Generative AI and Investor Processing of Financial Information

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Abstract

This paper provides descriptive evidence on retail investors' use and perceptions of generative AI (GenAI) to process financial information and inform investment decisions. Our survey of 2,175 retail investors, complemented by an analysis of 40,000 investor questions posed to a GenAI chatbot, reveals three key findings. First, we observe widespread adoption, with nearly half of surveyed investors already using GenAI, primarily for gathering and interpreting financial or market data. Investors perceive GenAI as enhancing their ability to process complex information quickly and easily. Second, more sophisticated retail investors understand and leverage GenAI's strengths to a greater extent. These investors lead GenAI adoption and utilization, using it for more complex tasks and drawing from a broader range of sources. Third, while nearly two-thirds of investors plan to continue or start using GenAI and believe it will become a standard tool for investors, many non-users remain skeptical. This hesitancy toward future GenAI adoption appears related to concerns about data privacy and response quality, as well as younger and less sophisticated investors having difficulty identifying or leveraging the processing benefits of GenAI. This disparity suggests that while overall adoption is likely to increase, it may also widen the gap between more and less sophisticated investors, challenging expectations of democratized access to complex financial information for all retail investors. This nuanced perspective on GenAI's future in retail investing highlights the need for further research into its long-term impact on investor behavior and market dynamics.

Keywords: Generative AI; information processing; investment decisions; retail investors
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1. Introduction

Generative AI (GenAI, hereafter) has the potential to reshape how retail investors acquire, process, and act on financial information. Retail investors have historically had minimal access to advanced financial information processing tools, and GenAI offers them a highly accessible and sophisticated resource. However, despite GenAI's transformative promise, we know little about its adoption and use among retail investors, which makes it difficult to understand its potential consequences for capital markets. To address this gap, we combine survey data from over 2,000 retail investors with archival analysis of more than 40,000 actual investor queries to a GenAI chatbot on a major brokerage platform. Using this descriptive evidence, we document the extent and nature of GenAI adoption, examine adoption patterns across different investor segments, and explore investor perceptions of GenAI's future role in investment decision-making.

Concurrent research documents GenAI's potential to enhance financial decision-making through summarization (Kim et al., 2024a; Wong et al., 2024), signal extraction (Bai et al., 2023; Bernard et al., 2024; Jha et al., 2024; Kim et al., 2024b), and forecasting (Chen et al., 2024; Kim et al., 2024c; Lopez-Lira and Tang, 2024). However, these studies focus on *potential* GenAI use cases rather than actual adoption. Further, current evidence cannot speak to potentially important negative consequences stemming from disparities in retail investors' adoption and use of GenAI. To support research examining GenAI's potential effects—both positive and negative—on financial information processing, investor behavior, and market outcomes, we need to first establish whether, why, and how retail investors adopt GenAI, as well as differences in adoption across investors. Our study seeks to fill these gaps in understanding and establish a foundation for future research.

We survey 2,175 retail investors recruited from Prolific, an online survey platform, and Public, a popular retail brokerage platform. Results reveal three key themes. First, we find significant adoption of GenAI among retail investors, with nearly half (47%) of respondents using GenAI to process financial information or inform their investment decisions. The frequency of GenAI use varies among these current users, with 41% using it rarely and 32% using it weekly or more often, suggesting investors are still experimenting with how to best integrate GenAI into their investment processes. Current users are primarily leveraging GenAI to enhance their understanding and information gathering, including for information integration tasks such as interpreting financial data (44%) and defining financial terms (41%), or information acquisition tasks such as searching for information (29%). They also use GenAI to process a variety of sources of financial information, most often third-party financial information that is frequently released such as market data (42%) and news articles (40%).

Second, more sophisticated retail investors (measured by financial education) identify and leverage GenAI's comparative advantages to a greater extent. Investors overall cite accelerated information processing (65%) and simplified processing of complex data (59%) as GenAI's primary benefits. Regression results indicate sophisticated retail investors are even more likely to cite these benefits. This appreciation for GenAI's capabilities translates into sophisticated retail investors using GenAI for more diverse and complex tasks, such as performing financial calculations, cross-firm or industry comparisons, and sentiment analysis. They also use GenAI to process a broader range of information sources, including earnings releases, earnings call transcripts, and analyst output. Overall, our findings imply there may be a growing GenAI gap in retail investing, where more sophisticated investors could gain further advantages in processing information and making informed investment decisions through using GenAI.

Third, results portray a nuanced perspective on the future of GenAI in retail investing. Most investors anticipate GenAI will become a standard investing tool in the future (76%). Among investors who have used GenAI, 74% believe it improves financial information processing, and 80% plan to continue using GenAI in the future. Among investors who have not used GenAI, nearly half (47%) plan to do so in the future. These trends suggest a likely significant increase in future adoption rates. However, investors nonetheless identify several key limitations of GenAI for investing tasks, including concerns about reliability and accuracy (54%), data privacy (50%), and response quality (46%). Further, the optimism about future adoption is tempered for non-users. More than half of non-users are uncertain or skeptical of GenAI improving processing (55% of non-users), and nearly a quarter indicate they are unlikely to use GenAI in the future (24% of non-users). A determinants analysis of future GenAI adoption intentions suggests that this hesitancy toward future GenAI adoption may be driven by concerns about data privacy and response quality, as well as by younger and less sophisticated investors who may struggle to identify or leverage the potential processing benefits of GenAI.

To supplement our survey findings, we conduct an analysis of over 40,000 actual retail investor questions posed to Alpha, a GenAI chatbot integrated into Public's brokerage app. We use a machine learning model to classify questions into mutually exclusive categories based on their primary intent. Consistent with our survey evidence, investors most commonly use Alpha to explain or interpret financial information. For example, investors ask questions such as "How healthy are their margins?" or "How is their battery business performing?" Investors also frequently use the tool for stock screening based on specific criteria such as recent financial performance, market movements, or industry characteristics, or to receive digestible overviews of otherwise time-consuming investment research tasks. Also consistent with our survey, market data is by far the most prevalent information source processed with Alpha, likely reflecting its widespread salience on the brokerage platform. Investors also routinely use Alpha to process common investment research information, such as analyst forecasts and evaluations, background information on companies, financial numbers, earnings calls, and financial news.

We conclude by offering suggestions for future research on how GenAI influences financial information processing, investor behavior, and market outcomes. Our descriptive evidence highlights widespread adoption of GenAI among retail investors, who believe it helps simplify investment research and aid with information processing.[1] This is particularly significant given the documented challenges retail investors face in processing financial information (Lee, 1992; Miller, 2010). Future research could examine whether this reliance on GenAI leads to improvements in information processing or more timely and informed investment decisions. Additionally, we document disparities in GenAI adoption related to differences in investor sophistication and perceptions of its benefits and limitations. This raises important questions about whether GenAI narrows or widens gaps between retail and professional investors and affects market-level dynamics. Finally, we encourage research into the evolving nature of investor-GenAI interactions, including how the design and functionality of these tools might overcome adoption barriers, mitigate cognitive biases, or shape investors' reliance on specific information sources.

Our study contributes to the emerging literature on the role of GenAI in processing financial information. Concurrent research largely focuses on how investors and other parties *can* use GenAI to process financial information. For example, several working papers document the potential value of GenAI as a tool to extract nuanced signals from financial information (Bai et al.,

[1] Our survey focuses on two online user groups, so our sample investors could be more technology-capable and thus more open to GenAI than the typical retail investor. However, other industry organizations such as FINRA survey retail investors using online tools, suggesting they perceive online investors to be important and representative of retail investors more generally.

2023; Bernard et al., 2024; Chen et al., 2024; de Kok, 2024; Jha et al., 2024; Kim et al., 2024a, 2024b, 2024c; Lopez-Lira and Tang, 2024; Wong et al., 2024). Other research explores potential behavioral consequences of individual investors relying on GenAI for financial information processing tasks (Croom, 2024; Croom et al., 2024). We fill a gap in this literature by providing descriptive evidence of how retail investors are *actually using* GenAI in practice. This evidence provides a foundation for future research to explore the interplay between GenAI, financial information processing, and investor and market outcomes. Specifically, our findings highlight the importance of understanding both how GenAI processes financial data and how human interactions with these tools shape their outputs and investors' reliance on them. Such insights are vital for understanding the broader impact of GenAI on investor outcomes.

Our study also has implications for regulators and managers. We find that a significant proportion of investors are already using GenAI to process financial information and inform their investment decisions, with even more planning to adopt these tools in the future. For regulators, this rapid adoption underscores the need to closely monitor how investors are leveraging GenAI and the potential consequences of such reliance. Our study provides a starting point for this understanding, paving the way for future research to explore these effects in greater depth. For managers, the findings suggest that many investors will increasingly rely on GenAI to interpret financial reports, either directly or indirectly. This trend means that managers must recognize how GenAI tools distill and extract key signals from their financial disclosures, as investors will likely rely more on these GenAI-driven insights rather than manually processing reports themselves.

2. Background

GenAI is a rapidly advancing technology that has reshaped the way individuals and organizations interact with information and perform tasks. What distinguishes GenAI from earlier

AI technologies is its adaptability and accessibility. While previous AI tools were typically designed for narrow applications—such as sentiment analysis or text classification—GenAI can process unstructured information from diverse sources and generate contextually relevant responses for a wide range of tasks.[2] Moreover, GenAI uses natural language processing to engage in conversational, user-friendly interactions, allowing individuals to ask open-ended questions and receive relevant, easy-to-understand answers.[3] This interactivity makes GenAI more accessible to non-experts while also functioning as a highly intuitive and personalized tool for handling complex tasks. Importantly, GenAI tools such as ChatGPT are now available to nearly everyone, often at little or no cost, democratizing access to their advanced processing capabilities.

The combination of speed, accessibility, and adaptability makes GenAI potentially valuable in fields that require complex information processing, such as financial analysis (e.g., Kim et al., 2024a, 2024c). Retail investors in particular have historically lacked access to advanced processing tools, often relying on manual research or simple keyword searches to process financial information. GenAI offers these investors a powerful "copilot" that can assist with acquiring or integrating complex financial information into their investment judgments. For example, GenAI can rapidly analyze and synthesize insights from diverse information sources and lengthy reports—such as regulatory filings, analyst reports, and financial news— presenting complex data in an easily digestible format. These capabilities allow retail investors to more easily perform sophisticated tasks such as stock screening, trend identification, and cross-company comparisons. Further, GenAI can personalize financial information summaries, conduct in-depth financial

[2] While most GenAI applications in finance and accounting are powered by large language models (LLMs), we use the broader term GenAI because these tools extend beyond text-based tasks. Investors can, for instance, upload images, charts, or graphics for analysis, or use GenAI to process verbal information, such as earnings call recordings, interviews, or presentations. Although language is central to these functions, the overarching technology that enables these capabilities is GenAI.

[3] See de Kok (2024) for a more detailed and technical discussion of how GenAI operates.

statement analysis, and provide contextual explanations in layman's terms. This makes complex financial information more accessible to investors of all levels of financial sophistication, potentially reducing information processing costs and empowering retail investors to make more informed and timely investment decisions. As a result, many investors are likely already leveraging these tools to inform their investment strategies.

Indeed, a wide array of GenAI tools are already accessible to retail investors, ranging from versatile general-purpose platforms to those tailored specifically for financial analysis. Platforms such as ChatGPT, Google Gemini, and Microsoft Copilot are designed to accommodate a broad set of functionalities, enabling investors to apply these tools across various investment-related tasks. These functionalities include the ability to acquire custom-requested financial information and assist with a personalized analysis of that information. For instance, investors can input documents such as earnings releases, annual reports, or earnings call transcripts into GenAI for summaries, comparisons, interpretations, and detailed responses to custom queries. These tools often have internet access, allowing investors to bypass manual searches for financial data by having GenAI retrieve and process custom-requested information directly from the web. Additionally, several finance-specific GenAI platforms cater directly to investors. Public, a popular retail brokerage platform, offers a GenAI assistant that uses real-time news and financial information to answer questions about securities and market trends (Public.com, 2023). Similarly, a startup called FinChat offers a customized investment research terminal equipped with GenAI (FinChat.io, 2023). On the professional side, investment companies such as Morgan Stanley and JPMorgan have developed internal GenAI-equipped platformed for use by asset managers, financial advisors, and institutional investors (Son, 2023; Reuters, 2024).

Despite the advantages GenAI offers and its widespread availability, investors may be hesitant to adopt GenAI for several reasons. First, investors could share concerns discussed in the popular press and on social media about the reliability and accuracy of GenAI outputs. For instance, during the first launch demo of Microsoft's Copilot GenAI (previously called "Bing AI"), the tool made several factual errors when analyzing Gap and Lululemon earnings reports (Leswing, 2023). These early, widely publicized failures could have created enduring skepticism among investors about the reliability of GenAI for financial tasks. Second, investors may face status quo bias, preferring to rely on traditional methods of processing financial data, even when those methods are more labor-intensive and potentially outdated. Investors might also believe learning how to best use GenAI is too costly, or have privacy concerns related to the data processed by these tools. Third, investors may harbor algorithmic aversion, where they are skeptical of GenAI or believe human judgment to be superior to that of an AI tool. Investors might also be overconfident in their abilities and may not see the need for external assistance from tools such as GenAI. Given these potential barriers, it is difficult to assess the true extent of GenAI adoption among retail investors. However, understanding how investors are using these tools and the factors influencing their adoption is crucial for determining the future role of GenAI in financial markets. We use survey evidence to describe the current state of GenAI usage among retail investors, perceived benefits and limitations, and factors that influence its adoption. We also rely on a dataset of actual questions asked by investors to a GenAI tool to evaluate GenAI usage.

3. Survey Evidence

3.1 Subject Pool

We recruit respondents from two subject pools to complete our survey.[4] First, we use filtering tools on Prolific, an online survey platform, to recruit 1,100 respondents from a pool of workers with investment experience to form a representative sample of the population of retail investors who might engage with GenAI. We drop 62 respondents who report "never" making investments, resulting in a final sample of 1,038 investors. Prolific respondents receive $1.00 in exchange for participation and complete the study in an average (median) of 7.3 (5.8) minutes. Second, we partner with Public to include a subset of our survey questions in their 2024 Public Retail Investor Report.[5] Public is a brokerage app offering commission-free investing in stocks, ETFs, bonds, options, and crypto. Public has a GenAI tool for its investors called Alpha, so we expect Public investors likely have exposure to GenAI. Public distributed the survey to current platform users with active accounts for at least one year (i.e., those who hold at least cash in their accounts). A total of 1,374 investors from Public complete the survey. We drop 237 respondents who do not answer one or more of our survey questions, leaving 1,137 respondents from Public. We combine respondents from both pools, creating a full sample of 2,175 respondents.

Table 1 presents the demographic characteristics of the investors who participated in our survey. The median age of our respondents is in the 35-44 range, and 35.5% are female. Over half of our respondents have taken at least one finance or accounting course. They have invested in a variety of assets, including stock of individual companies (86.5%), a stock index, ETF, or mutual fund (70.4%), cryptocurrency (58.1%), and bonds (38.5%). They vary in how actively they trade;

[4] The Institutional Review Board (IRB) at the affiliated university approved the use of human subjects for the surveys reported in this paper.
[5] The 2024 Public Retail Investor Report can be found at https://public.com/research/2024-retail-investor-report.

25.9% buy or sell investments weekly or more, 35.8% do so monthly, and 38.3% rarely do so. Altogether, our respondents appear largely representative of the typical pool of retail investors (Lin et al., 2022).[6] However, because participation on Prolific requires some level of technological familiarity and Public is a more modern, mobile-driven brokerage platform, our respondents may be somewhat more technologically adept than the typical retail investor, all else equal. Thus, we caveat that our survey results may not fully represent the complete population of retail investors, and may instead reflect current GenAI usage by the investor subset more open to GenAI.

3.2 Survey Design and Delivery

We developed our initial survey instrument based on discussions with peer academics. After creating an initial set of questions, we solicited feedback from three professionals working at organizations who routinely engage with individual investors to better understand what those in practice would want to know about individual investors' use and perceptions of GenAI. Our final survey contained 11 questions followed by a set of demographic questions, which we administered to Prolific subjects via Qualtrics. Public selected 10 of the questions along with a set of demographic questions to include in their Retail Investor Survey administered to current users.

3.3 Current Use of GenAI

We first examine the extent to which retail investors have used GenAI. Table 2, Panel A reports that 1,026 respondents (47.2%) have used GenAI to process financial information or inform investment decisions while 1,149 (52.8%) have not. We refer to these groups as "users" and "non-users" throughout the paper. Of GenAI users, 9.4% report using GenAI daily or more, 22.8%

[6] A 2021 FINRA survey by Lin et al. (2022) reports that retail investors are 40% female and have a median age between 35 and 54. Additionally, 38% of all retail investors—and 47% of those under age 55—traded four or more times in a 12-month period. Investment patterns include 79% holding individual stocks, 58% mutual funds, 33% cryptocurrency, 32% ETFs, and 31% bonds. The demographics and investment patterns of our sample generally align with those documented by FINRA, with one notable exception: a higher rate of crypto investment (58% vs. 33%). However, this difference may be attributable to differences in question phrasing, as our survey asked about lifetime investment ("have you ever invested...?") rather than current ownership as in the FINRA survey.

weekly, 26.6% monthly, and 41.2% rarely. This pattern suggests a sizable proportion of users rely on GenAI on a routine basis to process financial information or inform investment decisions, while others are still experimenting with how to integrate GenAI into their investment processes.

Table 2, Panel B reports results of regressions assessing determinants of GenAI adoption by investors. We examine determinants of *User* (with 0 = non-users and 1 = users) and *GenAI Frequency* (with 0 = rarely and 3 = daily or more) among users. We include as regressors four measures that plausibly affect usage. *Sophistication* is the number of accounting and finance courses taken sorted into terciles (with 0 = 0 courses, 1 = 1-3 courses, and 2 = 4 or more courses). *Trading Activity* is the frequency of buying or selling investments (with 0 = rarely and 3 = daily or more). *Age* is respondents' reported age based on the ranges in Table 1. Finally, we use robust standard errors and include survey fixed effects to control for unobserved differences in our Prolific and Public respondents and their response patterns.[7]

Results suggest that more sophisticated investors and more active traders are more likely to have used GenAI to process financial information or inform investment decisions and to do so more frequently. These results indicate that financial education and active engagement with the capital markets are key drivers of GenAI adoption and frequent use among retail investors, perhaps because these investors might better understand the comparative advantages of GenAI in a financial setting, an idea we return to in section 3.6. However, this finding may reflect that less sophisticated investors simply have little interest in investment research altogether.[8] Older investors are less likely to have used GenAI, but among users, age has no effect on frequency of

[7] We use OLS for this and all subsequent regressions. Results for tests with binary dependent variables hold when using probit or logit models.

[8] We ask Prolific participants how often they use financial information (e.g., earnings release, 10-K, etc.) to evaluate a company. While those who engage in more investment research are more likely to use GenAI, including this measure in our regression does not diminish the significance of investor sophistication, providing some support that less sophisticated investors are less likely to use GenAI, irrespective of their investment research inclinations.

use. This suggests that once older investors overcome the initial barriers to GenAI adoption, they appear just as likely to engage with GenAI as their younger counterparts.

Table 2, Panel C reports the GenAI platforms retail investors have used to process financial information or inform investment decisions. Among GenAI users, the vast majority use ChatGPT (74.6%), suggesting investors may be drawn to familiar, well-established tools, even if alternatives exist, potentially highlighting the importance of awareness costs in GenAI adoption. However, other platforms, such as Google Gemini (37.3%) and Microsoft Copilot (35.8%) are also widely used, indicating that retail investors could be experimenting with different tools based on their unique capabilities. Public Alpha is used by 18.1% of respondents, with usage concentrated among Public respondents (41.6%) rather than Prolific respondents (< 1%). The high usage of Alpha by Public users suggests that integration of GenAI tools is an avenue for brokerage platforms to facilitate GenAI-driven investment research among their users.

3.4 Information Processing with GenAI

We next examine how investors currently use GenAI, focusing on two key elements: 1) the processing tasks investors perform using GenAI and 2) the information sources investors process using GenAI. Since we focus on specific uses of GenAI, our analyses in this section are limited to GenAI users. However, we examine how use of GenAI as an information processing tool varies based on users' *Sophistication* and *Trading Activity*. These groups likely face significantly different processing constraints and requirements given archival findings that sophisticated investors face lower information processing costs (e.g., Lee, 1992; Bhattacharya, 2001; Blankespoor, deHaan, and Marinovic, 2020 for a review). Thus, understanding differences in their uses of GenAI is informative for industry and research. We also include two control variables that may also affect how investors use GenAI: *Age and GenAI Frequency*.

3.4.1 Processing Tasks

We provide investors a list of financial information processing tasks and ask them to select all the ways they have processed information using GenAI. Table 3, Panel A presents the processing tasks, our corresponding variable names, and the percent of users indicating they have performed that processing task using GenAI, listed in descending order of frequency. Table 3, Panel B presents regression results. We present the regressions grouped into acquisition and integration tasks. Within each group, we list tasks from less complex to more complex.

Investors most commonly report using GenAI for relatively less complex information integration tasks such as asking for an explanation or interpretation (*Explain;* 44.2%) and defining financial terms (*Define*; 41.2%). They also report using GenAI for less complex information acquisition tasks such as searching for specific information within a document (*Search*; 28.7%) and retrieving financial information from the internet (*Retrieve*; 28.2%). These most common uses of GenAI suggest that investors on average are primarily using these tools to enhance their understanding of financial information and simplify the investment research process. Investors less commonly report using GenAI for more complex information integration tasks, such as calculating financial ratios (*Calculate*; 21.4%), summarizing information (*Summarize*; 21.0%), assessing sentiment (*Sentiment*; 14.9%), or comparing information across firms or industries (*Compare*; 14.0%). However, more sophisticated users are generally more likely to use GenAI for these more complex integration tasks, suggesting that sophisticated users rely on GenAI for a more diverse and advanced set of tasks.[9] These differences are consistent with experimental and archival research documenting that more sophisticated investors acquire and integrate information

[9] Results in this section are partly a reflection of how investors process financial information more generally, even without GenAI. For instance, investors use GenAI most commonly for interpreting financial information, but even without GenAI, this is likely one of investors' most common tasks. In this sense, our results are a joint function of the processing tasks investors perform in general, as well as the extent to which they rely on GenAI for such tasks.

differently than less sophisticated investors (e.g., Maines and McDaniel, 2000; Bhattacharya, 2001; Frederickson and Miller, 2004; Elliott, 2006; Elliott et al., 2007; Miller, 2010; Battalio et al., 2012; Cade et al., 2023).

Interestingly, 27.4% of GenAI users from our Prolific sample report asking GenAI for a recommendation on a financial decision, despite most GenAI platforms, such ChatGPT and Alpha, having restrictions on providing explicit financial advice.[10] Regression results suggest that less sophisticated investors are more likely to ask GenAI for recommendations. While these investors are unlikely to receive explicit advice from GenAI, we found in hand-testing that GenAI tools often respond to such requests by redirecting toward analyst information, including analyst price targets and recommendations. Thus, it is possible that less sophisticated investors, in seeking advice from GenAI, actually end up processing analyst information they would not otherwise. Further, the greater reliance of less sophisticated investors on firms or intermediaries to interpret and recommend is consistent with prior survey evidence (Elliott et al., 2008) and archival findings of firms providing investors with conference calls, guidance, and other aids when firm information is complex (e.g., Bushee et al., 2003; Guay et al., 2016).

3.4.2 Information Processed

We next provide investors a list of financial information sources and ask them to select all sources they have processed using GenAI. Table 4, Panel A presents the sources, our corresponding variable names, and the percent of users indicating they have processed that source using GenAI, listed in descending order of frequency. Table 4, Panel B presents regression results.

[10] Results for *Advice* are limited to respondents from our Prolific subsample. Respondents from our Public subsample did not have the option to select the *Advice* option in the survey.

We present the sources of information grouped into third-party information versus firm-released information. Within each group, we list from relatively more raw to more prepared information.

Users most often rely on GenAI to process third-party sources of financial information such as market data (*Market;* 41.9%), news articles (*News*; 39.7%), and social media (*Social*; 27.6%), suggesting investors use GenAI most often to process real-time, frequent information that is salient within their information environment. For instance, they may use GenAI to interpret patterns in market data (e.g., causes of stock price fluctuations or unusual volume), or to explain the financial implications of a news article. Users less commonly report using GenAI to process firm-released information such as earnings releases (*Earnings*; 25.4%), earnings call transcripts (*Transcript*; 12.8%), 10-Ks/10-Qs, etc. (all < 10%). However, more sophisticated users are more likely to use GenAI to process a broader range of sources, including relatively more prepared third-party information such as industry reports and analyst output, and all firm-released information.

Overall, results about investors' current use of GenAI suggest that GenAI is being used to process a wide range of tasks and information sources, but usage patterns are not uniform across all investor types. Investors are primarily using GenAI to enhance their understanding of financial information, most often real-time data such as market information and news articles. However, the relatively limited use of GenAI for extracting summaries or signals from complex documents such as financial statements and conference call transcripts points to untapped potential in GenAI's application, especially given recent research on GenAI's capabilities in these areas (e.g., Bai et al., 2023; Kim et al., 2024a, 2024b; Wong et al., 2024). Further, more sophisticated investors leverage GenAI for more complex tasks and a wider range of information sources. These patterns imply that while GenAI has the potential to democratize access to financial insights, its current usage may widen the gap between more and less sophisticated retail investors, similar to how prior technologies like XBRL initially benefited investors unequally (e.g., Hodge et al., 2004; Blankespoor et al., 2014; Bhattacharya et al., 2018).

3.5 Investor Perceptions of GenAI Tools

We next document investor perceptions of GenAI as a tool for processing financial information and informing investment decisions. We include the full sample of respondents in these analyses and compare how perceptions differ across GenAI users and non-users using *User*, which is an indicator variable equal to one for GenAI users and zero for non-users.

3.5.1 Perceptions of GenAI

Table 5, Panel A presents investors' beliefs about whether using GenAI improves or worsens investors' processing of financial information and investment decisions, reported for our full sample and separately for GenAI users and non-users. More than half of investors (58.7% overall) believe GenAI improves processing of financial information and investment decisions. Regression results presented in Table 5, Panel B indicate this perception is stronger among GenAI users compared to non-users, indicating that hands-on experience tends to improve views of GenAI's benefits or that those who perceive benefits are more likely to use GenAI. Results within non-users suggest significant uncertainty regarding GenAI's potential benefits. While a sizeable portion (45.1%) of non-users believe GenAI improves processing of financial information and investment decisions, 40.7% of non-users are unsure if GenAI improves or worsens processing, suggesting that many non-users may not be well-informed about how GenAI works or its actual impact on decision-making. Furthermore, the relatively low proportion (14.2%) of non-users who believe GenAI worsens decision-making highlights that active resistance is low, implying that education of its benefits might encourage broader adoption.

Table 5, Panel C presents investors' beliefs about whether GenAI will level the playing field between professional and nonprofessional investors, reported for our full sample and separately for GenAI users and non-users. About half of investors (49.9%) agree that GenAI will level the playing field. Regression results presented in Table 5, Panel D indicate this agreement is stronger among users compared to non-users. Non-users appear more skeptical, with only 39.1% agreeing GenAI will level the playing field. This gap in perception suggests that non-users' hesitancy to use GenAI may stem from uncertainty about its ability to offer them a substantial market advantage. In section 5, we offer directions for future research into how GenAI affects retail investor processing and information asymmetry between retail and institutional investors.

3.5.2 Perceived Benefits

To better understand variation in investor adoption of GenAI, we next explore investor perceptions of the benefits and limitations of GenAI. We present respondents with seven potential benefits and eight potential limitations of using GenAI to process financial information or inform investment decisions. We constructed the lists based on discussions in the popular press and on social media, as well as our conversations with various investment industry professionals.

Table 6, Panel A presents the potential benefits, our corresponding variable names, and the percent of investors who believe the item is a benefit of GenAI, listed in descending order of frequency. Results are reported for our full sample and separately for GenAI users and non-users. The most cited benefit of GenAI from both users and non-users is quicker processing of information (*Speed*; 64.7% overall). This suggests all investors acknowledge GenAI as a tool to improve processing efficiency and underscores a collective recognition of GenAI's role in streamlining financial analysis. The next two most cited benefits across all users are that GenAI makes it easier to deal with more complex tasks, such as processing complex information (*Simplify*; 58.8% overall) and comparing different information (*Compare*; 55.6% overall).

Regression results presented in Table 6, Panel B indicate that users are more likely to recognize these three benefits of GenAI, as well as GenAI's ability to help identify hidden trends and understand risks. These findings reinforce that firsthand experience using GenAI increases the perception that GenAI holds financial information processing benefits. Though self-selection into GenAI usage may drive some of these results, it is also plausible that simply trying GenAI can convince investors of the potential benefits the tool offers. More sophisticated users primarily value GenAI for two benefits: its speed and ease of processing complex information. While these users rely on GenAI for more complex tasks (as discussed in section 3.4), they do not cite other benefits. This pattern suggests that GenAI's rapid processing and ability to simplify complexity could be key benefits for complex tasks.

3.5.3 Perceived Limitations

Table 7, Panel A presents the potential limitations, our corresponding variable names, and the percent of investors who believe the item is a limitation of GenAI, listed in descending order of frequency. Results are reported for our full sample and separately for GenAI users and non-users, revealing several themes. First, both users and non-users most often highlight limitations in GenAI's responses, listing the reliability/accuracy of GenAI as the top limitation (*Accuracy*; 54.0% overall). A perceived lack of transparency or source attribution in GenAI responses (*Transparency*; 42.9%) could contribute to the perceived lack of reliability or accuracy. Many investors also list a lack of quality responses as a limitation (*Quality*; 45.7%), suggesting that even factually correct GenAI responses often fall short of investor expectations. Regression results presented in Table 7, Panel B indicate that non-users are significantly more likely to cite these items as limitations, suggesting non-users' lack of use could be driven in part by a distrust for GenAI output or belief that the tools are just not good enough yet.

Second, investors highlight more system or society-wide limitations of GenAI. Investors list a lack of data privacy and security as the second greatest limitation (*Privacy*; 50.4% overall). Again, non-users are significantly more likely to cite this limitation, suggesting data privacy concerns may be holding back some investors from using GenAI. Respondents also list the risk of legal/regulatory consequences as a limitation (42.1%), but this does not differ by GenAI usage.

Third, some investors cite lack of personalization or customizability as a limitation (*Custom*; 32.3%). Interestingly, users are significantly more likely to list this limitation, suggesting that once investors integrate GenAI as a routine processing tool, they shift their focus toward quality-of-life platform improvements. One implication of this finding is that GenAI tools may become increasingly personalized as more investors adopt GenAI and demand such personalization. In fact, such personalization has already developed in tools such as ChatGPT and Google Gemini. When enabled by the user, ChatGPT and Google Gemini's "memory" features stores key details from conversations over time to develop a profile of the users' background and preferences. Finally, less than one-third of investors list the cost of using or difficulty learning how to use as limitations, consistent with GenAI being a widely accessible and powerful tool for retail investors. However, non-users and older users are more likely to identify GenAI as being difficult to learn. This suggests that as GenAI tools and their features rapidly evolve and develop, these groups may find the learning costs to be an increasingly daunting hurdle, even if such tools are generally intuitive to learn and use. Alternatively, these groups may believe GenAI is intuitive to use but find it too costly to learn how to *effectively* implement GenAI in their research process.

The results in this section reveal both GenAI's potential for retail investors and significant challenges. Investors generally perceive GenAI as a valuable tool for enhancing efficiency, managing complexity, and potentially democratizing access to financial insights. However, these benefits are counterbalanced by concerns about reliability, data privacy, and the quality of GenAI-generated outputs. Notably, a divide emerges between users and non-users, with users consistently reporting more benefits and fewer limitations, suggesting that hands-on experience significantly improves perceptions of GenAI. This experience gap highlights a potential barrier to widespread adoption and equitable impact, a theme we discuss further in the next section.

3.6 Future Use of GenAI

We conclude our survey analysis by examining investors' intentions to adopt GenAI in the future and identifying obstacles to its broader adoption. Table 8, Panel A reports that 62.6% of investors believe they are more likely than not to use GenAI in the future for processing financial information or informing investment decisions. As expected, these intentions are higher among current GenAI users (80.4%), but notably, even 46.6% of non-users express interest in future adoption, suggesting likely future increases in GenAI adoption. Despite this positive outlook, 53.4% of non-users report being unsure or unlikely to use GenAI, reflecting a considerable segment of investors resistant to or apathetic about future GenAI usage.

To better understand these barriers to adoption, we analyze determinants of future GenAI adoption intentions. We construct an indicator variable equal to 1 for participants likely to adopt GenAI and 0 for those unsure or unlikely to adopt. Table 8, Panel B presents a regression analysis that explores the role of current GenAI usage, investor sophistication, trading activity, age, and perceptions of GenAI's benefits and limitations in shaping adoption intentions. As expected, current GenAI users, frequent users, and active traders are more likely to adopt GenAI in the future, emphasizing the role of familiarity and active engagement in shaping adoption intentions.

Several key obstacles to adoption emerge from our analysis. First, the positive coefficient on *Sophistication* indicates that less sophisticated retail investors are less likely to adopt GenAI in the future. This finding suggests that less sophisticated investors, who may lack the knowledge, confidence, or interest to leverage GenAI effectively, may be less likely to reap the potential benefits offered by GenAI.

Second, the positive coefficient on age suggests that younger investors, despite being more likely to have used GenAI (Table 2), exhibit lower intentions for continued future adoption. One possibility for this counterintuitive finding is that younger investors, due to limited experience, are less equipped to identify powerful use cases where GenAI could provide substantial value or insight. This finding highlights a potentially nuanced age dynamic, where younger investors may be quicker to try new GenAI technologies for surface-level tasks, but less likely to leverage GenAI's capabilities into their long-term investment processes, a dynamic seen paralleled in the management literature (Kellogg et al., 2024).

Third, there is a negative coefficient on the response quality limitation and positive coefficients on *all* processing benefits. Furthermore, these coefficients are strongest among non-users. This suggests that among non-user investors, concerns about response quality, combined with less inclination to recognize the processing benefits of GenAI, are key obstacles to investor adoption of GenAI. These patterns may stem from the highly publicized failures and shortcomings of early GenAI models (Leswing, 2023), even though performance has improved dramatically in newer models (Hughes et al., 2024; Mollick, 2024). Furthermore, the lack of media attention on investment-specific GenAI applications may further limit understanding of its potential value.

Addressing these misconceptions through improved communication strategies and examples of successful investment applications (e.g., Kim et al., 2024a, 2024b, 2024c) could encourage broader adoption.

Finally, there is a significant negative coefficient on the data privacy limitation, indicating that data privacy concerns may be holding back future GenAI adoption among investors. For instance, investors may be hesitant to share details of their financial positions or investment behavior without greater assurance of security over their conversations. Although most platforms offer private chat modes, investors may not be aware or trusting of such features, suggesting a need for greater transparency and security with respect to privacy policies.

Overall, while GenAI has the potential to transform financial decision-making and democratize access to advanced tools, significant barriers must be addressed to realize this vision. Effectively addressing concerns about response quality, privacy, and usability will be critical, as will targeted education and communication strategies to bridge the gap between users and non-users. The future impact of GenAI will likely depend on how successfully these challenges are addressed and how effectively the technology is tailored to meet the diverse needs of different investor segments.

4 Descriptive Archival Data

4.1 Data

We supplement our survey findings with a detailed analysis of retail investor interactions with Alpha, a fine-tuned GPT-4 generative AI chatbot integrated into Public's brokerage platform. At the time of data collection in July 2024, Alpha was available to all Public brokerage account holders. Alpha combines GPT-4's natural language processing and conversational capabilities with real-time financial data, such as SEC filings, earnings transcripts, market data, analyst ratings, and news reports. Alpha does not provide explicit financial advice; rather, it serves as a processing copilot, helping investors process financial information and make their own informed judgments about specific securities or the broader market. Investors can ask Alpha to perform custom tasks or answer custom questions, or can choose from a set of suggested question prompts that appear throughout their interactions. We obtain from Public a random sample of 40,381 retail investor questions posed to Alpha in mid-2024. These questions represent a small subset of the millions of questions that have been asked by investors on the platform. Due to data constraints, we do not have access to Alpha answers or full conversation threads.

4.2 Classification

We use a machine learning model to classify Alpha questions along two dimensions, similar to those documented in our survey evidence: (1) the type of task the investor asks Alpha to perform (task classification), and (2) the information source investors seek help processing (information classification). We perform each of these two classification schemes independently, so each question has a task classification and an information classification.

Our task classification and information classification categories largely align with the “Processing Tasks” (Table 3) and “Information Sources Processed” (Table 4) categories in our survey. However, some differences in classification naturally arise based on the applied functionality of Alpha. First, investors cannot upload attachments to Alpha, and Alpha does not have access to certain information sources in our survey (i.e., social media, ESG reports, or personal notes/info). We therefore drop these sources from our information classification categories because investors cannot ask Alpha to process them. Second, whereas our survey focuses on concrete tasks and information, investors often ask Alpha general, high-level questions that are beyond the scope of our survey, such as stock screening (e.g., “Show me some stocks at

52-week highs") and company overviews (e.g., "How's MSFT been doing?"), so we add categories to account for these tasks. Third, some categories in our survey are by nature less frequently seen in Alpha questions (e.g., asking about 8-Ks or performing topic identification). Since machine learning requires each category to appear a sufficient number of times for proper training, we combine these less frequent categories with other categories (e.g., we combine 8-Ks with news).

To execute our classification, we employ a two-stage process combining manual categorization and machine learning. First, we manually classify a training set of 1,500 questions. Our sample includes both unique investor-generated questions and Alpha-suggested questions chosen by investors, with the latter creating repeated instances of the same question in our sample.[11] To account for this, we selected our manual classification set of 1,500 unique questions through weighted random sampling, ensuring that questions occurring more frequently were more likely to be selected for manual classification. We then assign each unique question to a single, mutually exclusive category based on its primary intent. While some questions could logically fall into multiple categories, we use mutually exclusive classification to reduce complexity in the training process, avoid overfitting, and improve the model's predictive accuracy. This approach also reflects the fact that investors typically ask questions with a dominant purpose, even if secondary purposes might be present.

We then train a Sentence-BERT (SBERT) model using this training set. SBERT is particularly well-suited to our classification task because, unlike models based on word frequency or pre-trained word embeddings, SBERT generates contextual embeddings that capture the nuanced intent of each question. This capability allows us to account for the specific financial context in which Alpha operates, making the model more accurate in distinguishing types of

[11] Several Alpha-suggested questions in our sample are identical except for variations in the ticker symbol. For these, we replace the ticker with 'TIC,' treating each as a single unique question for classification purposes.

questions. We train SBERT using 1,200 questions from the manually classified set and use the remaining 300 as a holdout sample to evaluate the model's performance. In some cases, the model is unable to definitively classify a question due to ambiguity in the phrasing or the lack of a clear match to any single category. When this occurs, we instruct the model to assign the question to the best-fitting category based on the available context, which allows us to minimize unclassified questions while maintaining a high level of categorization accuracy. The SBERT model correctly classifies roughly three-quarters of manually-reviewed questions, with an accuracy of 0.75 for task classification and 0.73 for information source classification.[12]

We use the trained model to predict the task and information source categories for the remaining questions in our dataset. From our sample of classified questions, we remove 1,917 questions classified as incomplete or incoherent. We also remove 2,999 questions classified as asking for explicit advice or guidance because Alpha does not provide responses to these questions. Finally, we remove 6,223 questions classified as asking for app support or account assistance because these questions are beyond the scope of Alpha's functionality and our research question. Our final sample contains 29,242 retail investor questions to Alpha.

4.3 Results

4.3.1 Alpha Processing Tasks

Table 9 presents the task classification of the 29,242 Alpha questions, along with sample questions in each category. Consistent with our survey evidence, investors most frequently use Alpha to explain or interpret financial information (13,877 questions, 47.5%), reinforcing our

[12] Further, the model's deviations from our manual classification seem generally reasonable, given the ambiguity of some questions. For instance, the task model classified "What is SERV likely to do?" as a *provide general company assessment* task whereas we classified it as a *Background* task. Similarly, the info model classified "What is the dividend yield of QQQI?" as *Market* information whereas we classified it as *Background* information.

finding that investors primarily rely on GenAI to help interpret or explain financial or market data. For example, questions such as "How healthy are their margins?” or "How is their battery business performing?" show how investors seek contextual explanations to interpret market movements and company performance.

Investors also frequently use Alpha to screen for stocks based on specific criteria, such as recent financial performance, market movements, or industry characteristics (8,121 questions, 27.8%), reflecting GenAI’s utility in helping investors more efficiently identify investment opportunities aligned with their strategies. Other common but less frequent tasks include asking Alpha for general company assessments (2,508 questions, 8.6%), background research on companies (1,436 questions, 4.9%), and financial information summaries (1,357 questions, 4.6%). These tasks reflect GenAI’s role in transforming otherwise time-consuming investment research tasks into digestible overviews. Additionally, investors use Alpha to retrieve key financial figures (1,063 questions, 3.6%), reflecting GenAI’s utility in simplifying access to financial data. Finally, investors also use Alpha to define investment terminology (497 questions, 1.7%), evaluate trends in performance (324 questions, 1.1%), and compare companies or segments (59 questions, 0.2%).

4.3.2 Information Sources Processed with Alpha

Table 10 presents the information sources classification of the 29,242 Alpha questions, along with sample questions representative of each category. Consistent with the survey evidence, investors most often use Alpha to process third-party sources of financial information, with market data being the most common (21,552 questions, 73.7%). Questions around market data typically focus on evaluating stock market performance and understanding the reasons for stock price movements. This prevalent use-case of Alpha among Public investors aligns with market data being the most readily available and continuously updated information on brokerage platforms.

Investors also routinely use Alpha to process common investment research information, such as analyst forecasts and evaluations (2,371 questions, 8.1%), background information on companies (1,427 questions, 4.9%), and financial numbers (1,333 questions, 4.6%).[13] These findings suggest that GenAI serves a key role in making investment research more accessible to retail investors. Investors also occasionally use Alpha to process earnings calls (749 questions, 2.6%), financial news stories (692 questions, 2.4%), and industry information (321 questions, 1.1%). Finally, a small subset of investors use Alpha for educational information (485 questions, 1.7%), such as information on how markets operate, highlighting that GenAI can also serve an investor education role.

4.4 Caveats

While our analysis of investor interactions with Alpha provides valuable insights, our findings are subject to several caveats. First, our classification of Alpha questions is mutually exclusive, which may understate the true magnitude of certain categories. For example, only 3% of Alpha's questions involve the pure retrieval of information, but many other tasks—such as explanations or stock screening—inherently involve Alpha retrieving data. Thus, our findings likely represent a lower bound on the frequency of each category. Second, unlike other GenAI tools, Alpha does not allow users to upload documents for analysis. This limitation may lead us to underestimate the extent to which investors use GenAI for certain tasks or information sources that rely on custom attachments, such as summarizing documents. Third, Alpha provides suggested questions that investors may choose to ask in place of their own custom questions. It is possible that these suggestions could influence the distribution of questions in ways that may not fully

[13] Although investors do not always explicitly ask for the analyst or expert reports, we classify questions in this bucket if Alpha would respond with analyst information. For instance, asking "What is forecasted for Honda?" would return analyst forecasts and price targets.

reflect how investors interact with other AI tools. However, we assume that the suggested questions largely reflect the types of inquiries investors would otherwise make on their own.

5 Areas for Future Research

Our results provide insights into retail investors' current uses and perceptions of GenAI and raise important questions about the future trajectory of GenAI in transforming retail investing. Building on our descriptive findings, we conclude by offering suggestions for future research.

5.1 Effects on Investor Processing

Future research could examine if and how the primary benefits of GenAI cited by our respondents—quicker and easier information processing—translate into improved decisions by retail investors: e.g., more informative written opinions (e.g., Seeking Alpha articles), more timely decisions, engagement with more firms, broader diversification, and more informed investment decisions. In addition, while we focus on retail investors, sophisticated investors or analysts might also benefit, with potential evidence like more insightful questions of management on conference calls or more thorough analyst reports. Finally, research could revisit the question of whether and how retail investors affect market pricing if GenAI improves their processing ability.

A related question is whether GenAI usage narrows the performance gap between retail and professional investors. Given our finding that sophisticated retail investors are more likely to adopt GenAI and use it for more complex tasks, research could also examine the potential for GenAI to exacerbate disparities across investors. Additionally, exploring how GenAI's equalizing effect varies across different market conditions would provide valuable insights.

Future research could also examine if using GenAI changes the information sources retail investors rely on. For example, we found in hand-testing that GenAI often responds to requests for investment advice by redirecting investors toward analyst reports, which might lead investors to process analyst information they would not otherwise. GenAI could also empower retail investors to process more complex, unstructured data that is otherwise challenging to analyze manually. The prediction is nuanced, though, as retail investors might reduce their direct use of sources like EDGAR filings or news articles in favor of using GenAI to find and summarize sources for them.[14]

5.2 GenAI Processing

Our findings suggest a growing trend of investors outsourcing research and analysis to GenAI, which highlights the critical need for future studies to examine how GenAI itself processes financial information. For example, given investors' reliance on GenAI for interpretation, future research could investigate how GenAI processes and prioritizes among sources, including news, firm financials, and market data. Studies could explore GenAI's handling of ambiguous or conflicting information, its reliance on non-financial factors such as ESG, and its incorporation of real-time information. Additionally, research could examine how various GenAI platforms (e.g., general vs. finance-specific, etc.) differ in their approaches and ability to detect financial irregularities compared to traditional methods. Finally, research could explore how variations in user prompts affect the nature or quality of GenAI output, and how GenAI might adapt when given information about an investor's specific portfolio, investment goals, or risk preferences.

5.3 Investor-GenAI Interaction

Our survey describes the tasks and information sources that retail investors process using GenAI. Over time, these tasks and sources will evolve, raising the need to examine the dynamics of human-GenAI collaboration in investing. Studies could also investigate how investors integrate

[14] This point aligns with concerns expressed by SEC Chair Gary Gensler, who warned that GenAI could amplify herding behavior among investors by concentrating attention on a limited set of signals derived from dominant GenAI platforms, reducing market efficiency and increasing systemic risk (SEC, 2023, 2024).

GenAI-generated insights with their own judgments and whether GenAI enhances decision quality or introduces new challenges. Another open question is whether GenAI helps mitigate investors' cognitive biases or inadvertently reinforces them or creates new ones.

Our findings indicate that investors favor well-known GenAI platforms like ChatGPT for financial analysis, with Public users also preferring integrated tools like Public's Alpha. Future research could explore investor adoption and usage when GenAI is integrated in a brokerage platform or designated as finance-specific. A specific question is whether specialized or personalized GenAI tools increase adoption and trust compared to generic ones. Specialized GenAI might better serve both novice investors seeking education and experienced investors desiring advanced customization, potentially driving broader adoption. Additionally, investors may interact differently with GenAI tools tailored to specific investment goals or risk preferences, providing insights into effective personalization.

Future research could also explore the impact of GenAI user interfaces on investor behavior: for example, how GenAI transparency, such as making the sources and reasoning behind GenAI outputs more visible, affects investor adoption rates, trust in GenAI, and misinformation susceptibility. More broadly, studies could examine how the presentation of GenAI output—including different types of data visualizations, summaries, or explanation methods—affects adoption, processing, confidence, and decision-making speed. Further, examining user experience across demographic groups could inform the development of more accessible GenAI platforms.

Our findings reveal disparities in current adoption and anticipated future use of GenAI across age groups, suggesting opportunities for targeted education. Future research could explore the most effective educational approaches for various demographics to promote wider adoption and more effective use of GenAI tools. Studies could also examine the long-term learning effects of using GenAI tools, such as whether continued use of GenAI over time improves investors' financial literacy and investment skills, or instead diminishes their independent abilities.

6 Conclusion

This study examines retail investors' adoption and perceptions of GenAI for processing financial information and making investment decisions. Our survey of 2,175 retail investors, complemented by an analysis of 40,000 GenAI chatbot queries, reveals three key findings. First, we observe widespread adoption, with nearly half of surveyed investors already using GenAI, primarily for interpreting financial data and gathering insights from third-party sources. Investors perceive GenAI as enhancing their ability to process complex information quickly and easily. Second, we identify a sophistication gap, where more sophisticated retail investors are at the forefront of GenAI adoption, using it for complex tasks across a broader range of sources. Third, we observe a nuanced future outlook: while most investors plan to adopt or continue using GenAI and believe it will become a standard tool, many non-users remain skeptical due to accuracy and privacy concerns, and struggle to identify GenAI's benefits perhaps due to a lack of sophistication or experience. This disparity suggests that while overall adoption is likely to increase, it may also widen the gap between more and less sophisticated investors, challenging expectations of democratized access to financial information. These findings provide crucial insights into the evolving landscape of retail investing and raise important questions about the long-term impact of GenAI on investor behavior and market dynamics.

Our study contributes to the emerging literature on GenAI in financial information processing by providing empirical evidence of how retail investors actually use these tools. We find widespread adoption of GenAI among retail investors, which has implications for regulators designing investor education and safeguards, as well as managers disclosing to investors who are now likely to rely on GenAI-driven insights rather than manually processing financial reports. Our findings provide a foundation for future research to explore the interplay between GenAI, financial information processing, and investor and market outcomes, highlighting the importance of understanding both GenAI's data processing capabilities and human-GenAI interactions in shaping investment decisions.

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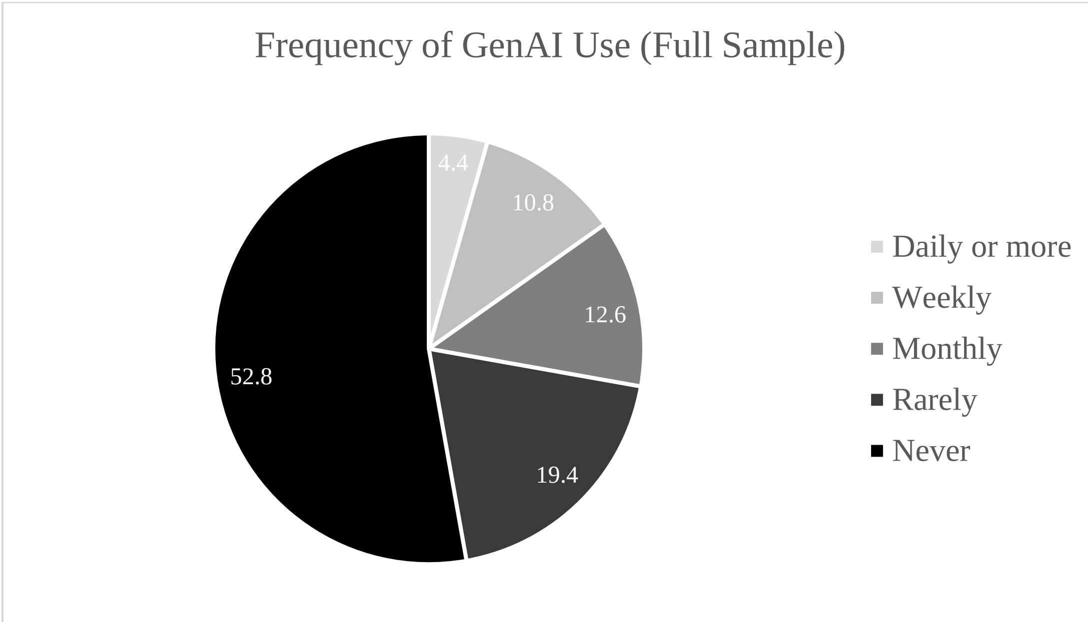
Figure 1: Survey Respondents' Frequency of GenAI Use



See Table 2, Panel A for descriptive statistics of investors' frequency of GenAI use

Table 1: Demographic Characteristics of Survey Respondents

Age	% of Full Sample N = 2,175
18-24	6.8
25-34	21.6
35-44	23.6
45-54	23.9
55+	24.1

Gender	
Male	62.6
Female	35.5
Non-binary / third gender	0.9
Prefer not to say	1.0

Accounting and Finance Courses	
0	44.9
1-3	30.3
4-9	18.2
10+	6.6

Which of the following have you ever invested in?	% of Full Sample N = 2,175
Stock of individual company	86.5
Stock index, ETF, or mutual fund	70.4
Bonds	38.5
Cryptocurrency	58.1
Options	15.8
Other (e.g., Real Estate, Alternative Assets, etc.)	28.1

How frequently do you buy or sell investments?	
Daily or more	7.3
Weekly	18.6
Monthly	35.8
Rarely	38.3
Never	0.0

Table 2: Survey Respondents' Current Use of Generative AI

Panel A: Frequency of GenAI Use

How frequently do you use generative AI to process financial information or inform investment decisions?	**% of Full Sample N = 2,175**	**% of Users N = 1,026**	**% of Non-users N = 1,149**
Daily or more	4.4	9.4	0.0
Weekly	10.8	22.8	0.0
Monthly	12.6	26.6	0.0
Rarely	19.4	41.2	0.0
Never	52.8	0.0	100.0

Panel B: Determinants of GenAI Use

	User (1,0)	*GenAI Frequency*
Sophistication	0.11***	0.18***
	(8.47)	(4.90)
Trading Activity	0.11***	0.33***
	(10.23)	(9.73)
Age	-0.03***	0.02
	(-3.45)	(0.91)
Survey Fixed Effects	Yes	Yes
Observations	2,175	1,026
Adjusted R^2	0.11	0.11

Panel C: GenAI Platforms Used

Which generative AI tools have you used to process financial information or help with investment research?	**% of Users N = 1,026**
ChatGPT	74.6
Google Gemini	37.3
Microsoft Copilot	35.8
Public Alpha	18.1†
Claude	4.9
Llama 2	2.8
Other‡	4.3

†41.6% among Public respondents. < 1% among Prolific respondents
‡ Examples include FinChat, Pluto, and BeeBee

The dependent variable in Panel B reflects investor usage of GenAI to process financial information or inform investment decisions. See Appendix A for other variable definitions. T-statistics are in parentheses. ***, ** and * indicate statistical significance at the 10%, 5% and 1% level. Figure 1 presents a visual representation of investors' frequency of GenAI use (i.e. Panel A).

Table 3: Survey Respondents' GenAI Processing Tasks

Panel A: Descriptive Statistics

How have you processed financial information using generative AI?	**Variable**	**% of Users N = 1,026**
Asked for an explanation or interpretation	*Explain*	44.2
Asked for definitions of financial terms	*Define*	41.2
Searched for a mention or a keyword, company, or industry	*Search*	28.7
Asked to retrieve financial information from the internet	*Retrieve*	28.2
Calculated financial ratios or amounts	*Calculate*	21.4
Summarized financial documents or information	*Summarize*	21.0
Identified the topics discussed in financial documents	*Topics*	17.5
Identified trends in financial data	*Trends*	16.4
Assessed sentiment (positive or negative)	*Sentiment*	14.9
Compared financial information across firms or industries	*Compare*	14.0
		N = 584†
Asked for a recommendation for a financial decision	*Advice*	27.4

Panel B: Regressions

	Acquisition			Integration							
	Less complex → More complex			Less complex → More complex							
	Retrieve	*Search*	*Topics*	*Define*	*Explain*	*Advice*	*Calculate*	*Summarize*	*Sentiment*	*Trends*	*Compare*
Sophistication	0.01	0.01	0.05***	0.00	-0.01	-0.07***	0.03*	0.05***	0.03*	0.02	0.04***
	(0.43)	(0.76)	(3.11)	(0.24)	(-0.49)	(-2.87)	(1.79)	(2.97)	(1.84)	(1.58)	(2.92)
Trading Activity	0.02	0.01	0.01	0.00	-0.01	0.03	0.01	0.04***	0.00	0.01	0.01
	(1.37)	(0.49)	(0.96)	(0.27)	(-0.54)	(1.29)	(0.49)	(3.23)	(0.09)	(0.55)	(1.10)
Age	-0.02*	-0.01	-0.02*	-0.04***	-0.04***	-0.00	-0.02**	-0.02**	-0.03***	0.00	-0.01
	(-1.88)	(-0.74)	(-1.88)	(-3.36)	(-3.02)	(-0.07)	(-2.13)	(-2.30)	(-3.33)	(0.40)	(-1.22)
GenAI Frequency	0.06***	0.08***	0.07***	0.04**	0.05***	0.05**	0.09***	0.08***	0.05***	0.05***	0.05***
	(4.29)	(5.12)	(5.45)	(2.53)	(3.03)	(2.23)	(7.07)	(6.41)	(4.31)	(4.22)	(4.46)
Survey Fixed Effects	Yes	Yes	Yes	Yes	Yes	N/A	Yes	Yes	Yes	Yes	Yes
Observations	1,026	1,026	1,026	1,026	1,026	584†	1,026	1,026	1,026	1,026	1,026
Adjusted R^2	0.03	0.03	0.05	0.07	0.09	0.02	0.08	0.09	0.03	0.07	0.05

The dependent variable in Panel B is an indicator equal to one if participants use GenAI to perform the specific task, and zero otherwise. See Appendix A for other variable definitions. T-statistics are in parentheses. ***, ** and * indicate statistical significance at the 10%, 5% and 1% level. † notes that only Prolific respondents had the option to select the "*Advice*" option in the survey.

Table 4: Survey Respondents' Information Sources Processed with GenAI

Panel A: Descriptive Statistics

What sources of financial information have you processed using generative AI?	**Variable Name**	**% of Users N = 1,026**
Market data (e.g., stock prices, volume, etc.)	*Market*	41.9
News articles	*News*	39.7
Social media	*Social*	27.6
Analysts or expert reports	*Analyst*	25.9
Economic indicators (e.g., interest rates, market indices, GDP)	*Indicator*	25.8
Earnings releases	*Earnings*	25.4
Industry reports	*Industry*	19.7
Personal notes or commentary	*Personal*	19.6
Earnings call transcripts	*Transcript*	12.8
10-Ks / 10-Qs or annual/quarterly reports	*10KQ*	8.8
8-Ks or non-earnings company press releases	*8K*	4.4
ESG reports	*ESG*	3.4

Panel B: Regressions

	Third-Party Information							Firm-Released Information				
	Raw → Prepared							Raw → Prepared				
	Market	*Indicator*	*Social*	*News*	*Personal*	*Industry*	*Analyst*	*8K*	*10K/Q*	*ESG*	*Transcript*	*Earnings*
Sophistication	0.00	0.03	-0.01	0.00	0.03*	0.04***	0.04**	0.03***	0.04***	0.01**	0.03**	0.04**
	(0.17)	(1.50)	(-0.75)	(0.01)	(1.88)	(2.75)	(2.40)	(3.33)	(3.15)	(2.03)	(1.98)	(2.45)
Trading Activity	0.01	0.00	-0.04**	0.04**	-0.03**	-0.00	0.01	0.02**	0.02**	0.01	0.02*	0.05***
	(0.81)	(0.24)	(-2.39)	(2.53)	(-2.43)	(-0.19)	(0.75)	(2.19)	(2.08)	(1.11)	(1.86)	(3.17)
Age	-0.01	-0.00	-0.02	0.02	-0.01	0.00	-0.01	-0.01*	-0.03***	-0.01**	-0.03***	-0.04***
	(-0.91)	(-0.41)	(-1.43)	(1.20)	(-1.27)	(0.26)	(-0.97)	(-1.67)	(-4.38)	(-1.98)	(-2.90)	(-4.13)
GenAI Frequency	0.09***	0.09***	0.09***	0.03*	0.05***	0.09***	0.09***	0.01*	0.02**	0.02***	0.05***	0.08***
	(5.56)	(6.45)	(5.83)	(1.67)	(3.75)	(6.59)	(6.32)	(1.75)	(2.17)	(3.18)	(4.40)	(5.81)
Survey Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,026	1,026	1,026	1,026	1,026	1,026	1,026	1,026	1,026	1,026	1,026	1,026
Adjusted R^2	0.03	0.06	0.03	0.01	0.03	0.06	0.05	0.03	0.04	0.02	0.05	0.09

The dependent variable in Panel B is an indicator equal to one if participants use GenAI to process information from the respective source, and zero otherwise. See Appendix A for other variable definitions. T-statistics are in parentheses. ***, ** and * indicate statistical significance at the 10%, 5% and 1% level.

Table 5: Survey Respondents' Perceptions of GenAI

Panel A: Processing Benefits Descriptives

Do you believe using generative AI tools <u>improves or worsens</u> investors' processing of financial information and investment decisions?	**% of Full Sample N = 2,175**	**% of Users N = 1,026**	**% of Non-users N = 1,149**
Significantly improves (7)	6.6	10.8	2.9
Moderately improves (6)	17.4	23.9	11.7
Somewhat improves (5)	34.7	39.5	30.5
Neither improves nor worsens (4)	29.7	17.3	40.7
Somewhat worsens (3)	5.8	5.8	5.7
Moderately worsens (2)	2.6	1.2	3.8
Significantly worsens (1)	3.2	1.5	4.7
Mean Score (out of 7)	**4.69**	**5.07**	**4.35**

Panel B: Processing Benefits Regression

User	**0.59******
	(10.79)
Sophistication	0.05
	(1.62)
Trading Activity	0.08***
	(2.70)
Age	0.07***
	(3.13)
Survey Fixed Effects	Yes
Observations	2,175
R^2	0.13

Panel C: Level Playing Field Descriptives

Generative AI tools will help level the playing field between professional and nonprofessional investors.	**% of Full Sample N = 2,175**	**% of Users N = 1,026**	**% of Non-users N = 1,149**
Strongly agree (7)	6.0	8.5	3.7
Moderately agree (6)	13.7	19.4	8.5
Somewhat agree (5)	30.2	33.8	26.9
Neither agree nor disagree (4)	27.1	19.4	33.9
Somewhat disagree (3)	9.7	9.0	10.3
Moderately disagree (2)	6.8	5.8	7.6
Strongly disagree (1)	6.7	4.1	9.1
Mean Score (out of 7)	**4.32**	**4.65**	**4.03**

Panel D: Level Playing Field Regression

User	**0.55******
	(8.24)
Sophistication	0.05
	(1.23)
Trading Activity	0.00
	(0.01)
Age	0.05*
	(1.88)
Survey Fixed Effects	Yes
Observations	2,175
R^2	0.06

The dependent variable in Panels B and D is participants' scaled responses to the questions in Panels A and C, respectively. See Appendix A for other variable definitions. T-statistics are in parentheses. ***, ** and * indicate statistical significance at the 10%, 5% and 1% level.

Table 6: Survey Respondents' Perceived Benefits of GenAI

Panel A: Listed as a benefit

What do you believe are the benefits of using generative AI to process financial information or inform investment decisions?	**Variable**	**% of Full Sample N = 2,175**	**% of Users N = 1,026**	**% of Non-users N = 1,149**
Quicker to process information	*Speed*	64.7	75.5	55.1
Easier to process complex information	*Simplify*	58.8	71.1	47.8
Easier to compare different information	*Compare*	55.6	66.5	45.9
Easier to identify hidden trends/insights	*Trends*	44.8	52.0	38.5
Lower risk of human errors	*Errors*	42.3	45.4	39.4
Lower risk of cognitive bias	*Bias*	37.7	42.9	33.0
Easier to understand risks	*Risks*	34.3	44.6	25.1

Panel B: Benefit Regressions

	Speed	*Simplify*	*Compare*	*Trends*	*Errors*	*Bias*	*Risks*
User	**0.09*** **	**0.12*** **	**0.10*** **	**0.05** **	**-0.02**	**0.02**	**0.13*** **
	(5.21)	**(6.29)**	**(5.27)**	**(2.37)**	**(-0.81)**	**(1.18)**	**(6.44)**
Sophistication	0.02*	0.02**	0.02	0.01	-0.01	-0.01	0.01
	(1.77)	(1.97)	(1.35)	(0.81)	(-0.46)	(-1.17)	(0.92)
Trading Activity	0.02*	0.03***	0.00	0.01	0.01	0.01	-0.00
	(1.79)	(2.57)	(0.32)	(0.77)	(0.88)	(0.89)	(-0.34)
Age	-0.03***	-0.02***	-0.02***	-0.01	0.00	-0.01*	-0.02**
	(-4.32)	(-2.85)	(-2.77)	(-1.12)	(0.20)	(-1.81)	(-2.38)
Survey Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,175	2,175	2,175	2,175	2,175	2,175	2,175
R^2	0.35	0.34	0.34	0.21	0.18	0.19	0.16

The dependent variable in Panel B is an indicator equal to one if participants cite the respective benefit, and zero otherwise. See Appendix A for other variable definitions. T-statistics are in parentheses. ***, ** and * indicate statistical significance at the 10%, 5% and 1% level.

Table 7: Survey Respondents' Perceived Limitations of GenAI

Panel A: Listed as a limitation

What do you believe are the limitations of using generative AI to process financial information or inform investment decisions?	**Variable**	**% of Full Sample N = 2,175**	**% of Users N = 1,026**	**% of Non-users N = 1,149**
Lack of reliability/accuracy	*Accuracy*	54.0	53.1	54.5
Lack of data privacy and security	*Privacy*	50.4	51.1	49.8
Lack of quality responses	*Quality*	45.7	46.6	44.8
Lack of transparency in responses	*Transparency*	42.9	44.0	41.9
Risk of legal/regulatory consequences	*Legal_Risk*	42.1	44.8	39.6
Lack of customizability/personalization	*Custom*	32.3	37.8	27.4
Difficulty of learning how to use	*Learning*	30.2	27.9	32.3
Cost of using	*Cost*	28.4	30.0	26.9

Panel B: Limitation Regressions

	Accuracy	*Privacy*	*Quality*	*Transparency*	*Legal_Risk*	*Custom*	*Learning*	*Cost*
User	**-0.10*** **	**-0.06*** **	**-0.06*** **	**-0.05** **	**-0.00**	**0.06*** **	**-0.05** **	**0.01**
	(-4.86)	**(-2.75)**	**(-2.92)**	**(-2.36)**	**(-0.18)**	**(3.01)**	**(-2.50)**	**(0.62)**
Sophistication	0.02*	0.01	0.01	0.02	0.00	0.03**	0.02*	0.01
	(1.94)	(0.83)	(0.37)	(1.38)	(0.23)	(2.54)	(1.65)	(1.04)
Trading Activity	0.00	-0.03***	0.00	0.02	-0.03**	-0.02	-0.02	-0.02
	(0.39)	(-2.77)	(0.38)	(1.50)	(-2.55)	(-1.54)	(-1.47)	(-1.38)
Age	-0.05***	-0.03***	-0.05***	-0.02**	-0.03***	-0.02**	0.02**	-0.00
	(-5.90)	(-3.36)	(-5.55)	(-2.12)	(-3.42)	(-1.99)	(2.24)	(-0.37)
Survey Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,175	2,175	2,175	2,175	2,175	2,175	2,175	2,175
R^2	0.15	0.18	0.15	0.10	0.13	0.06	0.01	0.02

The dependent variable in Panel B is an indicator equal to one if participants cite the respective limitation, and zero otherwise. See Appendix A for other variable definitions. T-statistics are in parentheses. ***, ** and * indicate statistical significance at the 10%, 5% and 1% level.

Table 8: Survey Respondents' Future Use of Generative AI

Panel A: Likelihood of Use in Future

How likely are you to use generative AI tools in the future to process financial information or inform investment decisions? **Responses:**	**% of Full Sample N = 2,175**	**% of Users N = 1,026**	**% of Non-users N = 1,149**
Extremely likely (7)	13.6	22.1	5.9
Moderately likely (6)	18.7	26.6	11.6
Somewhat likely (5)	30.3	31.7	29.1
Neither likely nor unlikely (4)	20.5	10.7	29.2
Somewhat unlikely (3)	5.3	3.8	6.6
Moderately unlikely (2)	5.2	3.3	7.0
Extremely unlikely (1)	6.4	1.8	10.6
Mean Score (out of 7)	4.73	5.36	4.18

Panel B: Likely Future Use Indicator Regression

	Full Sample	**Users**	**Non-users**
User	0.21***		
	(10.32)		
GenAI Frequency		0.04***	
		(2.99)	
Sophistication	0.03**	0.03*	0.03*
	(2.81)	(1.84)	(1.72)
Trading Activity	0.04***	0.02*	0.04**
	(3.47)	(1.74)	(2.35)
Age	0.02**	0.02*	0.02
	(2.23)	(1.75)	(1.44)
Limitation_Accuracy	-0.01	0.04	-0.04
	(-0.35)	(1.64)	(-1.41)
Limitation_Privacy	-0.06***	-0.03	-0.07**
	(-3.13)	(-1.24)	(-2.32)
Limitation_Quality	-0.06***	-0.04*	-0.07**
	(-2.83)	(-1.75)	(-2.12)
Limitation_Transparency	0.03	0.01	0.05*
	(1.61)	(0.47)	(1.71)
Limitation_Legal_Risk	-0.03*	-0.04	-0.03
	(-1.74)	(-1.57)	(-0.91)
Limitation_Custom	-0.02	-0.01	-0.02
	(-0.89)	(-0.22)	(-0.75)
Limitation_Learning	-0.01	-0.03	0.01
	(-0.27)	(-1.34)	(0.47)
Limitation_Cost	0.02	0.03	0.00
	(1.13)	(1.30)	(0.12)
Benefits variables	Included (All positive and significant)	Included (All positive and significant except *Trends*)	Included (All positive and significant)
Survey Fixed Effects	Yes	Yes	Yes
Observations	2,175	1,026	1,149
R^2	0.29	0.17	0.22

The dependent variable in Panel B is an indicator equal to one for participants likely to adopt GenAI (5 or higher on scale) and zero for those unsure or unlikely to adopt (4 or lower on scale). See Appendix A for other variable definitions. Each *Limitation_* variable equals one if participants cite the respective item as a limitation, and zero otherwise. Similarly, *Benefits* variables equal one if participants cite an item as a benefit, and zero otherwise. For parsimony, individual *Benefits* variables are untabulated. T-statistics are in parentheses. ***, ** and * indicate statistical significance at the 10%, 5% and 1% level.

Table 9: Descriptive Archival Data—Tasks Investors Ask Alpha to Perform

Task	# of Questions
Explain or Interpret	**13,877 (47.5%)**
Why is TIC moving?	
How healthy are their margins?	
How is their battery business performing?	
Screen for securities	**8,121 (27.8%)**
Show me some stocks at 52 week highs	
What are some interesting companies working on climate change?	
What stocks have a negative beta?	
Provide general company assessment	**2,508 (8.6%)**
What are some pros and cons of this investment?	
How's MSFT been doing?	
What do you think about Ferrari stocks?	
Background	**1,436 (4.9%)**
What does this company do?	
What's their AI strategy?	
Where does most of their revenue come from?	
Summarize	**1,357 (4.6%)**
Summarize their most recent earnings call	
Give me a TL;DR on recent headlines	
Summarize coinbase latest earnings report	
Retrieve	**1,063 (3.6%)**
What is the P/E ratio?	
How many vehicles did they deliver last quarter?	
What was Nvidia's gaming revenue in 2023?	
Define	**497 (1.7%)**
What's coupon vs yield rate?	
What does high liquidity mean?	
If a stock splits, what happens to my position?	
Trends	**324 (1.1%)**
How has growth trended over the last year?	
How has TIC stock performed the last six months?	
How has theater attendance been trending?	
Compare (companies or segments)	**59 (0.2%)**
How does gaming compare to other revenue segments?	
Net Sales by Geography	
How does Tsla compare to RIVN ?	
Total	**29,242**

Table 9 presents the count and percentage of investor questions posed to Alpha, classified into mutually exclusive task categories. Each category represents a distinct type of task, with three representative sample questions provided for illustration.

Table 10: Descriptive Archival Data—Information Sources Investors Process with Alpha

Information Acquired or Processed	# of Questions
Market	**21,552 (73.7%)**
What stocks have unusual trade volume today?	
Why is ASML up so much today?	
How is Nissans stock doing this month?	
Analyst	**2,371 (8.1%)**
What is TIC projected to reach in six months?	
What are the five year projections for Delta?	
What is forecasted for Honda?	
Background information	**1,427 (4.9%)**
When is their next earnings call?	
What are their top holdings?	
What do they sell?	
Financial numbers	**1,333 (4.6%)**
What are the caterpillars earnings?	
Give me an overview of their financials	
How do their earnings hold up to their estimates?	
Earnings call	**749 (2.6%)**
How did they view their performance during the latest earnings call?	
Summarize Spotify's latest conference call	
What opportunities were highlighted during the latest earnings call?	
News	**692 (2.4%)**
What are the latest news relating to TIC?	
What's the top stock market news today?	
What news is coming up this week from the fed?	
Educational information	**485 (1.7%)**
Can earning calls affect stock value?	
What happens if I have to sell the bond before maturity?	
Why is intrinsic value important?	
Industry	**321 (1.1%)**
Show me new defense and technology stocks	
Can you tell me about semiconductor companies that are making AI chips?	
Who are Groupon's competitors? What is the industry competitive landscape?	
General information	**312 (1.1%)**
Tell me about Nvidia	
Are we in an economic recession?	
What are some commodities I can invest in	
Total	**29,242**

Table 10 presents the count and percentage of investor questions posed to Alpha, classified into mutually exclusive information source categories. Each category represents a distinct type of financial information processed, with three representative sample questions provided for illustration.

Appendix A

Variable Definitions

User	Indicator equal to one if respondent has used GenAI to process financial information or inform investment decisions, else zero.
GenAI Frequency	Frequency of using GenAI to process financial information or inform investment decisions with 0 = never, 1 = rarely, 2 = monthly, 3 = weekly, and 4 = daily or more
Sophistication	The number of combined finance and accounting courses taken sorted into terciles with 0 = 0 courses, 1 = 1-3 courses, and 2 = 4 or more courses
Trading Activity	Frequency of buying or selling investments with 0 = never, 1 = rarely, 2 = monthly, 3 = weekly, and 4 = daily or more
Age	Investor age with 0 = 18-24, 1 = 25-34, 2 = 35-44, 3 = 45-54, and 4 = 55 or older