13 describe fixed-income-sleeve returns. These results differ from the equity comparison, particularly in the three- and five-year windows, while remaining sensitive to the choice of an unmatched broad bond reference.

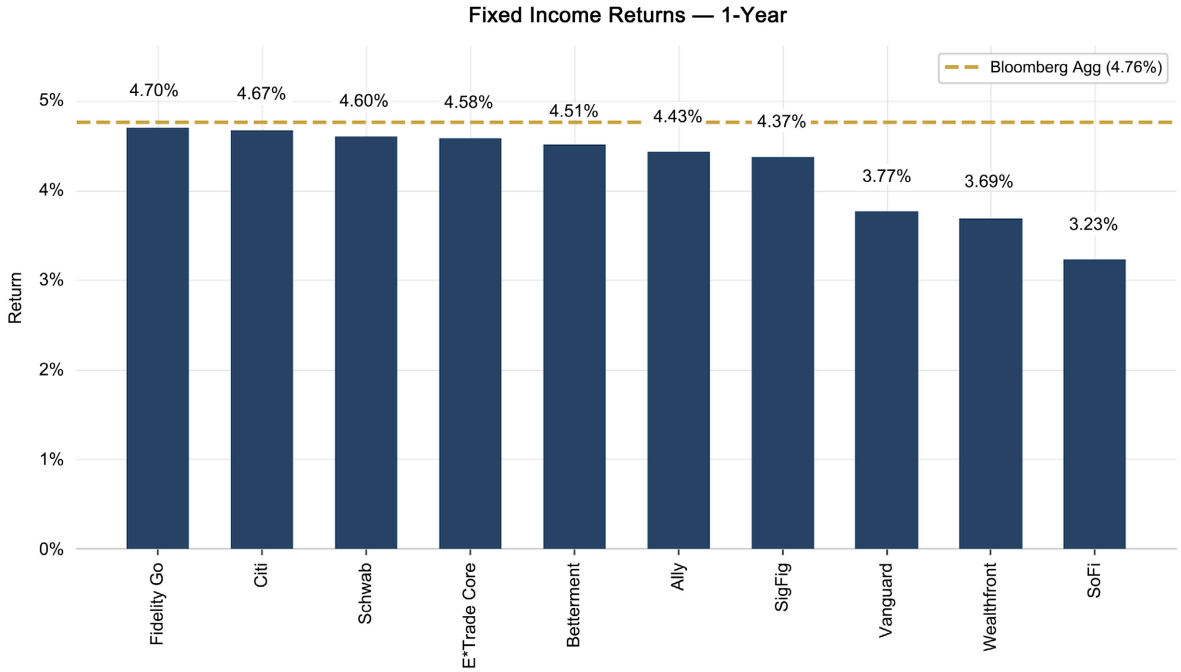


Figure 10. Fixed-income returns, 1-year.

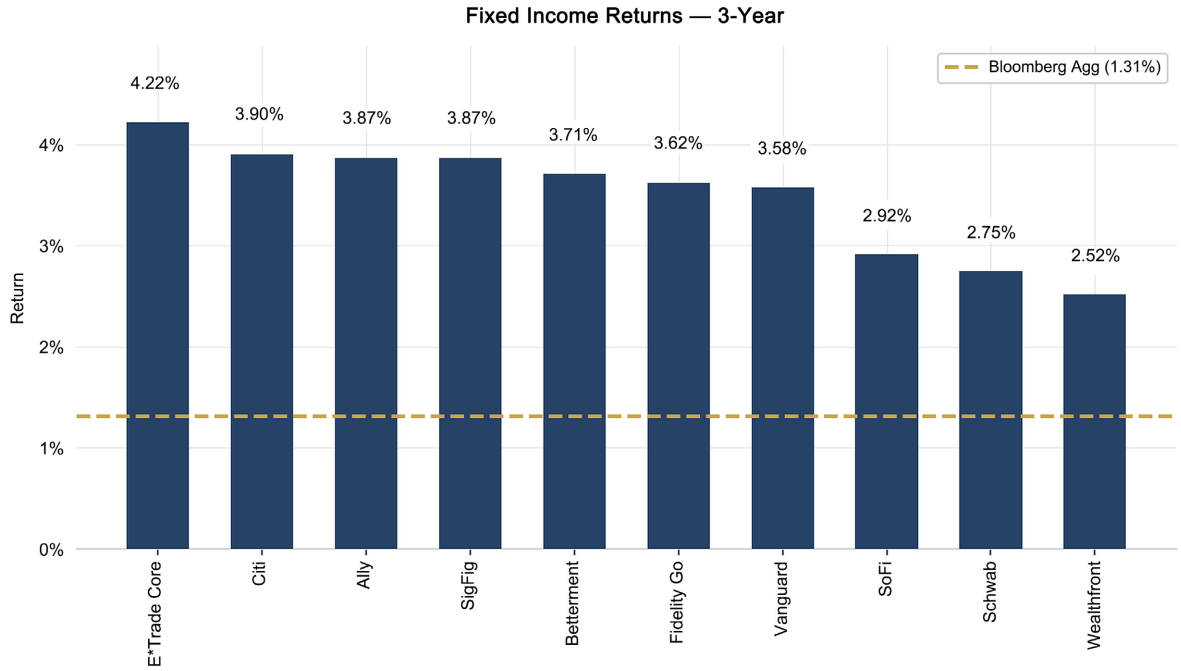


Figure 11. Fixed-income returns, 3-year annualized.

During the one-year period, fixed-income returns ranged from 3.23% to 4.70%. Fidelity Go achieved the highest return (4.70%), while SoFi produced the lowest (3.23%). Most platforms generated returns close to the Bloomberg U.S. Aggregate Bond Index benchmark (4.76%), indicating relatively similar bond portfolio performance across providers.

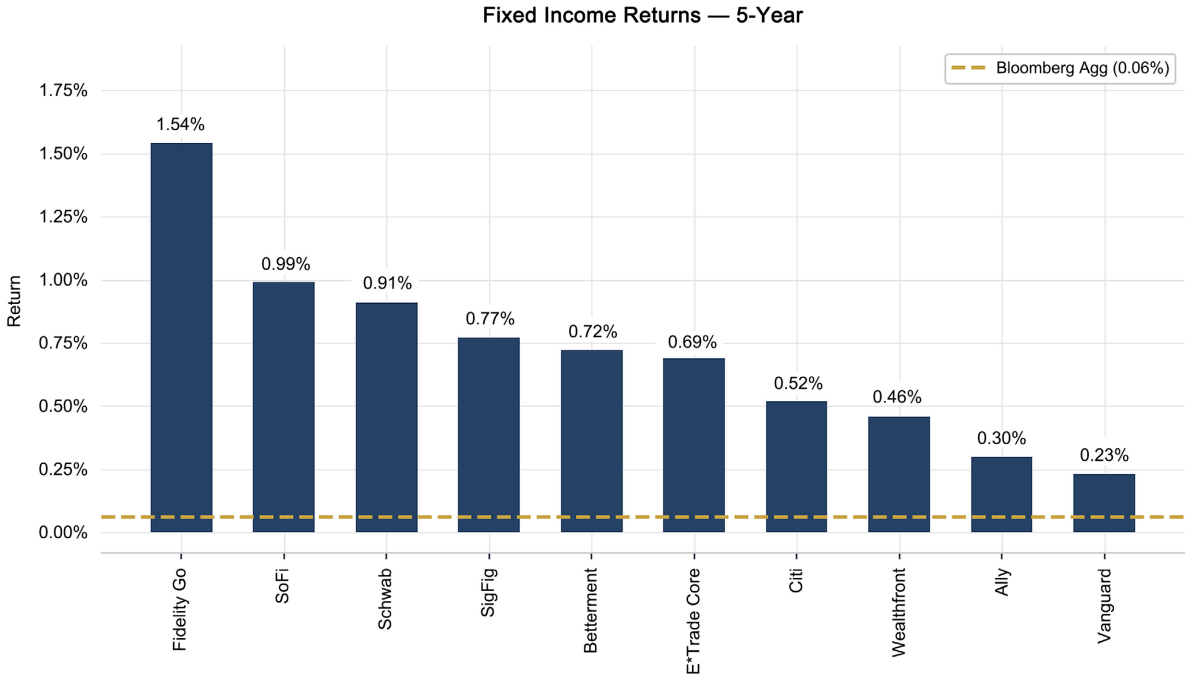


Figure 12. Fixed-income returns, 5-year annualized.

Cross-account dispersion in the fixed-income sleeve was modest in absolute percentage-point terms in the one-year window. This does not establish comparable bond strategies or exposure to the same credit, duration, and tax risks.

Although several platforms approached the benchmark, none substantially exceeded it during the one-year period.

In the three-year annualized window, the reported fixed-income return of each selected account exceeded the Bloomberg U.S. Aggregate Bond Index value shown in the supplied comparison (1.31%).

Annualized fixed-income returns ranged from 2.52% to 4.22%, with E*Trade Core achieving the highest return (4.22%). Even the lowest-performing platform, Wealthfront (2.52%), nearly doubled the benchmark return.

This is a consistent positive difference from the selected broad bond reference across the ten accounts. It is not, without allocation-matched adjustment, evidence that automated bond management outperformed comparable investments.

The fixed-income components generated higher returns than the Bloomberg U.S. Aggregate Bond Index during the three-year period. This finding is descriptively notable, but it should not be interpreted as evidence of superior algorithmic bond management without controlling for duration, municipal-bond exposure, credit quality, high-yield allocation, international debt, tax status, and cash holdings.

The same direction of the broad-index comparison appears in the five-year trailing window.

All ten selected fixed-income sleeves exceeded the displayed five-year Bloomberg U.S. Aggregate Bond Index reference (0.06%). The reported account values

ranged from 0.23% to 1.54%, with Fidelity Go recording the highest value (1.54%).

Five-year annualized fixed-income values were lower than the corresponding three-year values, but the positive differences relative to the broad index occurred in both overlapping windows.

The consistency of this finding across both medium-term and long-term investment horizons indicates that higher returns than the selected broad bond reference were observed across all ten fixed-income components over both the three- and five-year periods. The consistency of the pattern strengthens its descriptive relevance, although differences in portfolio composition prevent the benchmark gaps from being interpreted as pure management outperformance.

	1-Year		3-Year		5-Year	
Portfolio	**Return**	**vs Bench**	**Return**	**vs Bench**	**Return**	**vs Bench**
Ally Invest Robo Portfolios	4.43%	**-0.33%**	3.87%	**+2.56%**	0.30%	**+0.24%**
Betterment	4.51%	**-0.25%**	3.71%	**+2.40%**	0.72%	**+0.66%**
Citi Wealth Builder	4.67%	**-0.09%**	3.90%	**+2.59%**	0.52%	**+0.46%**
E*Trade Core	4.58%	**-0.18%**	4.22%	**+2.91%**	0.69%	**+0.63%**
Fidelity Go	4.70%	**-0.06%**	3.62%	**+2.31%**	1.54%	**+1.48%**
Schwab Intelligent Portfolios	4.60%	**-0.16%**	2.75%	**+1.44%**	0.91%	**+0.85%**
SigFig	4.37%	**-0.39%**	3.87%	**+2.56%**	0.77%	**+0.71%**
SoFi	3.23%	**-1.53%**	2.92%	**+1.61%**	0.99%	**+0.93%**
Vanguard Digital Advisor	3.77%	**-0.99%**	3.58%	**+2.27%**	0.23%	**+0.17%**
Wealthfront (Risk 4.0 ; 2016)	3.69%	**-1.07%**	2.52%	**+1.21%**	0.46%	**+0.40%**
Bloomberg U.S. Agg (benchmark)	**4.76%**	—	**1.31%**	—	**0.06%**	—

Figure 13. Fixed-income returns by platform (alphabetical).

Figure 13 summarizes fixed-income performance across all investment horizons.

Three major patterns emerge.

First, most fixed-income-sleeve returns fell within a relatively narrow absolute range, with the five-year range shown in Table 2 equal to 1.31 percentage points.

Second, unlike equity returns, fixed-income returns consistently exceeded the corresponding market benchmark during both the three-year and five-year periods.

Third, the direction of the difference from this selected index was shared by all ten accounts, but the size and cause of the difference remain untested.

Taken together, the bond-sleeve results are a notable descriptive pattern rather than a demonstrated competitive advantage of algorithmic portfolio management. Duration, municipal-bond exposure, credit quality, international assets, cash allocation, and the gross-of-fees basis of sleeve returns all limit comparisons with the Bloomberg U.S. Aggregate Bond Index.

The positive three- and five-year reference differences do not support an assertion that all selected accounts produced uniformly weak bond-sleeve outcomes. Their relevance to investor uptake nevertheless remains a hypothesis: no adoption measure is linked to the reported portfolio outcomes.

3.4. Risk-Adjusted Performance (Sharpe Ratio)

Figures 14-17 report the source-provided Sharpe ratios for the ten selected accounts. Sharpe ratios summarize reported excess returns relative to volatility; their interpretation depends on the risk-free rate, return frequency, estimation conventions, and underlying allocation.

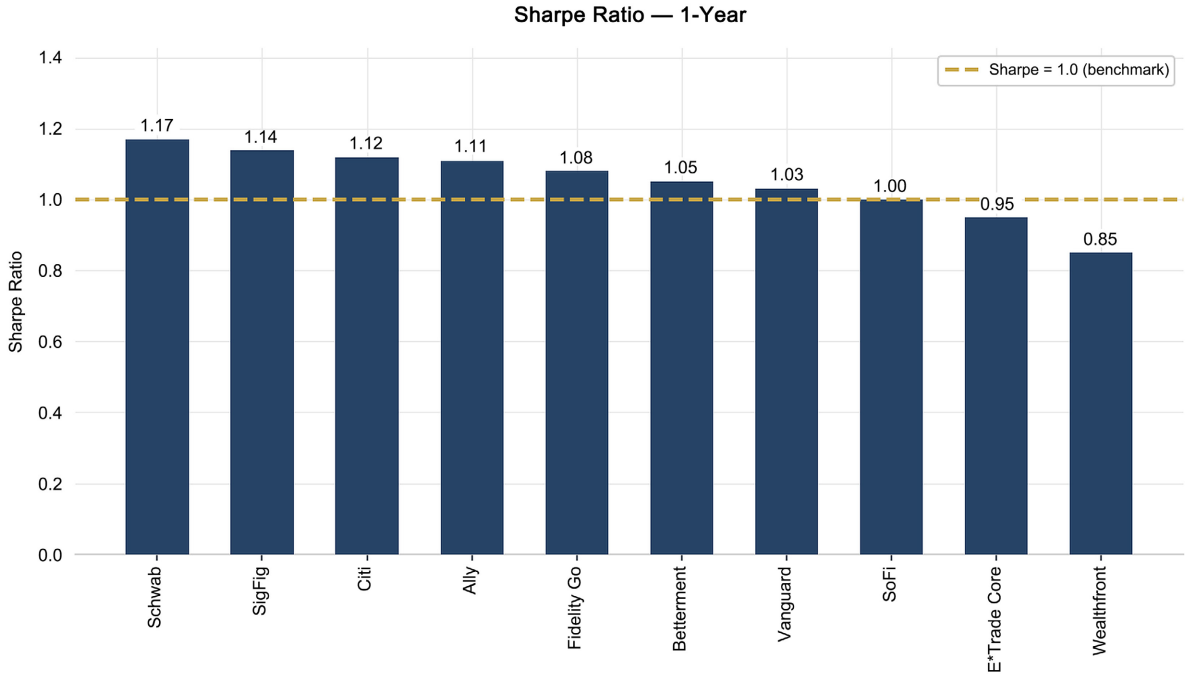


Figure 14. Sharpe ratios, 1-year.

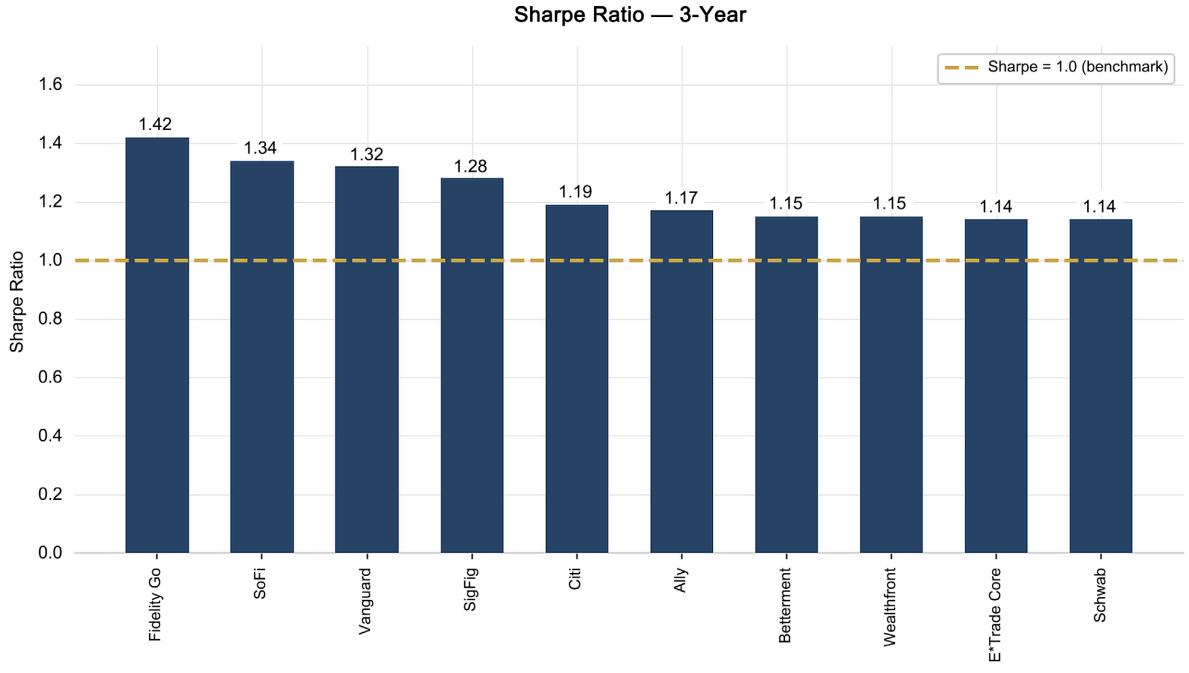


Figure 15. Sharpe ratios, 3-year annualized.

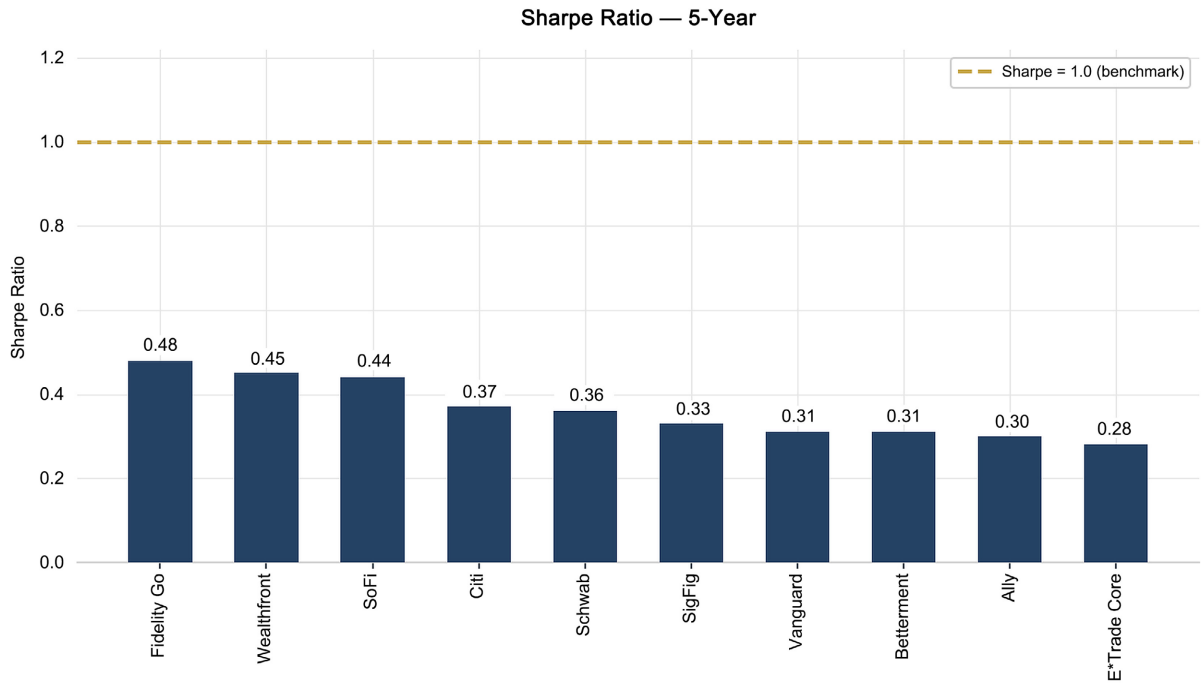


Figure 16. Sharpe ratios, 5-year annualized.

During the one-year period, Sharpe ratios ranged from 0.85 to 1.17. Schwab Intelligent Portfolios recorded the highest value (1.17), while Wealthfront recorded the lowest value (0.85). Eight of the ten platforms achieved Sharpe ratios at or above 1.0, including SoFi at exactly 1.00.

The one-year results indicate relatively limited cross-platform variation in risk-adjusted performance. However, the value of 1.0 is used here only as a descriptive reference point rather than as a universal threshold of portfolio quality. The interpretation of a Sharpe ratio depends on the risk-free rate, return frequency, volatility calculation, investment period, and selected comparison portfolio.

The three-year period produced the highest risk-adjusted values in the analysis. Sharpe ratios ranged from 1.14 to 1.42, with Fidelity Go recording the highest value (1.42). All ten selected platforms had three-year Sharpe ratios above 1.0.

Cross-platform dispersion remained relatively limited, with most values concentrated between 1.14 and 1.34. These figures indicate that the selected portfolios generated comparatively favorable returns relative to their reported volatility during this period.

The result should not be interpreted as proof of superior risk management without comparison with matched portfolio benchmarks. Differences in asset allocation and risk exposure may contribute to the observed ratios.

Risk-adjusted performance was lower over the five-year horizon than over the one- and three-year horizons. The reported Sharpe ratios ranged from 0.28 to 0.48, with Fidelity Go recording the highest value (0.48) and E*Trade Core recording the lowest value (0.28).

All selected five-year Sharpe ratios were lower than their three-year counter-

parts. Because these are nested trailing windows, the cross-window contrast does not demonstrate that risk-adjusted performance declined in successive years or that macroeconomic conditions caused a decline.

All five-year ratios were below 1.0. Rather than treating a fixed value as a universal quality threshold, the ratios should be interpreted comparatively across platforms and, where possible, against allocation-matched benchmarks calculated using the same return and risk-free-rate conventions.

	1-Year		3-Year		5-Year	
Portfolio	**Sharpe Ratio**	**Std Dev**	**Sharpe Ratio**	**Std Dev**	**Sharpe Ratio**	**Std Dev**
Ally Invest Robo Portfolios	**1.11**	10.29%	**1.17**	9.15%	0.30	10.28%
Betterment	**1.05**	11.40%	**1.15**	9.72%	0.31	11.25%
Citi Wealth Builder	**1.12**	11.32%	**1.19**	9.61%	0.37	10.55%
E*Trade Core	0.95	11.35%	**1.14**	9.71%	0.28	10.80%
Fidelity Go	**1.08**	9.75%	**1.42**	8.42%	0.48	9.68%
Schwab Intelligent Portfolios	**1.17**	9.96%	**1.14**	8.71%	0.36	9.60%
SigFig	**1.14**	10.87%	**1.28**	9.28%	0.33	10.38%
SoFi	**1.00**	12.05%	**1.34**	9.87%	0.44	10.84%
Vanguard Digital Advisor	**1.03**	9.09%	**1.32**	8.15%	0.31	9.54%
Wealthfront (Risk 4.0 ; 2016)	0.85	10.98%	**1.15**	9.14%	0.45	10.54%

Figure 17. Sharpe ratios by platform (alphabetical).

Figure 17 summarizes the Sharpe ratios across all investment horizons. Three important patterns emerge.

First, medium-term performance produced the highest risk-adjusted returns, with every platform achieving Sharpe ratios above 1.0.

Second, cross-platform dispersion in the reported ratios was relatively limited for some horizons, but the data do not establish identical diversification or risk-management strategies.

Third, five-year Sharpe ratios were lower than the corresponding shorter-window values for the selected accounts. The design does not identify whether market conditions or platform choices account for this difference.

Overall, the Sharpe ratios were highest over the three-year horizon and showed relatively limited cross-platform dispersion during the one- and three-year periods. The substantially lower five-year values demonstrate that risk-adjusted outcomes varied considerably across investment horizons. These results provide descriptive support for questioning a simple performance-deficiency explanation, but they do not directly test whether risk-adjusted performance influences investor adoption.

3.5. Overall Performance Comparison

To provide a comprehensive evaluation of platform performance, the four performance indicators were considered together across the three investment horizons. Rather than focusing on a single return measure, this comparison assesses the overall consistency of each robo-advisor in delivering competitive portfolio performance.

The comparison reveals that no individual platform consistently outperformed all competitors across every performance dimension. Platforms that ranked highly in total portfolio returns did not necessarily achieve the strongest equity returns, fixed-income returns, or risk-adjusted performance. Similarly, platforms that excelled in one investment horizon did not always maintain the same ranking over longer periods.

SoFi, Fidelity Go, and Wealthfront appeared near the upper end of some measures, whereas Vanguard Digital Advisor and E*Trade Core appeared lower on others. Because no composite ranking or statistical superiority test was specified, these observations should not be treated as an overall league table.

The returns of several accounts were close on some measures, but similarity in reported outcomes does not establish similar portfolio strategies. Neither these rankings nor the cross-platform averages identify investment-management skill, expected future returns, or the consequences of a particular investor's platform choice.

The overall comparison indicates that the selected accounts did not display uniformly weak performance. This pattern provides a limited basis for explanations that attribute previously reported low current use entirely to poor investment outcomes. However, the analysis does not determine whether performance is a primary, secondary, or insignificant influence on adoption, because adoption behavior is not observed in the dataset.

3.6. Summary of Results

Several important findings emerge from the comparative analysis.

First, the ten selected accounts showed positive total and equity returns in all reported windows, with modest dispersion on some indicators. Comparisons with the S&P 500 are contextual and not allocation-matched.

Second, each selected fixed-income sleeve showed a higher reported return than the displayed Bloomberg U.S. Aggregate Bond Index reference in the three- and five-year windows. Differences in exposure and fee treatment prevent this pattern from establishing superior algorithmic bond management.

Third, the source-reported Sharpe ratios were highest in the three-year window and lower in the five-year window. These differences describe overlapping trailing periods; they do not establish temporal deterioration or attribute changes to macroeconomic conditions.

Finally, the findings concern portfolio performance, whereas the limited-use evidence comes from separate research. Their juxtaposition motivates, but cannot adjudicate, hypotheses about adoption. Uniformly weak outcomes are not apparent in the selected account summaries; whether performance influences take-up requires direct testing.

4. Discussion

4.1. What Performance Evidence Can—and Cannot—Explain

The primary empirical objective of this study was to evaluate the performance of

ten selected U.S. robo-advisory portfolios and to assess what the observed patterns imply for performance-based explanations of limited adoption. The results show relatively modest differences among the selected platforms, comparatively strong medium-term risk-adjusted outcomes, and fixed-income returns that exceeded the selected broad bond reference index over the three- and five-year periods.

These results do not demonstrate that investment performance has no effect on adoption. Neither investor-level use nor a statistical relationship between performance and platform choice is observed. The evidence is sufficient to describe the selected accounts and to question a blanket characterization of them as uniformly weak performers; it cannot assess whether their realized or perceived performance is necessary, sufficient, or irrelevant for adoption. Trust, perceived risk, digital competence, personal advice, and provider distribution remain candidate mechanisms based on other research.

This interpretation extends previous research by questioning the assumption that satisfactory investment performance necessarily produces widespread technology adoption. Prior studies suggest that investors may also evaluate robo-advisors through psychological, technological, and institutional considerations, although the present dataset does not estimate the relative importance of these factors.

4.2. Behavioral Explanations: Trust, Digital Financial Literacy, and Human Preference

The following behavioral explanations are derived from prior studies rather than directly measured in the present dataset. They should therefore be understood as plausible mechanisms that help interpret the performance findings and that require direct testing with investor-level data. The findings align closely with recent behavioral finance research emphasizing the importance of investor trust. Cheng et al. (2019) demonstrated that trust in both the technology and the financial institution significantly influences adoption intentions, while Cao et al. (2025) further argued that technological trust, firm-specific trust, and institutional trust jointly determine investors' willingness to rely on robo-advisory services. The present performance findings are consistent with prior research suggesting that satisfactory investment outcomes may coexist with continuing trust-related concerns. The present study does not directly measure whether such concerns constrained adoption among the investors represented in the cited studies. Evidence from emerging markets further supports the central role of trust. Bashir et al. (2025) found that trust remains one of the strongest predictors of robo-advisory adoption among young retail investors, suggesting that trust barriers are not limited to mature financial markets but represent a broader condition for robo-advisor acceptance.

A second possible mechanism is digital financial literacy. Prior research distinguishes subjective confidence with financial technology from objective financial

knowledge (Aristei & Gallo, 2025). Investor confidence may shape willingness to delegate investment decisions, but no literacy variable was collected in the present account-level performance dataset.

A third explanation concerns investors' continued preference for human financial advisors. Previous studies consistently report that investors value emotional reassurance, personalized communication, and professional judgment that extend beyond objective portfolio returns (Senteio & Hughes, 2024; Mahmud et al., 2025). Financial decisions frequently involve uncertainty, anxiety, and long-term planning, circumstances in which interpersonal trust remains highly influential. Robo-advisors may successfully optimize portfolios, yet they currently provide only limited emotional support and personalized interaction compared with experienced human advisors. These findings are consistent with Zhu et al. (2023), who reported that many investors perceive AI-enabled financial advisory systems as insufficiently transparent and difficult to understand, thereby limiting their willingness to rely exclusively on automated advice.

Together, these strands of prior research suggest testable demand-side factors. Their presence or importance among users of the specific accounts analyzed here remains unknown.

4.3. Institutional Explanations: Incentives, Market Structure, and AI Adoption

The institutional discussion is also derived from earlier literature. The present performance tables do not measure provider profitability, customer acquisition, product withdrawal, regulation, marketing intensity, or organizational strategy. Consequently, the following mechanisms are hypotheses rather than findings of this study.

Banks and investment firms possess established reputations and distribution channels that may influence take-up. Product design, fees, acquisition costs, cross-selling objectives, and the fit between automated and human advice may also affect how robo-advisory services are marketed. These possibilities require provider-level evidence; the present data do not substantiate a claim that particular institutions discontinued products because of profitability or organizational incentives.

This supply-side perspective complements investor-level adoption research. It proposes that diffusion may depend on both willingness to use an automated service and the incentives of firms to provide or promote it, without implying that either mechanism was estimated here.

More broadly, these findings contribute to the emerging literature on AI-enabled financial services. Rather than replacing human advisors entirely, robo-advisors increasingly appear to function as complementary technologies within hybrid advisory systems. Recent studies suggest that collaborative human-AI decision-making frequently produces better outcomes than either fully automated or fully human advice alone (Mahmud et al., 2025). Consequently, future development

may focus less on complete automation and more on effective integration between algorithmic decision support and professional financial expertise.

4.4. Theoretical Contributions

This study contributes to the literature in three important ways.

First, the analysis documents that the selected accounts were not uniformly weak on the supplied performance indicators. The comparison is descriptive and does not reject a statistical explanation of limited investor use, because no performance-adoption relationship is observed.

Second, the study develops an integrated interpretive framework that connects the observed performance evidence with behavioral and institutional mechanisms identified in prior research. The framework should not be interpreted as a statistically tested causal model. Instead, it specifies candidate relationships among objective performance, investor trust, digital financial literacy, preferences for human advice, and institutional incentives that can be examined in future survey, experimental, or longitudinal research.

Third, the framework frames a boundary to performance-only narratives of AI adoption: reported technical or financial outputs need not correspond directly to users' decisions. Consistent with the financial-services perspective of Shetty et al. (2026), it treats trust, comprehension, personal advice, and firm incentives as testable conditions rather than established determinants in this sample.

4.5. Literature-Informed Analytical Framework

Figure 18 organizes a literature-informed set of candidate relationships for subsequent studies. It is a conceptual map, not a fitted causal model or an empirically validated explanation. Performance, trust, literacy, preferences for human advice, and institutional incentives would need to be observed jointly to test the proposed relationships.

The first component concerns account-level performance. The present study provides returns and Sharpe ratios for selected portfolios, but it does not establish that algorithmic sophistication or competitive portfolio management is a necessary condition for adoption.

The second dimension involves behavioral factors, including investor trust, digital financial literacy, and preferences for human financial advice. Even when robo-advisors provide satisfactory investment outcomes, investors may remain reluctant to rely on algorithmic decision-making if they lack confidence in artificial intelligence or feel uncomfortable delegating important financial decisions to automated systems.

The third component comprises possible institutional influences, including pricing, business strategy, regulation, and the use of hybrid financial advice. The effect of such features on uptake is an empirical question that could be examined by combining provider characteristics with actual investor choices.

Taken together, these dimensions provide a literature-informed structure for

future research rather than a confirmed explanation of the robo-advisor paradox. The framework extends performance-based accounts by specifying behavioral and institutional mechanisms that can be tested through investor surveys, experiments, platform-level adoption data, and longitudinal analyses.

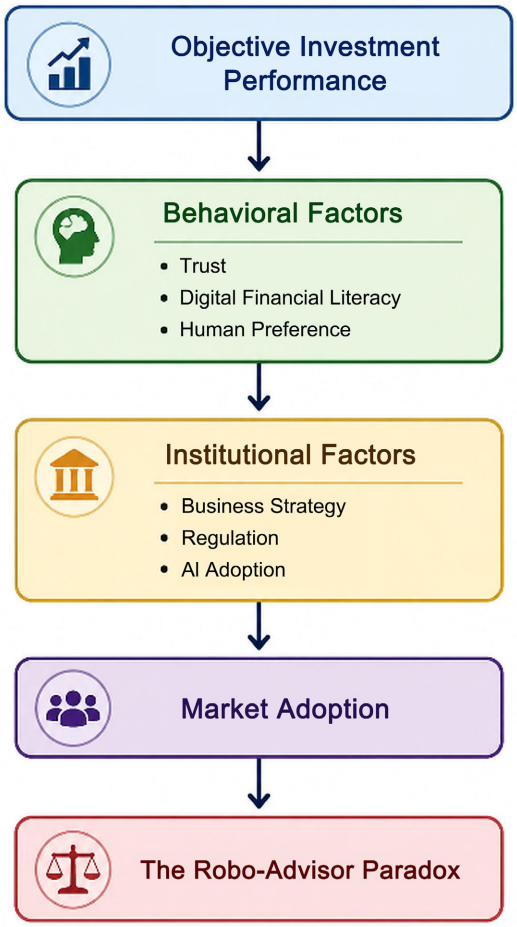


Figure 18. Literature-informed conceptual framework for future adoption research; proposed relationships are not tested in this study.

4.6. Practical Implications

The findings also have several practical implications.

For providers, these results suggest the value of evaluating communications and customer experience alongside portfolio performance rather than assuming that stronger returns alone will deliver greater take-up. Transparency, understandable explanations, and access to human support are reasonable candidates for future user testing, consistent with the trust research reviewed above (Nourallah, 2023).

Financial institutions may also benefit from expanding hybrid advisory models that combine automated portfolio management with periodic access to human financial advisors. Such approaches preserve the efficiency advantages of automation while addressing investors' continuing preference for interpersonal guidance.

For policymakers and financial educators, research on digital financial literacy

points to a possible role for clear information about automated advice. However, the present analysis does not estimate whether educational interventions would increase use or improve investor outcomes.

4.7. Limitations and Future Research

Several limitations should be acknowledged.

First, the sample is restricted to ten purposively selected U.S. accounts from one reporting provider. Account allocations, fee conventions, portfolio composition, and product conditions vary; results are neither nationally representative nor a controlled comparison of manager skill. Reproducibility requires the exact dated source extract, because live online performance tables are subsequently updated.

Second, only portfolio-performance outcomes were observed. No investor survey, account-level adoption series, assets-under-management trajectory, or matched performance-adoption panel was available. Hence neither the prevalence of use nor its behavioral or institutional causes can be inferred from the portfolio comparison.

Third, the analysis focuses primarily on investment outcomes rather than the underlying characteristics of AI algorithms. Because most commercial robo-advisory platforms disclose limited information regarding algorithm design, explainability, personalization mechanisms, and machine learning architecture, it remains difficult to evaluate how algorithmic sophistication influences investment performance and investor trust. Greater transparency from financial institutions would enable future studies to investigate the relationship between AI design, investment outcomes, and user acceptance more directly.

A further limitation concerns evidence of adoption. The illustrative survey estimate is drawn from a 2022 nonprobability study and is not a contemporaneous, nationally representative 2026 rate. Moreover, current account use, expressed interest, assets under management, and hybrid-advice participation measure different things. Future research should distinguish these outcomes and link them to appropriately measured performance perceptions and actual choices.

Finally, this study examines adoption from the perspective of retail investors in the United States. Future research should investigate whether the robo-advisor paradox differs across institutional environments, regulatory systems, and cultural contexts. Comparative international studies may reveal how financial regulation, digital infrastructure, and investor culture jointly shape the adoption of AI-enabled financial advisory services.

5. Conclusion

This paper examined the descriptive performance of ten selected U.S. robo-advisory accounts across total portfolio returns, equity-sleeve returns, fixed-income-sleeve returns, and Sharpe ratios in one-, three-, and five-year trailing windows. Its purpose was to clarify what such performance evidence can and cannot establish about a proposed gap between technical capability and investor adoption.

Across several measures, the selected accounts did not exhibit uniformly weak reported outcomes. In the three- and five-year windows, their fixed-income sleeves produced higher reported returns than the broad Bloomberg U.S. Aggregate Bond Index reference; however, exposures and return conventions were not matched. Three-year Sharpe ratios were also relatively high in the supplied snapshot, while five-year values were lower. These comparisons are descriptive and cannot establish superior algorithmic skill or a temporal deterioration in performance.

No investor adoption behavior was observed. The study therefore cannot determine the effect of performance on use or verify whether trust, literacy, personal advice, or organizational incentives explain uptake. Those mechanisms emerge from the cited literature and form propositions for further study, not findings supported by the present performance dataset.

The main contribution is a bounded comparison of reported portfolio indicators coupled with an explicit distinction between measured outcomes and hypothesized adoption mechanisms. A stronger test would match dated performance histories to investors' perceptions, actual account decisions, provider characteristics, and suitable risk-adjusted benchmarks.

The study accordingly suggests practical questions for providers and educators about transparency, explanation, and human support rather than claiming to estimate the adoption effect of any intervention. Its descriptive findings also underscore the need for careful benchmarking and transparent reporting of return conventions.

The proposed robo-advisor paradox is best treated as a research question rather than a confirmed causal pattern: selected accounts may display satisfactory reported performance while separate surveys document limited use, but the connection between these observations remains unmeasured. Future research integrating investment outcomes and investor decisions can determine under what behavioral and institutional conditions automated advice gains acceptance.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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