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From Likes to Wallets: Exploring the Relationship Between Social Media and FinTech Usage

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Abstract

This study uses national data to contribute to ongoing discussions regarding social media's role in influencing investors in the digital economy. Grounded in social network theory, social media engagement was examined for its influence on FinTech usage, specifically cryptocurrency investments, mobile trading applications, and financial podcasts. Results showed a significant relationship between social media use for investment decisions and the embrace of FinTech. Individuals who actively engage with social media for this purpose had higher odds of investing in cryptocurrency and a higher likelihood of using both mobile trading applications and financial podcasts. However, these results were not consistent across all platforms amongst social media users. Our findings show that social media platforms enable peer influence and recommendations through networks that shape financial decisions and behaviors. FinTech firms can strategically harness social ties and the inherent information flows within social networks to broaden their reach and impact in the financial services landscape.

Keywords: social media; FinTech; social network theory; cryptocurrency investing; mobile trading apps; financial podcasts

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1. Introduction

The rapid evolution of financial technology (FinTech) has reshaped how individuals interact with financial services, from mobile banking and digital payments to cryptocurrency investing and robo-advisory platforms [1]. At the same time, social media has become an influential medium for financial information exchange, shaping investment decisions, risk perceptions, and overall financial behaviors [2,3]. According to Forbes Advisor [4], 79% of Americans from the Millennial and Gen Z age groups have sought financial advice from social media. Given the growing integration of digital finance and online social networks, it is critical to examine how social media engagement influences FinTech adoption, particularly in cryptocurrency investments and mobile trading applications.

Existing literature suggests that social media is pivotal in financial decision-making by facilitating access to market information, promoting peer-to-peer discussions, and fostering trust in digital financial platforms [4–6]. Platforms like Reddit, Twitter, and Stocktwits are hubs for retail investor discussions, contributing to herd behavior and speculative trading [2]. Additionally, influencers and financial content creators on YouTube, TikTok, and

Instagram have emerged as key sources of financial knowledge, particularly for younger investors with lower levels of financial satisfaction [7]. While some research highlights the democratizing potential of these platforms, concerns persist regarding misinformation, increased financial risk-taking, and the gamification of investing [8].

Despite the growing body of research on the influence of social media on investment behaviors, key gaps remain. First, while prior studies have examined how social media influences stock market participation [8], less attention has been given to how specific platforms shape FinTech adoption, particularly cryptocurrency investments and mobile trading applications. Second, previous studies often focus on high-level social media effects but fail to differentiate between the varying roles that different platforms play in financial decision-making [9]. Social media platforms differ significantly in content type [10], audience engagement, and credibility, making it crucial to examine their distinct impacts on FinTech engagement. Finally, most research on this topic relies on small-scale surveys or experimental studies, limiting generalizability.

As financial markets evolve in a digital-first environment, understanding the intersection of social media and FinTech adoption holds important implications for investors, financial educators, and policymakers. The increasing reliance on social media for financial guidance necessitates greater efforts in digital financial literacy, regulatory oversight, and platform accountability. By shedding light on these dynamics, this study uses national data to inform ongoing discussions on how social media can either empower or mislead investors in the digital economy.

2. Literature Review

2.1. FinTech and Social Media Integration

Although FinTech and social media are frequently praised for democratizing investment access, much of the current literature tends to gloss over some of the deeper challenges this integration presents. While digital platforms have certainly opened doors to broader financial participation [2,6], there is often an assumption that access automatically translates to empowerment. FinTech's rise has fundamentally altered investment planning by democratizing financial tools and enabling broader access to sophisticated investment strategies [11]. The use of social network theory to explain how investment decisions are shaped is helpful, but often does not go far enough in addressing how misinformation spreads or how emotional reactions get amplified through these networks [12]. Research has consistently demonstrated that social media engagement, notably through platforms like Twitter, Reddit, and TikTok, significantly impacts the adoption and utilization of FinTech services, such as cryptocurrency trading, mobile trading applications, and financial podcasts [2,6]. Lee et al. [13] and Hudson et al. [14] further emphasize the dual-edged nature of this interaction, illustrating how peer-driven recommendations and investor sentiment can both empower and mislead investors at different levels. Moreover, studies rarely dig into how different platforms produce different kinds of engagement. A one-size-fits-all approach still dominates despite growing evidence that these differences matter [15]. This literature underscores a clear critical need for enhanced financial literacy among social media users, particularly given the risks associated with misinformation, speculative investing behaviors, and heightened market volatility [6,16].

2.2. Social Media Usage and Cryptocurrency Investing

Social media has become an essential source of financial information, particularly influencing cryptocurrency investment behaviors among retail investors [17]. Prior literature demonstrates that social media platforms, such as Reddit, Twitter, YouTube, and TikTok, significantly impact investor sentiment, trading behaviors, and the overall adoption of

cryptocurrency investments [2,8,9], but often without distinguishing between thoughtful engagement and impulsive reactions to trending content. These platforms serve not only as forums for peer discussions but also as venues for disseminating timely market information and speculative investment advice, fostering both informed decision-making and herd behavior [14,18]. This is particularly concerning for younger or less experienced investors who may rely heavily on "finfluencers" or viral posts for advice—sources that are rarely vetted and often driven by visibility rather than accuracy [7,9]. Although differences between platforms are sometimes mentioned, they are not always explored in depth [2,6]. For instance, Reddit, known for community discussions, influences investors differently compared to platforms like Twitter or Stocktwits, which emphasize quick, sentiment-driven interactions [6,15]. More critically, there is limited discussion of how misinformation, market manipulation, and herd behavior thrive in these spaces [8,13]. The broader infrastructure of social media, including algorithms and monetization incentives—is rarely addressed, even though these factors play a huge role in what information gets amplified. There is a growing need for research that digs deeper into these issues rather than simply documenting trends.

2.3. Social Media, Digital Dissemination of Financial Information (Podcasts), and Mobile Trading Applications

Beyond cryptocurrency investing, social media significantly impacts the broader landscape of digital financial services, including financial podcasts and mobile trading applications. Financial podcasts, which offer in-depth discussions and analyses of market trends, have grown in popularity, driven partly by social media promotion and recommendation [19–21]. Podcasts serve as accessible platforms for financial education [22], often attracting listeners who are actively seeking more detailed financial insights beyond short-form content available on social media [23]. While these tools can offer valuable financial insights, many podcasts operate without oversight and may present one-sided or even misleading views under the guise of education [20–22]. Notably, FinTech industry leaders have used podcasts to engage with investors and raise awareness of its usefulness. For example, Wharton FinTech and Breaking Banks are popular podcasts that have been used to connect with investors while discussing FinTech industry trends and sharing insights [24,25]. This study used podcasts as a proxy for digital engagement.

Digital platforms such as robo-advisors have seen increased usage driven by social media's influence [24]. These platforms appeal particularly to younger investors, offering ease of access, low barriers to entry, and engaging interfaces that sometimes incorporate gamification elements [26]. Social media platforms amplify the visibility and attractiveness of mobile access to financial services, frequently promoting investment apps through influencer marketing, viral trends, and targeted advertising [27]. More work is needed to understand the consequences of this shift toward highly influential, fast-paced investing environments, especially for less experienced or younger users navigating complex markets with limited guidance. This study extends the literature by examining another digital platform with similar characteristics, mobile trading applications, to better understand social media's influence on its use.

2.4. Gaps in the Current Literature

While existing research has extensively covered general aspects of social media's influence on investment behaviors, several gaps remain. Notably, studies rarely provide comprehensive comparisons of how specific platforms uniquely affect the use of podcasts and mobile trading applications. Furthermore, the literature often neglects to investigate how investors with various profiles—such as age, financial literacy, and investment experience—interact with platform-specific engagement patterns.

Understanding the unique characteristics of different social media platforms is crucial because each platform attracts distinct user groups and facilitates specific interaction styles. Reddit and YouTube often foster community-driven discussions and detailed content, appealing to investors seeking comprehensive analyses or peer reviews. Conversely, Twitter, Instagram, and TikTok deliver shorter, trend-driven content that quickly disseminates investment ideas, often appealing to users looking for rapid updates or simplified financial advice [10,18]. Recognizing these distinctions helps stakeholders—from financial service providers to policymakers—better target their communication and intervention strategies, aligning them with specific user needs and behaviors.

2.5. Theoretical Framework and Hypotheses

Social network theory (SNT) is an interdisciplinary framework used to understand the patterns of relationships among individuals, groups, and organizations. It provides a model to explain how people or entities are connected through various types of ties. By using its foundational tool, the sociogram, SNT provides a graphical depiction of social interactions as a structured web of nodes (the individuals or entities) and edges (the connections between them) [26]. These connections can be based on a variety of factors, such as familial relationships, friendship, professional collaboration, information exchange, or shared interests. By examining the structure of these networks, there are identifiable patterns of influence, power, and social dynamics that would otherwise be invisible through traditional analysis.

An important concept within social network theory is the notion of "centrality," which refers to the position of an actor within the network and how much influence they have over the flow of resources, information, or power [28]. The three main types of centralities are degree centrality (how many direct connections an actor has), betweenness centrality (how often an actor lies on the shortest path between two other actors), and closeness centrality (how quickly an actor can reach any other actor in the network) [29]. These metrics allow key players or "hubs" to be identified within a network.

Another key aspect of social network theory is the concept of "weak ties" versus "strong ties." Strong ties are typically characterized by close relationships, such as family or close friends, where there is frequent communication and a high level of trust. Weak ties are more casual relationships that may not involve much communication but can be valuable for spreading information across a broader network and are often the bridge between otherwise disconnected groups, enabling the flow of information and ideas [12,30]. The theoretical underpinnings of SNT, particularly the roles of weak and strong ties in disseminating financial information, highlight how online interactions shape financial decision-making processes [12]. This concept has important implications for understanding how information spreads in communities and organizations.

Networks, though, are rarely static. They change and adapt as individuals form new relationships, encounter new people and entities, or experience shifts in their roles. Social network theory explores the dynamics of network growth and evolution, studying how relationships form, develop, and even dissolve over time. SNT examines various mechanisms of network growth, such as preferential attachment, where new connections are more likely to form with already well-connected individuals, creating an ongoing feedback loop. Recent emergencies are the roles and influences of mass media and social media in bridging ties between nodes or central actors in the sociogram [28,31]. In all, SNT provides an analytical tool for uncovering the intangible structures that shape behavior and influence outcomes.

Core SNT constructs such as tie strength and network structure are operationalized through proxies that capture network dynamics in digital financial communities. Specifi-

cally, reliance on social media platforms for investment decisions captures strong ties which are often associated with close communities where users engage in repeated interactions that support the creation of trust and influence from network members. Conversely, usage across multiple diverse platforms reflects the influence of weak ties that disseminate novel financial information through less frequent or more impersonal interactions. Though we do not model full network structures or centrality, the inclusion of distinct social media platforms allows an approximation of variation in respondents positioning within broader informational ecosystems, access to information sources, and potential exposure to influential nodes. These platforms function as bridging mechanisms that connect otherwise separate communities and amplify influential voices, consistent with how information and influence flow through social networks. By examining both the variety of platforms used and the degree of reliance on social media, this application of SNT provides a theoretically grounded lens for interpreting social influence in the context of digital financial decision-making, capturing how individuals' positions within informal digital networks relate to FinTech adoption behaviors.

Figure 1 illustrates the conceptual model adapted from SNT. Building on this theoretical framework and prior literature, we propose two main hypotheses. First, we hypothesize a positive relationship between relying on social media for information when making investment decisions and FinTech use, specifically cryptocurrency investing, transacting on mobile trading applications, and consuming financial podcasts. Next, among social media users, we hypothesize that users of different platforms relate to each FinTech behavior differently.

H1: *Relying on social media for information when making investment decisions is positively related to investing in cryptocurrency, transacting through mobile trading applications, and consuming financial podcasts.*

H2: *There are differences between social media platforms and cryptocurrency investing, transacting through mobile trading applications, and consuming financial podcasts.*

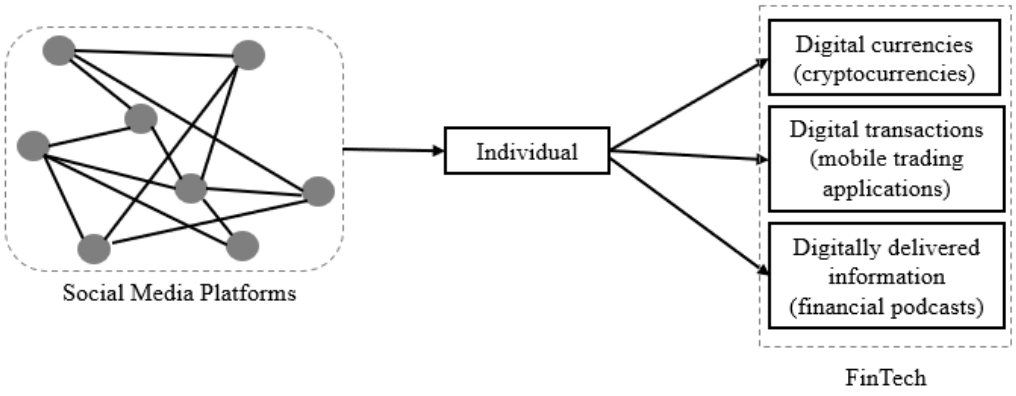


Figure 1. Conceptual model adapted from social network theory [30].

3. Materials and Methods

The 2021 National Financial Capability Study (NFCS) provided the data used in the current study. The NFCS is a national, cross-sectional dataset that has allowed researchers to track trends in the financial decision-making of American adults. It was commissioned by the FINRA Investor Education Foundation and consists of two parts, the State-by-State Survey (NFCS-SS) and the Investor Survey (NFCS-IS). The 2021 NFCS-SS provided questionnaires to 27,118 respondents [32] and was used to provide demographic information for the study. The NFCS-IS focuses specifically on investing behaviors and attitudes and

was administered as a follow-up survey to a subsample of 2824 NFCS-SS respondents who owned investments outside of retirement [33]. This portion of the survey provided data related to the key variables for the study. The structure of NFCS survey questions allowed respondents to choose responses of *prefer not to say* or *do not know* for some survey questions. In line with prior studies that have used the same dataset [34], those responses were treated as missing values given the challenge of inferring an accurate response. Listwise deletion was used to address missing values and maintain consistency across analyses by using the same sample for all estimates. Key variables were tested for significant mean differences to compare them with the full sample including missing values and none were found. The final sample size was 2044.

3.1. Data

Most of the sample were experienced investors, with nearly 69% reporting 10 years or more of investment experience. The sample was also weighted toward White (82%), married (67%), and male (64%) respondents. Forty-two percent were aged 65 or older, with a mix of 41% retired respondents and 38% working full-time. Risk preferences for the sample were spread across *average* (55%), *above average* (29%), and *substantial* (8%) categories. Similarly, the amount of investment assets reported ranged from 29% at the lower end of *less than* USD *50 K* to 26% *above* USD *500 K*. Full sample descriptives are shown in Table 1.

Table 1. Sample descriptives.

	Weighted n *	**%**	**n**	**%**
Investment Experience				
Less than 1 year	93.52	4.58	86	4.21
1 year to less than 2 years	173.66	8.50	155	7.58
2 years to less than 5 years	177.64	8.69	179	8.76
5 years to less than 10 years	229.27	11.22	219	10.71
10 years or more	1369.91	67.02	1405	68.74
Investment Assets				
Less than USD 50 K	610.57	29.87	592	28.96
USD 50 K up to USD 100 K	248.20	12.14	255	12.48
USD 100 K up to USD 500 K	691.45	33.83	674	32.97
USD 500 K up to USD 1 M	235.82	11.54	251	12.28
USD 1 M or more	257.95	12.62	272	13.31
Investment Risk Preference				
Take substantial financial risk	177.54	8.69	171	8.37
Take above average financial risk	554.09	27.11	584	28.57
Take average financial risk	1130.41	55.30	1117	54.65
Not willing to take any financial risk	181.96	8.90	172	8.41
Age				
18 to 24	68.25	3.34	56	2.74
25 to 34	142.98	7.00	143	7.00
35 to 44	272.97	13.35	264	12.92
45 to 54	244.12	11.94	264	12.92
55 to 64	470.74	23.03	463	22.65
65 and older	844.94	41.34	854	41.78
Gender				
Male	1304.92	63.84	1299	63.55
Female	739.08	36.16	745	36.45

Table 1. *Cont.*

	Weighted n *	%	n	%
Ethnicity				
White, non-Hispanic	1527.04	74.71	1683	82.34
Non-White	516.96	25.29	361	17.66
Employment Status				
Self-employed	166.14	8.13	170	8.32
Full-time	759.33	37.15	779	38.11
Part-time	128.12	6.27	132	6.46
Retired	842.43	41.21	835	40.85
Other	147.98	7.24	128	6.26
Marital Status				
Married	1367.23	66.89	1364	66.73
Single	372.42	18.22	365	17.86
Separated/Divorced/Widowed	304.36	14.89	315	15.41
	n	Mean	Std Dev	Min/Max
Objective financial knowledge	2044	4.38	1.41	0/6

Note. n = 2044; * Population weights were applied to reflect national, regional, and state weightings in terms of age, gender, ethnicity, education, and to ensure the results were representative of the broader population.

3.1.1. Dependent Variables

FinTech usage was the focus of the study and was measured across three dimensions: investing in digital currencies, transacting through digital platforms, and the digital delivery of financial information. Each dimension was evaluated independently in three distinct models. Model 1 examined predictors of investing in digital currencies. The dependent variable for Model 1 was cryptocurrency investing. This measure was operationalized with an item asking respondents, "Have you invested in cryptocurrencies, either directly or through a fund that invests in cryptocurrencies?" Binary responses were coded 1—*Yes* or 0—*No*.

Model 2 measured the construct of transacting through digital platforms, with the dependent variable defined as the frequency of placing orders through a mobile trading application. Specifically, responses of, "I place orders through a mobile app" when asked, "How often do you buy or sell investments for your non-retirement accounts in the following ways?" were used to operationalize transacting in digital platforms. Responses were categorized as 1—*Never*, 2—*Sometimes*, and 3—*Frequently*.

Model 3 investigated predictors of digital delivery of financial information, specifically the reliance on podcasts for making investment decisions. Podcasts were defined as digital audio or video programs covering a wide range of topics which can be professionally produced or informally hosted [35,36]. The dependent variable was measured as the level of reliance on podcasts for investment decisions. Respondents categorized their reliance on podcasts as 1—*not at all*, 2—*somewhat*, and 3—*a great deal* when asked the question, "How much do you rely on each of the following when making decisions about what to invest in?". Descriptive information for each dependent variable is included in Table 2.

Table 2. FinTech used for investment transactions and decisions.

	Weighted n *	%	n	%
Digital Currency Investing (Cryptocurrency)				
No	1625.56	79.53	1646	80.53
Yes	418.44	20.47	398	19.47
Mobile Trading Apps				
Never	1344.94	65.80	1378	67.42
Sometimes	359.04	17.57	347	16.98
Frequently	340.02	16.64	319	15.61
Podcasts for Financial Information				
Not at all	1477.38	72.28	1495	73.14
Somewhat	425.25	20.80	411	20.11
A great deal	141.37	6.92	138	6.75

* Population weights were applied to reflect national, regional, and state weightings in terms of age, gender, ethnicity, education, and to ensure the results were representative of the broader population.

3.1.2. Independent Variables

The key independent variables for each model were defined as follows: (1) the reliance on social media for investment decisions, and (2) the usage of various social media platforms for financial information. The use of social media platforms for financial information was measured with the prompt asking respondents, "Which, if any, of the following do you use for information about investing?". Each social media platform was coded with a dichotomous response of 1—*Yes* or 0—*No*. The complete list of each type of social media platform included in the models is detailed in Table 3.

Table 3. Key independent variables.

	Weighted n *	%	n	%
Social Media Groups Used for Investment Decisions				
Not at all	1628.17	79.66	1653	80.87
Somewhat	305.40	14.94	285	13.94
A great deal	110.44	5.40	106	5.19
Social Media Platforms Used for Investing Information				
YouTube	407.50	19.94	374	18.30
Facebook	215.28	10.53	203	9.93
Reddit	214.44	10.49	197	9.64
Twitter	201.88	9.88	189	9.25
LinkedIn	185.34	9.07	170	8.32
Instagram	171.76	8.40	152	7.44
Stocktwits	115.14	5.63	104	5.09
TikTok	103.57	5.07	99	4.84

Note. n = 2044; * Population weights were applied to reflect national, regional, and state weightings in terms of age, gender, ethnicity, education, and to ensure the results were representative of the broader population.

Reliance on social media for investment decisions was operationalized with the question, "How much do you rely on each of the following when making decisions about what to invest in?" and the response chosen was "social media groups or message boards where people post investment ideas". Responses were categorized as 1—*not at all*, 2—*somewhat*, and 3—*a great deal*.

Table 4 presents a correlation matrix for the social media platforms used as independent variables in each of the three analytic models. Spearman's rank order correlation was used due to the non-linear nature of each measure [37,38]. Results showed that most variables had low to moderate correlations ranging from 0.25 to 0.64 [39].

Table 4. Spearman's rank order correlation matrix.

	1	2	3	4	5	6	7	8
1. YouTube	1.00							
2. Facebook	0.51 ***	1.00						
3. Reddit	0.42 ***	0.35 ***	1.00					
4. TikTok	0.38 ***	0.44 ***	0.34 ***	1.00				
5. Instagram	0.48 ***	0.62 ***	0.34 ***	0.59 ***	1.00			
6. Twitter	0.47 ***	0.53 ***	0.43 ***	0.49 ***	0.64 ***	1.00		
7. LinkedIn	0.41 ***	0.42 ***	0.31 ***	0.39 ***	0.45 ***	0.42 ***	1.00	
8. Stocktwits	0.25 ***	0.30 ***	0.33 ***	0.26 ***	0.29 ***	0.32 ***	0.33 ***	1.00

Note. n = 2044; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5 includes descriptions for each of the study's control variables. Each model included control variables for demographic measures, such as age, gender, race, marital status, education, and employment status [40,41]. Prior research also supported controlling for the following variables: financial knowledge [42], investment experience, investment assets, and investment risk preference [25,43,44].

Table 5. Control variable measurements.

Variable	Measurement
Age	18–24, 25–34, 35–44, 45–54, 55–64, 65 and older
Gender	Male, female
Race	White non-Hispanic, non-White
Marital status	Married, single, separated/divorced/widowed
Education	HS or less, some college, associate's, bachelor's, post-graduate
Employment status	Self-employed, full-time, part-time, retired, other *
Objective financial knowledge	
Interest	(1) Suppose you had USD 100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?
Inflation	(2) Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account?
Bond pricing	(3) If interest rates rise, what will typically happen to bond prices?
Compounding	(4) Suppose you owe USD 1000 on a loan and the interest rate you are charged is 20% per year compounded annually. If you did not pay anything off, at this interest rate, how many years would it take for the amount you owe to double?
Mortgage	(5) A 15-year mortgage typically requires higher monthly payments than a 30-year mortgage, but the total interest paid over the life of the loan will be less.
Portfolio risk	(6) Buying a single company's stock usually provides a safer return than a stock mutual fund.
Investment experience	Less than a year ago, 1 year to less than 2 years ago, 2 years to less than 5 years ago, 5 years to less than 10 years ago, 10 years ago or more
Investment assets	Less than USD 50 K, USD 50 K up to USD 100 K, USD 100 K up to USD 500 K, USD 500 K up to USD 1 M, USD 1 M or more
Investment risk preference	Substantial financial risks, above average financial risks, average financial risks, not willing to take any financial risks

Note. * Other = student, homemaker, disabled, and unemployed.

Objective financial knowledge was included as a control variable due to its influence on investment decisions [45] and transacting in digital platforms [25]. In line with the guidance around two levels of financial knowledge in the literature—basic and sophisticated [46], this study focused on measuring basic financial knowledge as it is sufficient to influence the adoption and use of financial technologies [3,47]. Objective financial knowledge was measured with a variable comprising six financial literacy questions to gauge basic financial knowledge [25,48]. The questions assess knowledge of concepts such as compound interest, inflation, and bond pricing. Correct responses were summed to form a scaled variable, which ranged from 0 to 6 (n = 2044, M = 4.38, SD = 1.41). Responses of *do not know* and *prefer not to say* were treated as incorrect responses [34]. Reliability analysis for the financial knowledge scale resulted in a Cronbach's alpha of 0.62. Although this value is modest, it aligns with levels deemed acceptable in prior studies using this measure from the NFCS dataset [25,49,50].

In addition to objective financial knowledge, investment experience was used as a proxy for financial literacy which has been found to influence factors such as risk behaviors [24,44]. Social media was also found to mediate the relationship between financial literacy and financial behaviors [25], highlighting its significance as a control variable in this study's models. The question asking respondents, "when did you first start investing in non-retirement assets?", was used to measure investment experience. Responses were categorized as 1—*less than a year ago*, 2—*1 year to less than 2 years ago*, 3—*2 years to less than 5 years ago*, 4—*5 years to less than 10 years ago*, and 5—*10 years ago or more*.

Other control variables included were amount of investment assets owned and investment risk preference [25,26]. Investment assets were measured with the question that asked respondents, "What is the approximate total value of all of your investments in non-retirement accounts?". Responses were categorized and coded into five categories, as outlined in Table 5. Investment risk preferences were measured with the question asking respondents, "Which of the following statements comes closest to describing the amount of financial risk that you are willing to take when you save or make investments?". Categorical responses ranged from 1—*take substantial risk expecting to earn substantial returns* to 4—*not willing to take any risks*. Full descriptions of control variable measurements are outlined in Table 5.

3.2. Methods

Analyses were conducted in two stages for each model. The first stage explored the use of social media for investment decisions and its relationship with the study's dependent variables. The second stage of each model focused on a sample of social media users only and investigated the association between various types of social media platforms used for financial information. This approach first considered the broader role of social media usage for investment decisions and then extended the analysis to examine the source of financial information on FinTech usage. Population weights were applied to reflect national, regional, and state weightings in terms of age, gender, ethnicity, education, and to ensure the results were representative of the broader population [51].

Model 1 included two binary logistic regression models to investigate the relationship between the use of social media platforms for investment decisions and cryptocurrency investing. Binary logistic regression was appropriate due to the dichotomous nature of the model's dependent variable, cryptocurrency investing [52]. Models 2 and 3 used multinomial logistic regression to reflect the categorical nature of their dependent variables [53,54]. In line with this methodology, results were reported as relative risk ratios. Model 2 focused on transacting in digital platforms, while Model 3 examined the digital delivery of financial information—proxied with mobile trading applications and financial podcasts, respectively.

4. Results

4.1. Investing in Digital Currencies

Table 6 presents a summary of Model 1 results, which examined the relationship between reliance on social media for investment decisions, and the use of various social media platforms for financial information, on the dependent variable, cryptocurrency investing. Findings showed that investors who reported using social media for investment decisions (OR = 2.45, $p < 0.001$) had 2.45 times higher odds of investing in cryptocurrency compared to those who do not use social media for investment decisions. However, when the sample was limited to social media users only, users of the Reddit platform (OR = 0.58, $p < 0.01$) were the lone significant group associated with cryptocurrency investing. Interestingly, Reddit users had 42% lower odds of investing in cryptocurrencies than non-users of this platform.

Table 6. Model 1—summary weighted logistic regression results: the effect of social media use on digital currency investing.

		Cryptocurrency Investing		
	n	**β (SE)**	**OR**	**95% CI**
Social media—Investment Decisions	2044	0.88 (0.14) ***	2.45	[1.85, 3.24]
		Social Media Users Only		
Social media—Financial Information				
YouTube	391	−0.54 (0.28)	0.58	[0.33, 1.02]
Facebook	391	−0.26 (0.32)	0.77	[0.42, 1.43]
Reddit	391	−0.54 (0.27) *	0.58	[0.34, 0.99]
TikTok	391	−0.19 (0.37)	0.83	[0.40, 1.70]
Instagram	391	0.08 (0.38)	1.08	[0.52, 2.27]
Twitter	391	−0.52 (0.31)	0.60	[0.32, 1.10]
LinkedIn	391	−0.25 (0.32)	0.78	[0.42, 1.45]
Stocktwits	391	−0.21 (0.34)	0.81	[0.42, 1.58]

Note. OR = odds ratio; CI = confidence intervals; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Relative to respondents with extensive investment experience—*10 years or more*—those with less than 2 years of investment experience had higher odds of investing in cryptocurrency. In the logit model with the sample limited to social media users, only the category of *1 to 2 years* of investment experience had significantly higher odds relative to the most experienced group. In contrast, when compared to investors with investment assets *under* USD *50 K*, those with investment assets in the categories of USD *50 K to* USD *100 K*, USD *500 K to* USD 1 M, and USD 1 M *or more* had lower odds of investing in cryptocurrency, suggesting wealthier individuals may not be as attracted to digital currencies as those with lower levels of wealth. When the sample was limited to social media users only, there were no significant relationships found between the amount of investment assets and cryptocurrency investing. Investors who reported risk preferences of *substantial* and *above average* financial risks showed higher odds of investing in cryptocurrency compared to respondents who were willing to accept an *average* level of financial risk in both models. Not surprisingly, all age categories had higher odds of investing in cryptocurrencies when compared to retirees, *age 65 and older,* although age was not a significant factor when the sample was limited to social media users only. Lastly, female respondents had lower odds of investing in cryptocurrency than male. Full results are shown in Appendix A.

4.2. Transacting Through Digital Platforms

Model 2 examined the relationship between the use of social media platforms for financial information, relying on social media for investment decisions, and the dependent variable, mobile trading applications. Mobile trading applications were used as a proxy for the 'transacting in digital platforms' component of FinTech.

4.2.1. Mobile Trading Applications and Social Media for Information

In Model 2a, the relationship between relying on social media for investment decisions and the use of mobile trading applications was examined. Results showed that compared to respondents who report never using mobile trading apps, those who use social media for investment decisions had a higher likelihood of executing trades in a mobile trading platform *frequently* (RRR = 3.19, $p < 0.001$) or even *sometimes* (RRR = 2.62, $p < 0.001$). In other words, individuals who use social media for investment decisions are 3.19 times more likely to frequently use a mobile trading app and 2.62 times more likely to *sometimes* use one, compared to those who *never* use a mobile trading app, all else being equal. Summary results are included in Table 7.

Table 7. Multinomial logistic regression analysis examining the association between social media use for investment decisions and FinTech transactions and information dissemination—Models 2a and 3a.

	Mobile Trading Apps				**Financial Podcasts**		
	β (SE)	RRR	95% CI		β (SE)	RRR	95% CI
Never (ref category)				Not at all (ref category)			
Sometimes				Somewhat			
Social media	0.96 (0.19) ***	2.62	[1.79, 3.82]	Social media	1.48 (0.18) ***	4.37	[3.08, 6.22]
Frequently				A great deal			
Social media	1.15 (0.20) ***	3.19	[2.17, 4.68]	Social media	1.48 (0.18) ***	4.37	[3.08, 6.22]

Note. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Newer investors, those with less than 2 years of experience, were more likely to *sometimes* use mobile trading applications, relative to experienced investors with *10 years or more* of investment experience. Notably, all levels of investment experience up to 10 years were more likely to *frequently* use mobile trading apps relative to the same group of experienced investors. Relative to respondents willing to take an *average* level of financial risk, those willing to take *substantial* or *above-average* financial risk had a higher likelihood of *frequently* using a mobile trading app, whereas those *not willing to take financial risk* had a lower likelihood. Infrequent users of mobile trading apps had similar results, except the *substantial* financial risk preference category which was not significant in the model. The frequency of using mobile trading applications mattered with regard to the level of investment assets a respondent owned. For frequent users of mobile trading apps, all asset levels above USD 100 K had a significantly lower likelihood of trading in mobile applications compared to those with assets below USD 50 K. In contrast, for infrequent users or those who report using mobile trading apps sometimes, the category of investment assets between USD *50 K and* USD *100 K* was the only significant category showing a lower likelihood of using a mobile trading app compared to those with assets *below* USD *50 K*.

Non-white respondents had a higher likelihood of using mobile trading apps, relative to White respondents, no matter the frequency. Relative to respondents aged *65 and older*, all age categories were more likely to transact in mobile trading apps, with the only exception in the *55 to 64* age category. Investors in that age group did not show a significant relationship with frequently trading in mobile apps relative to those age *65 and older.*

4.2.2. Mobile Trading Applications and Social Media for Investment Decisions

Model 2b extended the initial analysis to examine the relationship between various social media platforms used for financial information and the use of mobile trading applications. Results indicated that Twitter users (RRR = 0.40, $p < 0.05$) were less likely to *frequently* use mobile trading apps, compared to respondents who reported *never* using them. Stocktwits users (RRR = 0.34, $p < 0.001$) were also significantly less likely to *sometimes* use mobile trading apps, relative to non-users. In other words, investors who use these social media platforms are less likely to engage with mobile trading apps *frequently* (Twitter) or even *sometimes* (Stocktwits) compared to those who never use them. Summary results are shown in Table 8.

Table 8. Summary results for multinomial logistic regression analysis of social media platforms in FinTech transactions and information delivery among social media users—Models 2b and 3b.

	Mobile Trading Apps				**Financial Podcasts**		
	β (SE)	RRR	95% CI		β (SE)	RRR	95% CI
Never (ref category)				Not at all (ref category)			
Sometimes				Somewhat			
Social Media Platforms Used for Financial Information				Social Media Platforms Used for Financial Information			
YouTube	−0.39 (0.39)	0.68	[0.32, 1.44]	YouTube	−0.78 (0.32) **	0.46	[0.24, 0.86]
Facebook	−0.06 (0.47)	0.94	[0.38, 2.37]	Facebook	0.01 (0.38)	1.01	[0.48, 2.12]
Reddit	0.44 (0.40)	1.55	[0.71, 3.37]	Reddit	0.23 (0.33)	1.25	[0.66, 2.38]
TikTok	−0.00 (0.62)	1.00	[0.30, 3.33]	TikTok	0.28 (0.50)	1.32	[0.49, 3.54]
Instagram	−1.20 (0.51)	0.30	[0.09, 1.00]	Instagram	−1.01 (0.52)	0.36	[0.13, 1.01]
Twitter	−0.57 (0.48)	0.57	[0.22, 1.45]	Twitter	−0.27 (0.37)	0.76	[0.37, 1.58]
LinkedIn	−0.11 (0.48)	0.89	[0.35, 2.31]	LinkedIn	0.39 (0.39)	1.48	[0.69, 3.15]
Stocktwits	−1.09 (0.55) *	0.34	[0.11, 0.98]	Stocktwits	−0.45 (0.43)	0.64	[0.28, 1.48]
Frequently				A great deal			
Social Media Platforms Used for Financial Information				Social Media Platforms Used for Financial Information			
YouTube	−0.66 (0.37)	0.52	[0.25, 1.07]	YouTube	−0.33 (0.42)	0.72	[0.32, 1.65]
Facebook	−0.33 (0.45)	0.72	[0.30, 1.72]	Facebook	−0.48 (0.46)	0.62	[0.25, 1.53]
Reddit	0.09 (0.38)	1.10	[0.52, 2.30]	Reddit	0.20 (0.40)	1.22	[0.55, 2.70]
TikTok	−0.10 (0.59)	0.91	[0.29, 2.87]	TikTok	−0.51 (0.54)	0.60	[0.21, 1.74]
Instagram	−0.29 (0.60)	0.75	[0.23, 2.42]	Instagram	−2.04 (0.59) **	0.13	[0.04, 0.41]
Twitter	−0.91 (0.46) *	0.40	[0.16, 0.99]	Twitter	0.36 (0.47)	1.44	[0.57, 3.63]
LinkedIn	−0.27 (0.48)	0.76	[0.30, 1.94]	LinkedIn	0.81 (0.47)	2.25	[0.90, 5.62]
Stocktwits	−0.62 (0.55)	0.54	[0.18, 1.58]	Stocktwits	−0.42 (0.51)	0.66	[0.24, 1.78]

Note. RRR = relative risk ratio; SE = robust standard error; CI = confidence intervals; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Less experienced investors, specifically those with less than 2 years of investment experience, had significantly higher likelihood of using mobile trading apps, relative to investors with more than 10 years of investment experience, no matter the frequency of use. Model 2b's findings related to risk preferences were consistent with findings in Model 2a. Relative to respondents willing to take an *average* level of financial risk, those willing to take substantial or *above-average* financial risk had a higher likelihood of *frequently* using a mobile trading app, whereas those *not willing to take financial risk* had a lower likelihood. Infrequent users of mobile trading apps had similar results, except the *substantial* financial risk preference category was not significant in the model. Investors with assets in the $500 K to $1 M range were less likely to report using mobile trading apps, than those who *never* use them, no matter the frequency. Full results for Models 2a and 2b are shown in Appendix B.

4.3. Digital Dissemination of Financial Information

Model 3 examined the relationship between the use of various social media platforms for financial information, and relying on social media for investment decisions, with the dependent variable, use of podcasts for financial information. Financial podcasts, a digital audio or visual medium that contains information on a range of financial topics, were used as a proxy for the 'digital delivery of financial information' component of FinTech. Podcast content and social media use, which captures interactions across social networks, were examined to better understand their impact on financial decisions.

4.3.1. Reliance on Financial Podcasts and Social Media for Information

Model 3a focused on financial podcasts for investment guidance to consider its relationship with social media used for investment decisions. Findings showed that when compared to respondents who do not use financial podcasts at all, users of social media for investment decisions have a higher likelihood of relying on financial podcasts for investment decisions. Specifically, those who use social media in this capacity had 4.4 times higher likelihood (RRR = 4.37, $p < 0.001$) of *somewhat* relying on financial podcasts and 9.2 times higher likelihood (RRR = 9.24, $p < 0.001$) of relying on it *a great deal*. Summary results are shown in Table 7.

Respondents with investment risk preferences of *above average* and *substantial* had a higher likelihood of using financial podcasts *a great deal*, relative to those with an average investment risk preference. Those who were not willing to take investment risk had a lower likelihood of *somewhat* relying on financial podcasts, relative to the same group. Investors who are more comfortable with investment risk tolerance also appear more comfortable with digitally sourced financial information. Interestingly, financial knowledge was found to be associated with a lower likelihood of using financial podcasts *a great deal*, specifically, for each one-unit increase in objective financial knowledge, the likelihood of using financial podcasts was 19% lower.

Younger adults, aged *18 to 24* and *25 to 34*, were more likely to rely *a great deal* or *somewhat*, respectively, on financial podcasts compared to those aged *over 65*. Among those who worked *full-time* compared to *retired* respondents, there was a higher likelihood of periodically using financial podcasts for investment guidance. Additionally, *non-white* investors also showed a higher tendency to sometimes use this resource. Full results can be found in Appendix C.

4.3.2. Reliance on Financial Podcasts and Various Social Media Platforms for Investment Decisions

Model 3b extended the above analysis by limiting the sample to social media users and examining the relationship between various social media platforms used for financial information and financial podcasts as a source of investment guidance. Surprisingly, the findings showed that YouTube users (RRR = 0.46, $p < 0.01$) had a lower likelihood of periodically relying on financial podcasts, relative to those who do not use financial podcasts at all. Instagram users (RRR = 0.13, $p < 0.01$) also had a lower likelihood of *frequently* using financial podcasts, relative to non-users. Summary results are shown in Table 8.

Respondents with investment assets in the USD *100 K to* USD *500 K* category had a higher likelihood of using financial podcasts, relative to those with assets *less than* USD *50 K*. Investors who are unwilling to take investment risks had a lower likelihood of relying on financial podcasts while those comfortable with *substantial* investment risk preferences had a higher likelihood of using financial podcasts, relative to those who reported an *average* risk preference. Self-employed and non-white respondents had a higher likelihood of *somewhat*

relying on financial podcasts, relative to retired and white respondents, respectively. Full results are included in Appendix C.

5. Discussion

This study provides empirical support for a significant relationship between social media use for information regarding investment decisions and the adoption of FinTech. Individuals who actively engage with social media for this purpose had higher odds of investing in cryptocurrency and a higher likelihood of using both mobile trading applications and financial podcasts. These findings support H_1 and align with earlier research that examined FinTech options individually [2,25]. However, these results did not apply across all platforms studied. When the sample was limited to social media users only, interesting dynamics were uncovered. For example, Reddit users were the only social media group with a significant relationship to cryptocurrency investing and were found to have lower odds of investing in that asset class, compared to non-users of that platform. Similarly, Twitter and Stocktwits users showed a lower likelihood of engagement with mobile trading applications while users of YouTube and Instagram platforms were less likely to rely on financial podcasts for investment guidance. The limited number of platforms showing a significant relationship with financial podcasts was unexpected given the significant relationship between social media use for financial topics in the first stage of Model 3. Furthermore, the lower likelihood of usage was also a surprise. This finding can be best explained by the sample studied in this model. The focus on social media users only likely highlights the differences between users of the various social media platforms. Taken together, these results support H_2 which predicted differences between social media platforms and each of the FinTech behaviors.

5.1. Theoretical Contributions

Grounded in social network theory (SNT), this study offers several key theoretical contributions. First, SNT provided a theoretical framework for understanding, and even visualizing, these relationships [27]. Key aspects of SNT, such as "weak ties" and "strong ties", help explain the flow of financial information through socialization platforms like social media, as well as how those ties may influence behaviors [12,30]. Although the data used in this study does not allow for distinctions between strong and weak ties, it does provide enough information to test for relationships, or networks. Our findings show that social media platforms enable peer influence and recommendations through these networks that shape financial decisions and behaviors. This dynamic positions FinTech firms to leverage social ties and information flow inherent in social networks and expand the financial services landscape to include a broader economic demographic.

Second, the distinctions among users of various social media platforms are novel contributions to the growing literature on FinTech usage in the personal finance domain. These findings suggest that users of social media platforms are not monolithic. Those who prefer platforms that allow them to join communities, like subreddits, may reflect differences in the type of information sought or browsing habits. Platforms that cater to 'followers' or are structured to allow users to track the postings or information shared by individuals may attract users most interested in seeking information from those they feel in relationship with, albeit distant or indirect. Lastly, by extending SNT to newer forms of financial information dissemination (e.g., podcasts), this study encourages scholars to explore how network theory applies beyond person-to-person connections to encompass algorithmic curation and influencer-driven communication. Further research focused on understanding preferences and demographics of various social media platforms is warranted.

5.2. Practical and Managerial Implications

From a practical standpoint, these findings carry important implications for FinTech firms, financial educators, and policymakers.

For FinTech Firms, the findings highlight the strategic advantage of leveraging social media engagement as a customer acquisition tool. FinTech firms can optimize marketing strategies by tailoring content and outreach to platform-specific behaviors. For example, platforms like Reddit, where users appear more skeptical of cryptocurrency, may be better suited for promoting education-focused content, whereas platforms like TikTok or YouTube might be more effective for highlighting mobile-friendly applications and gamified investing experiences. Moreover, understanding the demographic and behavioral characteristics of digital investors allows for more personalized product development. For instance, younger investors with high risk tolerance and lower wealth levels are more inclined toward mobile trading apps and cryptocurrency, suggesting a need for user interfaces and risk disclosures tailored to that segment. For financial educators, the findings emphasize the need for targeted digital financial literacy campaigns. Educators should prioritize teaching digital natives how to critically assess financial content on social media, differentiate between credible and misleading information, and evaluate risk–return trade-offs in digital assets. Additionally, financial podcasts and mobile trading platforms are increasingly being used as self-directed learning tools. Educators can partner with these mediums to deliver reliable and engaging content, helping bridge the gap between education and action.

Policymakers and regulators should be more aware of the influence of unregulated financial advice on social media that raises concerns around consumer protection, especially among younger or less experienced investors. Regulators may consider requiring clearer disclaimers, transparency of affiliations, or vetting of "finfluencers" providing investment guidance. There is also a growing need for oversight mechanisms specific to FinTech platforms that are popularized through social media. Regulatory frameworks must evolve to ensure that the rapid adoption of FinTech does not outpace the safeguards designed to protect retail investors.

Investors seem most comfortable investing in digital currencies and using digital platforms for financial transactions, both across the broader sample and amongst social media users in today's rapidly evolving digital economy. In contrast, the mass affluent, defined as those with investment assets in the USD 100 K to USD 1 M range [55], are reluctant to engage in transactions on digital platforms. Younger investors and those with higher risk preferences, however, appear comfortable leveraging FinTech to navigate the new digital landscape of personal finance. These findings appear in line with prior research that linked higher risk preferences with cryptocurrency investing [2]. It is important for financial professionals and policymakers to understand demographic differences for FinTech preferences so that products are appropriately targeted to those with the best fit for their benefits and risks while protections are in place for groups found to be vulnerable to mismatches. For example, women are less likely to invest in digital currencies, potentially due to barriers such as higher risk aversion or lower financial literacy levels. But as digital assets become more mainstream, this reluctance could place them on the wrong side of the digital wealth divide and susceptible to fraud and misinformation. Policymakers need to be alert and proactive with protections for users of social media platforms who may transact outside of regulated environments and consume unregulated financial information.

5.3. Limitations and Future Research Directions

There are several limitations to be noted. First, this study uses cross-sectional data from the 2021 National Financial Capability Study (NFCS), which allows associations between variables to be observed, but limits the ability to draw causal inferences. While

we find statistically significant links between social media use and various FinTech behaviors, the cross-sectional design does not allow us to determine the directionality of these relationships or to account for potential feedback effects, for instance, whether FinTech usage itself may influence how individuals engage with social media. Furthermore, the use of secondary data constrains the study through sampling, existing variables, and survey design. Data skews towards married, older, White men with at least five years of investment experience, which may introduce bias into the findings and reduce generalizability. The use of listwise deletion to handle missing data may reduce generalizability of the study's results if missing data is not completely random. Similarly, secondary data restricts the authors' ability to capture and explore detailed nuances between the various social media platforms included in the study. Second, the analysis primarily focuses on just a few aspects of FinTech and does not encompass a comprehensive range of available FinTech options. Therefore, findings may not be generalizable to all FinTech products and services. Third, the study includes measures, such as objective financial knowledge and investment experience, meant to serve as proxies for financial literacy but it does not offer an in-depth examination of how literacy may moderate the relationship between social media use and investment behavior. This is noteworthy given potential misinformation on social media platforms. Finally, the study treats all cryptocurrencies as a homogenous group, without distinguishing between the various types or characteristics of digital currencies. Important nuances and variations within the cryptocurrency market may be overlooked.

Future research could address these limitations by using longitudinal data in the analyses, considering an expanded scope of FinTech options, and exploring other digital assets. Such studies would enable researchers to examine temporal ordering and better test for causal mechanisms. Incorporating such designs would enhance our understanding of how digital financial behavior and social media engagement influence each other over time. Future research should further investigate factors driving the relationship between social media users and FinTech adoption, with a particular focus on financial literacy levels among different user groups. Exploring trust and credibility perceptions of content on social media compared to traditional FinTech platforms could yield valuable insights into investor decision-making processes. Additionally, future studies should examine algorithms, financial content format, and preferences across social media and FinTech platforms, such as news, advice, and investment tips. Further insights from various platforms will allow us to better understand how these preferences shape investors' behavior and engagement. Such research could also benefit from incorporating longitudinal studies or broader datasets to enhance generalizability and inform targeted policy and educational interventions.

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Appendix A

Table A1. Model 1a—weighted logistic regression results: the association between social media use and digital currency investing.

	Cryptocurrency Investing		
	β (SE)	**OR**	**95% CI**
Social media	0.88 (0.14) ***	2.45	[1.85, 3.24]
Investment Exp (ref 10 yr+)			
Less than 1 yr	0.46 (0.36)	1.59	[0.78, 3.22]
1 yr to less than 2 yr	1.02 (0.28) ***	2.79	[1.61, 4.82]
2 yr to less than 5 yr	0.42 (0.27)	1.52	[0.90, 2.56]
5 yr to less than 10 yr	0.18 (0.24)	1.20	[0.74, 1.93]
Age (ref aged 65+)			
18 to 24	1.48 (0.51) **	4.41	[1.61, 12.06]
25 to 34	1.27 (0.40) **	3.57	[1.63, 7.81]
35 to 44	1.21 (0.36) **	3.36	[1.67, 6.76]
45 to 54	1.33 (0.33) ***	3.78	[2.00, 7.17]
55 to 64	0.84 (0.29) **	2.31	[1.30, 4.10]
Investment Assets (ref less than USD 50 K)			
USD 50 K up to USD 100 K	−0.73 (0.25) **	0.48	[0.29, 0.79]
USD 100 K up to USD 500 K	−0.07 (0.21)	0.93	[0.61, 1.41]
USD 500 K up to USD 1 M	−0.78 (0.30) **	0.46	[0.26, 0.83]
USD 1 M or more	−0.62 (0.35)	0.54	[0.27, 1.08]
Investment Risk Preference (ref Average Risk)			
Take substantial risk	1.04 (0.26) ***	2.83	[1.70, 4.72]
Take above average risk	0.57 (0.18) **	1.78	[1.24, 2.53]
Not willing to take risk	−0.64 (0.35)	0.52	[0.27, 1.03]
Obj financial knowledge	−0.00 (0.06)	1.00	[0.89, 1.12]
Gender (ref Male)			
Female	−0.98 (0.20) ***	0.38	[0.25, 0.56]
Ethnicity (ref White non-Hispanic)			
Non-White	−0.11 (0.19)	0.90	[0.61, 1.32]
Employment (ref Retired)			
Self-employed	0.68 (0.34) *	1.98	[1.03, 3.82]
Full-time	0.28 (0.28)	1.32	[0.76, 2.29]
Part-time	−0.46 (0.41)	0.63	[0.28, 1.42]
Other $^{+}$	0.63 (0.38)	1.88	[0.89, 3.98]
Marital Status (ref Married)			
Single	0.19 (0.21)	1.21	[0.80, 1.83]
Separated/Divorced	0.35 (0.25)	1.42	[0.88, 2.29]
N	2044		
Log likelihood	−686.610		
Chi-square	340.76 ***		
Pseudo R^2	0.298		

Note. OR = odds ratio; CI = confidence intervals; $^{+}$ Other = student, homemaker, disabled, and unemployed; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A2. Model 1b—weighted logistic regression results: the relationship between various social media platforms and cryptocurrency investing for social media users.

	Cryptocurrency Investing		
	β (SE)	**OR**	**95% CI**
Social Media Platforms			
YouTube	−0.54 (0.28)	0.58	[0.33, 1.02]
Facebook	−0.26 (0.32)	0.77	[0.42, 1.43]
Reddit	−0.54 (0.27) *	0.58	[0.34, 0.99]
TikTok	−0.19 (0.37)	0.83	[0.40, 1.70]
Instagram	0.08 (0.38)	1.08	[0.52, 2.27]
Twitter	−0.52 (0.31)	0.60	[0.32, 1.10]
LinkedIn	−0.25 (0.32)	0.78	[0.42, 1.45]
Stocktwits	−0.21 (0.34)	0.81	[0.42, 1.58]
Investment Exp (ref 10 yr+)			
Less than 1 yr	1.26 (0.52) *	3.52	[1.27, 9.80]
1 yr to less than 2 yr	1.18 (0.45) **	3.26	[1.35, 7.86]
2 yr to less than 5 yr	0.31 (0.40)	1.37	[0.63, 2.97]
5 yr to less than 10 yr	0.29 (0.41)	1.34	[0.60, 3.00]
Age (ref aged 65+)			
18 to 24	0.29 (0.97)	1.33	[0.20, 8.86]
25 to 34	0.05 (0.89)	1.05	[0.18, 6.06]
35 to 44	0.38 (0.87)	1.46	[0.27, 8.01]
45 to 54	0.45 (0.86)	1.57	[0.29, 8.51]
55 to 64	0.28 (0.83)	1.32	[0.26, 6.78]
Investment Assets (ref less than USD 50 K)			
USD 50 K up to USD 100 K	−0.16 (0.40)	0.86	[0.39, 1.86]
USD 00 K up to USD 500 K	0.10 (0.33)	1.10	[0.58, 2.10]
USD 500 K up to USD 1 M	−0.25 (0.56)	0.78	[0.26, 2.32]
USD 1 M or more	−1.60 (1.02)	0.20	[0.03, 1.50]
Investment Risk Preference (ref Average Risk)			
Take substantial risk	1.17 (0.37) **	3.24	[1.56, 6.71]
Take above average risk	1.07 (0.29) ***	2.90	[1.63, 5.17]
Not willing to take risk	0.96 (0.60)	2.62	[0.80, 8.58]
Obj financial knowledge	0.17 (0.09)	1.18	[0.98, 1.42]
Gender (ref Male)			
Female	−1.08 (0.30) ***	0.34	[0.19, 0.62]
Ethnicity (ref White non-Hispanic)			
Non-White	−0.29 (0.30)	0.75	[0.42, 1.33]
Employment (ref Retired)			
Self-employed	0.42 (0.83)	1.52	[0.30, 7.78]
Full-time	0.46 (0.78)	1.59	[0.34, 7.34]
Part-time	0.13 (0.89)	1.14	[0.20, 6.54]
Other +	1.18 (0.88)	3.24	[0.58, 18.14]
Marital Status (ref Married)			
Single	0.18 (0.34)	1.20	[0.61, 2.36]
Separated/Divorced	0.51 (0.50)	1.67	[0.63, 4.47]
N	391		
Log pseudo-likelihood	−212.49		
Chi-square	115.71 ***		
Pseudo R^2	0.214		

Note. OR = odds ratio; CI = confidence intervals; + Other = student, homemaker, disabled, and unemployed; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Appendix B

Table A3. Model 2a—multinomial logistic regression results: the association between social media and digital transactions—mobile trading applications.

	Mobile Trading Apps		
	β (SE)	**RRR**	**95% CI**
Never (ref category)			
Sometimes			
Social media	0.96 (0.19) ***	2.62	[1.79, 3.82]
Investment Exp (ref 10 yr+)			
Less than 1 yr	1.05 (0.40) **	2.85	[1.30, 6.27]
1 yr to less than 2 yr	1.03 (0.34) **	2.79	[1.43, 5.46]
2 yr to less than 5 yr	0.39 (0.27)	1.48	[0.88, 2.49]
5 yr to less than 10 yr	−0.10 (0.25)	0.90	[0.55, 1.49]
Age (ref aged 65+)			
18 to 24	1.33 (0.57) *	3.79	[1.23, 11.67]
25 to 34	1.73 (0.40) ***	5.63	[2.56, 12.37]
35 to 44	1.54 (0.33) ***	4.67	[2.43, 8.99]
45 to 54	1.31 (0.30) ***	3.71	[2.08, 6.64]
55 to 64	0.60 (0.26) *	1.83	[1.10, 3.05]
Investment Assets (ref less than USD 50 K)			
USD 50 K up to USD 100 K	−0.63 (0.28) *	0.53	[0.31, 0.92]
USD 100 K up to USD 500 K	−0.23 (0.20)	0.80	[0.54, 1.17]
USD 500 K up to USD 1 M	−0.61 (0.32)	0.55	[0.29, 1.01]
USD 1 M or more	−0.36 (0.31)	0.70	[0.38, 1.27]
Investment Risk Preference (ref Average Risk)			
Take substantial risk	0.47 (0.32)	1.61	[0.86, 3.01]
Take above average risk	0.40 (0.18) *	1.48	[1.04, 2.11]
Not willing to take risk	−1.27 (0.44) **	0.28	[0.12, 0.66]
Obj financial knowledge	−0.00 (0.06)	0.99	[0.88, 1.13]
Gender (ref Male)			
Female	−0.12 (0.17)	0.89	[0.63, 1.24]
Ethnicity (ref White non-Hispanic)			
Non-White	0.39 (0.19) *	1.48	[1.01, 2.17]
Employment (ref Retired)			
Self-employed	0.38 (0.35)	1.46	[0.74, 2.88]
Full-time	0.40 (0.26)	1.48	[0.89, 2.48]
Part-time	−0.38 (0.37)	0.68	[0.33, 1.40]
Other^{+}	0.14 (0.36)	1.15	[0.56, 2.32]
Marital Status (ref Married)			
Single	−0.35 (0.21)	0.70	[0.46, 1.07]
Separated/Divorced	0.06 (0.25)	1.06	[0.65, 1.72]
Frequently			
Social media	1.15 (0.20) ***	3.19	[2.17, 4.68]
Investment Exp (ref 10 yr+)			
Less than 1 yr	1.81 (0.45) ***	6.08	[2.52, 14.66]
1 yr to less than 2 yr	1.83 (0.38) ***	6.22	[2.95, 13.12]
2 yr to less than 5 yr	1.06 (0.29) ***	2.90	[1.63, 5.15]
5 yr to less than 10 yr	0.57 (0.28) *	1.76	[1.01, 3.07]
Age (ref aged 65+)			
18 to 24	1.94 (0.63) **	7.03	[2.04, 24.16]
25 to 34	1.52 (0.50) **	4.55	[1.69, 12.23]
35 to 44	1.92 (0.44) ***	6.79	[2.89, 15.94]
45 to 54	1.14 (0.42) **	3.12	[1.38, 7.09]
55 to 64	0.65 (0.36)	1.92	[0.94, 3.91]

Table A3. *Cont.*

	Mobile Trading Apps		
	β (SE)	**RRR**	**95% CI**
Investment Assets (ref less than USD 50 K)			
USD 50 K up to USD 100 K	−0.52 (0.28)	0.59	[0.34, 1.03]
USD 100 K up to USD 500 K	−0.66 (0.24) **	0.52	[0.32, 0.84]
USD 500 K up to USD 1 M	−1.24 (0.34) ***	0.29	[0.15, 0.57]
USD 1 M or more	−1.14 (0.44) *	0.32	[0.14, 0.76]
Investment Risk Preference (ref Average Risk)			
Take substantial risk	1.35 (0.29) ***	3.85	[2.17, 6.83]
Take above average risk	0.70 (0.22) **	2.01	[1.31, 3.08]
Not willing to take risk	−1.37 (0.43) **	0.25	[0.10, 0.59]
Obj financial knowledge	−0.07 (0.07)	0.93	[0.81, 1.06]
Gender (ref Male)			
Female	−0.32 (0.22)	0.73	[0.48, 1.11]
Ethnicity (ref White non-Hispanic)			
Non-White	0.54 (0.22) *	1.72	[1.12, 2.67]
Employment (ref Retired)			
Self-employed	0.46 (0.43)	1.58	[0.67, 3.69]
Full-time	0.09 (0.36)	1.09	[0.54, 2.22]
Part-time	0.09 (0.52)	1.09	[0.39, 3.03]
Other +	−0.38 (0.48)	0.68	[0.27, 1.75]
Marital Status (ref Married)			
Single	−0.53 (0.26) *	0.59	[0.36, 0.98]
Separated/Divorced	−0.18 (0.28)	0.83	[0.48, 1.46]
N	2044		
Log pseudo-likelihood	−1217.438		
Wald Chi-square	484.01 ***		
Pseudo R^2	0.283		

Note. RRR = relative risk ratio; SE = robust standard error; CI = confidence intervals; + Other = student, homemaker, disabled, and unemployed; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A4. Model 2b—multinomial logistic regression results: the influence of various social media platforms on mobile trading applications among social media users.

	Mobile Trading Apps		
	β (SE)	**RRR**	**95% CI**
Never (ref category)			
Sometimes			
Social Media Platforms Used for Financial Information			
YouTube	−0.39 (0.39)	0.68	[0.32, 1.44]
Facebook	−0.06 (0.47)	0.94	[0.38, 2.37]
Reddit	0.44 (0.40)	1.55	[0.71, 3.37]
TikTok	−0.00 (0.62)	1.00	[0.30, 3.33]
Instagram	−1.20 (0.51)	0.30	[0.09, 1.00]
Twitter	−0.57 (0.48)	0.57	[0.22, 1.45]
LinkedIn	−0.11 (0.48)	0.89	[0.35, 2.31]
Stocktwits	−1.09 (0.55) *	0.34	[0.11, 0.98]
Investment Exp (ref 10 yr+)			
Less than 1 yr	1.71 (0.78) *	5.50	[1.19, 25.44]
1 yr to less than 2 yr	1.59 (0.36) *	4.90	[1.42, 16.88]
2 yr to less than 5 yr	0.32 (0.28)	1.38	[0.51, 3.75]
5 yr to less than 10 yr	0.23 (0.25)	1.25	[0.44, 3.61]

Table A4. *Cont.*

	Mobile Trading Apps		
	β (SE)	**RRR**	**95% CI**
Age (ref aged 65+)			
18 to 24	−0.04 (1.15)	0.96	[0.10, 9.07]
25 to 34	0.55 (0.97)	1.73	[0.26, 11.49]
35 to 44	1.00 (0.88)	2.72	[0.48, 15.29]
45 to 54	0.47 (0.86)	1.60	[0.29, 8.73]
55 to 64	−0.21 (0.80)	0.81	[0.17, 3.91]
Investment Assets (ref less than USD 50 K)			
USD 50 K up to USD 100 K	0.29 (0.55)	1.33	[0.45, 3.92]
USD 100 K up to USD 500 K	0.48 (0.43)	1.61	[0.69, 3.75]
USD 500 K up to USD 1 M	−1.63 (0.76) *	0.20	[0.04, 0.88]
USD 1 M or more	0.00 (1.10)	1.00	[0.12, 8.73]
Investment Risk Preference (ref Average Risk)			
Take substantial risk	0.88 (0.61)	2.42	[0.73, 8.04]
Take above average risk	0.84 (0.38) *	2.32	[1.10, 4.87]
Not willing to take risk	−2.73 (0.97) **	0.07	[0.01, 0.43]
Obj financial knowledge	−0.02 (0.13)	0.98	[0.77, 1.26]
Gender (ref Male)			
Female	−0.19 (0.41)	0.82	[0.37, 1.84]
Ethnicity (ref White non-Hispanic)			
Non-White	−0.22 (0.42)	0.80	[0.35, 1.83]
Employment (ref Retired)			
Self-employed	1.20 (0.90)	3.33	[0.57, 19.46]
Full-time	0.65 (0.81)	1.92	[0.40, 9.30]
Part-time	1.51 (0.94)	4.50	[0.71, 28.59]
Other +	1.12 (1.00)	3.06	[0.43, 21.59]
Marital Status (ref Married)			
Single	0.55 (0.47)	1.74	[0.69, 4.41]
Separated/Divorced	0.25 (0.61)	1.28	[0.39, 4.27]
Frequently			
Social Media Platforms Used for Financial Information			
YouTube	−0.66 (0.37)	0.52	[0.25, 1.07]
Facebook	−0.33 (0.45)	0.72	[0.30, 1.72]
Reddit	0.09 (0.38)	1.10	[0.52, 2.30]
TikTok	−0.10 (0.59)	0.91	[0.29, 2.87]
Instagram	−0.29 (0.60)	0.75	[0.23, 2.42]
Twitter	−0.91 (0.46) *	0.40	[0.16, 0.99]
LinkedIn	−0.27 (0.48)	0.76	[0.30, 1.94]
Stocktwits	−0.62 (0.55)	0.54	[0.18, 1.58]
Investment Exp (ref 10 yr+)			
Less than 1 yr	1.89 (0.75) *	6.62	[1.52, 28.80]
1 yr to less than 2 yr	1.61 (0.62) **	5.00	[1.49, 16.78]
2 yr to less than 5 yr	0.59 (0.50)	1.81	[0.68, 4.83]
5 yr to less than 10 yr	0.48 (0.53)	1.61	[0.57, 4.54]
Age (ref aged 65+)			
18 to 24	0.62 (1.07)	1.85	[0.23, 15.10]
25 to 34	0.27 (0.91)	1.30	[0.22, 7.81]
35 to 44	0.41 (0.84)	1.51	[0.29, 7.82]
45 to 54	−0.12 (0.82)	0.89	[0.18, 4.45]
55 to 64	−0.57 (0.76)	0.56	[0.13, 2.52]

Table A4. *Cont.*

	Mobile Trading Apps		
	β (SE)	**RRR**	**95% CI**
Investment Assets (ref less than USD 50 K)			
USD 50 K up to USD 100 K	−0.09 (0.53)	0.91	[0.32, 2.57]
USD 100 K up to USD 500 K	−0.27 (0.43)	0.76	[0.33, 1.76]
USD 500 K up to USD 1 M	−1.56 (0.70) *	0.21	[0.05, 0.83]
USD 1 M or more	−0.51 (1.04)	0.60	[0.08, 4.60]
Investment Risk Preference (ref Average Risk)			
Take substantial risk	1.64 (0.58) **	5.15	[1.65, 16.13]
Take above average risk	0.87 (0.38) *	2.38	[1.13, 5.00]
Not willing to take risk	−1.79 (0.77) *	0.17	[0.04, 0.77]
Obj financial knowledge	−0.09 (0.12)	0.91	[0.72, 1.16]
Gender (ref Male)			
Female	−0.24 (0.40)	0.78	[0.36, 1.71]
Ethnicity (ref White non-Hispanic)			
Non-White	0.43 (0.40)	1.54	[0.70, 3.40]
Employment (ref Retired)			
Self-employed	1.19 (0.86)	3.29	[0.61, 17.60]
Full-time	0.33 (0.77)	1.39	[0.31, 6.29]
Part-time	1.12 (0.92)	3.07	[0.51, 18.57]
Other +	0.75 (0.96)	2.11	[0.32, 13.77]
Marital Status (ref Married)			
Single	−0.37 (0.49)	0.71	[0.27, 1.87]
Separated/Divorced	−0.18 (0.61)	0.84	[0.25, 2.79]
N	391		
Log pseudo-likelihood	−329.328		
Wald Chi-square	171.82 ***		
Pseudo R^2	0.207		

Note. RRR = relative risk ratio; SE = robust standard error; CI = confidence intervals; + Other = student, homemaker, disabled, and unemployed; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Appendix C

Table A5. Model 3a—multinomial logistic regression results: the association between social media and digitally disseminated financial information—financial podcasts.

	Financial Podcasts		
	β (SE)	**RRR**	**95% CI**
Not at all (ref category)			
Somewhat			
Social media	1.48 (0.18) ***	4.37	[3.08, 6.22]
Investment Exp (ref 10 yr+)			
Less than 1 yr	0.35 (0.40)	1.43	[0.65, 3.12]
1 yr to less than 2 yr	0.07 (0.28)	1.07	[0.62, 1.85]
2 yr to less than 5 yr	0.39 (0.30)	1.48	[0.82, 2.67]
5 yr to less than 10 yr	0.03 (0.25)	1.03	[0.63, 1.68]
Age (ref aged 65+)			
18 to 24	0.82 (0.52)	2.26	[0.81, 6.30]
25 to 34	1.05 (0.40) **	2.87	[1.32, 6.24]
35 to 44	0.48 (0.34)	1.62	[0.84, 3.13]
45 to 54	0.48 (0.29)	1.61	[0.92, 2.83]
55 to 64	0.19 (0.24)	1.21	[0.75, 1.96]

Table A5. *Cont.*

	Financial Podcasts		
	β (SE)	**RRR**	**95% CI**
Investment Assets (ref less than USD 50 K)			
USD 50 K up to USD 100 K	0.28 (0.24)	1.32	[0.82, 2.11]
USD 100 K up to USD 500 K	0.09 (0.21)	1.09	[0.72, 1.65]
USD 500 K up to USD 1 M	0.16 (0.27)	1.17	[0.69, 2.01]
USD 1 M or more	0.13 (0.29)	1.14	[0.65, 2.01]
Investment Risk Preference (ref Average Risk)			
Take substantial risk	0.23 (0.25)	1.26	[0.78, 2.05]
Take above average risk	0.07 (0.17)	1.08	[0.77, 1.51]
Not willing to take risk	−1.19 (0.37) **	0.30	[0.15, 0.63]
Obj financial knowledge	−0.00 (0.06)	1.00	[0.89, 1.12]
Gender (ref Male)			
Female	−0.12 (0.17)	0.89	[0.64, 1.23]
Ethnicity (ref White non-Hispanic)			
Non-White	0.42 (0.18) *	1.53	[1.07, 2.17]
Employment (ref Retired)			
Self-employed	0.44 (0.29)	1.55	[0.87, 2.74]
Full-time	0.51 (0.24) *	1.67	[1.04, 2.69]
Part-time	0.04 (0.35)	1.04	[0.53, 2.05]
Other +	−0.10 (0.38)	0.90	[0.43, 1.91]
Marital Status (ref Married)			
Single	−0.12 (0.22)	0.89	[0.58, 1.36]
Separated/Divorced	0.32 (0.22)	1.39	[0.89, 2.13]
A great deal			
Social media	2.22 (0.23) ***	9.24	[5.91, 14.45]
Investment Exp (ref 10 yr+)			
Less than 1 yr	−0.60 (0.63)	0.55	[0.16, 1.89]
1 yr to less than 2 yr	−0.43 (0.48)	0.65	[0.26, 1.66]
2 yr to less than 5 yr	0.13 (0.48)	1.14	[0.44, 2.93]
5 yr to less than 10 yr	−0.07 (0.40)	0.93	[0.42, 2.05]
Age (ref aged 65+)			
18 to 24	2.10 (0.82) *	8.14	[1.64, 40.57]
25 to 34	1.28 (0.76)	3.61	[0.81, 16.04]
35 to 44	1.11 (0.70)	3.03	[0.76, 12.09]
45 to 54	0.36 (0.72)	1.43	[0.35, 5.88]
55 to 64	−0.20 (0.65)	0.82	[0.23, 2.94]
Investment Assets (ref less than USD 50 K)			
USD 50 K up to USD 100 K	−0.21 (0.44)	0.81	[0.34, 1.93]
USD 100 K up to USD 500 K	0.39 (0.36)	1.47	[0.72, 3.00]
USD 500 K up to USD 1 M	0.73 (0.51)	2.07	[0.76, 5.65]
USD 1 M or more	0.65 (0.58)	1.91	[0.61, 5.97]
Investment Risk Preference (ref Average Risk)			
Take substantial risk	1.41 (0.37) ***	4.11	[1.99, 8.48]
Take above average risk	0.75 (0.31) *	2.11	[1.15, 3.85]
Not willing to take risk	−0.73 (0.74)	0.48	[0.11, 2.04]
Obj financial knowledge	−0.21 (0.10) *	0.81	[0.67, 0.98]
Gender (ref Male)			
Female	−0.23 (0.29)	0.80	[0.45, 1.42]
Ethnicity (ref White non-Hispanic)			
Non-White	0.25 (0.29)	1.28	[0.73, 2.25]

Table A5. *Cont.*

	Financial Podcasts		
	β (SE)	**RRR**	**95% CI**
Employment (ref Retired)			
Self-employed	1.07 (0.73)	2.92	[0.71, 12.10]
Full-time	1.19 (0.66)	3.28	[0.90, 11.95]
Part-time	0.92 (0.73)	2.51	[0.60, 10.55]
Other +	−0.06 (0.84)	0.94	[0.18, 4.91]
Marital Status (ref Married)			
Single	−0.06 (0.34)	0.94	[0.49, 1.83]
Separated/Divorced	−0.15 (0.49)	0.85	[0.33, 2.25]
N	2044		
Log pseudo-likelihood	−1071.698		
Wald Chi-square	370.30 ***		
Pseudo R^2	0.256		

Note. RRR = relative risk ratio; SE = robust standard error; CI = confidence intervals; + Other = student, homemaker, disabled, and unemployed; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A6. Model 3b—multinomial logistic regression results: the influence of various social media platforms and digital dissemination of financial information—financial podcasts among social media users.

	Financial Podcasts		
	β (SE)	**RRR**	**95% CI**
Not at all (ref category)			
Somewhat			
Social Media Platforms Used for Financial Information			
YouTube	−0.78 (0.32) **	0.46	[0.24, 0.86]
Facebook	0.01 (0.38)	1.01	[0.48, 2.12]
Reddit	0.23 (0.33)	1.25	[0.66, 2.38]
TikTok	0.28 (0.50)	1.32	[0.49, 3.54]
Instagram	−1.01 (0.52)	0.36	[0.13, 1.01]
Twitter	−0.27 (0.37)	0.76	[0.37, 1.58]
LinkedIn	0.39 (0.39)	1.48	[0.69, 3.15]
Stocktwits	−0.45 (0.43)	0.64	[0.28, 1.48]
Investment Exp (ref 10 yr+)			
Less than 1 yr	−0.15 (0.56)	0.86	[0.29, 2.58]
1 yr to less than 2 yr	0.08 (0.50)	1.08	[0.40, 2.88]
2 yr to less than 5 yr	−0.07 (0.46)	0.93	[0.38, 2.28]
5 yr to less than 10 yr	−0.32 (0.48)	0.73	[0.28, 1.87]
Age (ref aged 65+)			
18 to 24	−0.94 (0.92)	0.39	[0.06, 2.37]
25 to 34	−0.05 (0.80)	0.95	[0.20, 4.54]
35 to 44	−0.24 (0.74)	0.78	[0.18, 3.34]
45 to 54	−0.19 (0.72)	0.83	[0.20, 3.39]
55 to 64	−0.62 (0.67)	0.54	[0.15, 1.98]
Investment Assets (ref less than USD 50 K)			
USD 50 K up to USD 100 K	0.56 (0.46)	1.75	[0.71, 4.28]
USD 100 K up to USD 500 K	0.78 (0.38) *	2.18	[1.04, 4.58]
USD 500 K up to USD 1 M	0.72 (0.67)	2.06	[0.56, 7.64]
USD 1 M or more	1.17 (0.98)	3.21	[0.47, 22.06]

Table A6. *Cont.*

	Financial Podcasts		
	β (SE)	**RRR**	**95% CI**
Investment Risk Preference (ref Average Risk)			
Take substantial risk	0.52 (0.50)	1.69	[0.63, 4.50]
Take above average risk	−0.61 (0.31)	0.54	[0.29, 1.00]
Not willing to take risk	−1.57 (0.66) **	0.21	[0.06, 0.75]
Obj financial knowledge	−0.18 (0.06)	0.83	[0.67, 1.04]
Gender (ref Male)			
Female	0.32 (0.34)	1.38	[0.71, 2.70]
Ethnicity (ref White non-Hispanic)			
Non-White	0.49 (0.35) *	2.20	[1.10, 4.39]
Employment (ref Retired)			
Self-employed	1.74 (0.76) *	5.72	[1.29, 25.44]
Full-time	0.97 (0.67)	2.63	[0.71, 9.75]
Part-time	0.87 (0.76)	2.40	[0.54, 10.62]
Other +	−0.09 (0.79)	0.92	[0.20, 4.27]
Marital Status (ref Married)			
Single	−0.18 (0.39)	0.83	[0.39, 1.80]
Separated/Divorced	−0.08 (0.50)	0.93	[0.35, 2.48]
A great deal			
Social Media Platforms Used for Financial Information			
YouTube	−0.33 (0.42)	0.72	[0.32, 1.65]
Facebook	−0.48 (0.46)	0.62	[0.25, 1.53]
Reddit	0.20 (0.40)	1.22	[0.55, 2.70]
TikTok	−0.51 (0.54)	0.60	[0.21, 1.74]
Instagram	−2.04 (0.59) **	0.13	[0.04, 0.41]
Twitter	0.36 (0.47)	1.44	[0.57, 3.63]
LinkedIn	0.81 (0.47)	2.25	[0.90, 5.62]
Stocktwits	−0.42 (0.51)	0.66	[0.24, 1.78]
Investment Exp (ref 10 yr+)			
Less than 1 yr	−0.92 (0.76)	0.40	[0.09, 1.78]
1 yr to less than 2 yr	−0.44 (0.65)	0.64	[0.18, 2.28]
2 yr to less than 5 yr	−0.06 (0.58)	0.94	[0.30, 2.93]
5 yr to less than 10 yr	−0.40 (0.61)	0.67	[0.21, 2.20]
Age (ref aged 65+)			
18 to 24	1.73 (1.45)	5.65	[0.33, 97.06]
25 to 34	1.89 (1.37)	6.64	[0.46, 96.72]
35 to 44	2.39 (1.33)	10.89	[0.86, 146.40]
45 to 54	1.66 (1.32)	5.27	[0.39, 70.43]
55 to 64	0.51 (1.30)	1.67	[0.13, 21.46]
Investment Assets (ref less than USD 50 K)			
USD 50 K up to USD 100 K	0.69 (0.57)	1.98	[0.65, 6.05]
USD 100 K up to USD 500 K	1.03 (0.48) *	2.79	[1.09, 7.18]
USD 500 K up to USD 1 M	1.24 (0.79)	3.45	[0.74, 16.15]
USD 1 M or more	1.73 (1.25)	5.63	[0.48, 65.45]
Investment Risk Preference (ref Average Risk)			
Take substantial risk	1.22 (0.57) *	3.38	[1.10, 10.40]
Take above average risk	−0.20 (0.43)	0.82	[0.36, 1.89]
Not willing to take risk	−2.64 (1.02) *	0.07	[0.01, 0.53]
Obj financial knowledge	−0.34 (0.14) *	0.71	[0.54, 0.93]
Gender (ref Male)			
Female	0.09 (0.44)	1.09	[0.46, 2.60]
Ethnicity (ref White non-Hispanic)			
Non-White	0.69 (0.44)	2.00	[0.85, 4.71]

Table A6. *Cont.*

	Financial Podcasts		
	β (SE)	**RRR**	**95% CI**
Employment (ref Retired)			
Self-employed	1.40 (1.16)	4.06	[0.42, 39.31]
Full-time	0.62 (1.06)	1.86	[0.23, 14.93]
Part-time	1.32 (1.18)	3.73	[0.37, 37.49]
Other $^{+}$	−0.88 (1.24)	0.41	[0.04, 4.74]
Marital Status (ref Married)			
Single	0.32 (0.49)	1.37	[0.52, 3.62]
Separated/Divorced	−0.39 (0.83)	0.68	[0.13, 3.45]
N	391		
Log pseudo-likelihood	−326.619		
Wald Chi-square	177.70 ***		
Pseudo R^2	0.214		

Note. RRR = relative risk ratio; SE = robust standard error; CI = confidence intervals; $^{+}$ Other = student, homemaker, disabled, and unemployed; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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