

Retail investor behavior and social media signals: exploring attention dynamics

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249

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Abstract

Purpose – This study aims to investigate how social media recommendations influence investor attention and retail investor activity in stock investing.

Design/methodology/approach – Using data from the Organisation for Economic Co-operation and Development (OECD)'s 2023 Adult Financial Literacy Survey across a sample of countries, the analysis employs a logistic regression model. To address potential endogeneity, both instrumental variable and propensity score matching techniques are applied.

Findings – Investor attention to social media influencers shows a positive and significant effect on stock investment. After adjusting for endogeneity, the main results remain robust. However, the moderating role of digital financial literacy is not consistent across all countries in the sample.

Research limitations/implications – The influencer recommendation question was newly introduced in this survey, limiting longitudinal comparisons. Additionally, the results are based on self-reported data from four countries.

Originality/value – This research contributes to the emerging field of digital behavioral finance and offers insights for the design of financial inclusion and education policies in increasingly digital environments.

Keywords Investor attention, Social media, Stock investment, Digital financial literacy, Investment decision-making, Digital financial behavior

Paper type Research article

1. Introduction

The growing influence of social media on the financial behavior of retail investors has attracted significant academic attention in recent years. These platforms have profoundly reshaped how investors access, interpret and process financial information, partially displacing traditional media outlets (Münster *et al.*, 2024). Their capacity for virality, immediacy and social validation has positioned social media as a key channel for disseminating market signals, raising concerns among regulators and market participants about its potential to trigger suboptimal investment decisions (Barber *et al.*, 2022).

From a behavioral perspective, a wide body of literature has examined the role of cognitive resources, overconfidence as a behavioral bias and limited attention as a scarce resource (Kahneman, 1973), noting that these factors may amplify market noise and undermine the efficiency of price formation processes (Alfieri *et al.*, 2025). These effects are further exacerbated in digital environments, where decision-making rationality is increasingly challenged (Warkulat and Pelster, 2024). Despite advances in this field, the literature has yet to thoroughly explore the mechanisms through which social media recommendations capture the

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attention of individual investors and shape their willingness to participate in equity markets. Recent studies have mostly focused on specific phenomena or asset classes, including short-termism in investment behavior (Kim, 2025), disposition effect (Chen and Ren, 2025) or cryptocurrency investment (Kim and Fan, 2025), without addressing how these platforms interact with critical individual competencies such as digital financial literacy (DFL).

DFL has emerged as a key competency to navigate the challenges of the digital financial ecosystem by enabling individuals to efficiently access, understand and use financial information (Mazzoli and Baiocco, 2025). Recent evidence shows that developing DFL is essential for the effective use of digital financial services and for managing associated risks; however, despite widespread digitalization, its effects on individuals' financial behavior and overall financial awareness remain insufficiently understood (Bhat *et al.*, 2024). Moreover, little is known about the moderating role of DFL in shaping the influence of social media recommendations.

In parallel, a growing body of international literature has emphasized the importance of DFL across diverse settings. For instance, Pak *et al.* (2026), drawing on evidence from South Korea, suggest that DFL is a key determinant of both the adoption of and the benefits derived from digital financial services, thereby contributing to financial inclusion in the digital era. In northern India, Showkat *et al.* (2025) demonstrated that financial literacy enhances the use of digital financial services and serves as a critical mechanism for women's economic empowerment, promoting gender equality. In the same country, Maheshwari and Samantaray (2025) find that financial literacy, together with artificial intelligence (AI)-based digital advisory services, encourages more rational investment decisions. Moreover, cross-country comparative studies highlight the role of financial capability in fostering digital monetary innovation, suggesting that strengthening financial literacy should be a strategic component in the design and implementation of central bank digital currencies across different national contexts (Mertzanis *et al.*, 2025).

In this respect, the present study aims to analyze the relationship between attention to social media influencer recommendations and the decision to invest in the stock market, considering the moderating role of DFL. For this purpose, a logistic regression model is employed using individual-level data from the 2023 Organisation for Economic Co-operation and Development (OECD)/International Network on Financial Education Survey (INFE) of Adult Financial Literacy, covering four countries with diverse socioeconomic environments: Brazil, Finland, the Philippines and Saudi Arabia. The study is guided by the following research questions: To what extent do influencer recommendations on social media influence individuals' decisions to invest in the stock market? What role does DFL play in moderating this relationship?

This research offers a novel contribution by examining an understudied phenomenon from an international comparative perspective, integrating both behavioral and digital variables. Moreover, it provides empirical evidence from a heterogeneous group of countries, allowing for the analysis of contextual differences in investor behavior. By combining social media attention and DFL levels, the study aligns with an emerging body of literature, aiming to understand the cognitive and technological determinants of financial decision-making in contemporary digital environments (Anwar, 2025).

The structure of the paper is as follows: Section 2 reviews the literature and presents the theoretical framework, Section 3 describes the study methodology, Section 4 reports the results, Section 5 discusses the findings and Section 6 concludes.

2. Literature review

In recent years, social media platforms have emerged as a key channel for shaping financial expectations and investment behavior among retail investors (Reichenbach and Walther, 2025). This influence stems not only from their ability to capture attention but also from their role as providers of qualitative information about companies, which significantly affects investment

decisions (Bayar and Kesici, 2024). These platforms have been identified as behavioral drivers that shape short-term investment decisions, particularly among younger individuals who tend to exhibit overconfidence in their financial knowledge (Kim, 2025). Despite these advances, much of the existing literature relies on single-country case studies or nationally limited samples, which restrict the generalizability of the findings (Lyócsa *et al.*, 2023). This national focus limits the understanding of the underlying mechanisms from a global perspective. Meanwhile, social media increasingly shapes markets: cases such as GameStop (Pedersen, 2022) and Twitter effects (Carosia *et al.*, 2020) illustrate how social media operates as a behavioral determinant of investment decisions across highly diverse environments. Even in countries with high levels of digital literacy, such as Finland, young adults report spending between 35 and 42 h per week online, with nearly 20 of those hours dedicated exclusively to social media use (Hylkilä *et al.*, 2023). Studies often rely on aggregated data, rarely examining individual influencer attention as an investment “attention shock” or comparing across countries. This limits micro-level evidence on how digital attention affects behavior. Since attention narrows choices and influencers can redirect it toward specific stocks, followers are more likely to invest.

The concept of digital finance has emerged as a response to rapid technological advancements in the financial sector (Al-Smadi, 2023), prompting individuals to acquire new competencies to navigate digital environments. Within this context, DFL has become essential for fostering informed, autonomous and responsible financial behavior (OECD, 2023). This competency enables individuals to analyze financial products, critically assess digital information and make rational investment decisions (Abdallah *et al.*, 2024). Empirical studies have demonstrated that higher levels of DFL are associated with improved investment outcomes and more effective retirement planning (Mazzoli and Baiocco, 2025). However, concerns remain about the reliability of social media as an information source. Wang *et al.* (2024) suggest that content disseminated by financial influencers is often low in analytical quality and high in emotional appeal, increasing the behavioral risks for retail investors. While prior literature has explored how digital competencies influence financial behavior in single-country contexts, such as Sweden (Hermansson *et al.*, 2022) or China (Wang *et al.*, 2024), few studies have systematically examined how the moderating role of DFL varies across countries with distinct institutional and technological landscapes. This gap is especially important, given the increasing globalization of digital financial content.

Given that influencers generate attention-grabbing events that particularly affect less sophisticated investors, it would be reasonable to expect that individuals with higher digital competencies would be less susceptible to such influence. DFL would provide analytical skills and critical thinking that would help individuals assess the quality of information and avoid impulsive choices, thereby attenuating the impact of attention to social media influencers on investment decisions.

2.1 Theoretical framework

The attention theory proposed by Barber and Odean (2008) offers a framework for understanding how stimuli originating from social media could influence individual financial behavior. This theory posits that attention functions as a selection mechanism prior to decision-making, determining which alternatives are considered before preferences shape the final choice. Because individual investors face a large universe of potential stocks, they tend to simplify their search process by focusing on those that have recently captured their attention. Although not all attention-grabbing stocks are ultimately purchased, the authors show that investors only buy stocks that have succeeded in attracting their attention. In this sense, influencers operate as agents who generate “attention-grabbing events,” capable of directing attention toward specific assets, similar to what occurs in traditional media such as Consumer News and Business Channel (CNBC), where a single mention can multiply trading volume within minutes. Thus, when an influencer highlights a stock, they produce an attention event that increases the likelihood that an individual investor will consider purchasing it.

Barber and Odean (2008) argue that individual investors face limited attention and rely on salient cues, while professionals reduce such constraints through systematic search, analytical tools and deeper fundamental analysis, recognizing that highlighted information is often already priced in. Higher DFL should make individuals behave more like professionals by improving risk understanding, critical evaluation and structured decision-making. Consequently, reliance on salient cues declines, which could reduce susceptibility to social media influencer recommendations. As an alternative to Barber and Odean (2008), the limited attention theory developed by Hirshleifer and Teoh (2003) emphasizes that investors face cognitive constraints that affect not only which assets they consider but also how they process available information. Investors tend to assimilate salient, low-cognitive-cost information more easily, while economically relevant information may be ignored if it fails to attract attention. These limitations contribute to distortions in asset valuation and to the persistence of market inefficiencies, as neither arbitrage nor professional analysis fully corrects price misalignments. Taken together, this theory complements Barber and Odean (2008) by explaining the underlying cognitive mechanisms that allow attention-driven effects on investment decisions to persist in financial markets.

Taken together, this theoretical framework suggests that signals emitted by social media influencers would operate as attention-grabbing events that would increase the likelihood that individuals consider investing in stocks, while higher levels of DFL would attenuate this effect by reducing reliance on salient cues in the decision-making process. Therefore, consistent with the theoretical framework, the following hypotheses are proposed:

- H1. Social media signals from influencers increase individuals' propensity to invest in stocks.
- H2. Individuals with higher digital financial literacy reduce the likelihood of social media influence on their investment decisions.

3. Method

3.1 Research design/model

This study uses microdata from the OECD/INFE 2023 International Survey of Adult Financial Literacy and focuses on Brazil, Finland, the Philippines and Saudi Arabia – countries where at least 8% of respondents reported both stock investing and paying attention to social media. The target population of this study consists of adult individuals from the general population who are potential retail investors, regardless of whether they currently participate in the stock market. The data are drawn from an OECD survey administered to adult individuals at the household level, which focuses on financial behaviors and decision-making within households. The unit of analysis is the individual respondent. Accordingly, the analysis captures both current investors and non-investors, allowing the study to examine factors associated with stock market participation and the influence of information signals. The results are therefore representative of potential individual or retail investors rather than professional or institutional investors. The unit of analysis is the individual respondent. Stock investment (SI) is modeled using a logistic specification with country fixed effects:

$$\Pr(SI_i = 1 | X) = \Lambda \left(\beta_0 + \beta_1 \cdot Atten_i + \beta_2 \cdot DFL_i + \beta_3 \cdot Gen_i + \beta_4 \cdot Age_i + \beta_5 \cdot Edu_i + \beta_6 \cdot ES_i + \beta_7 \cdot Inc_i + \sum_{h=1}^3 Country_h \right) \quad (1)$$

3.2 Data and variables

This section describes the measurement of the dependent variable (SI) and the independent variables of interest (Atten and DFL). The survey items used in this study are presented in [Appendix 1](#). In addition, the control variables were Gen, the respondent's gender; Age, the individual's age in years; Edu, educational attainment; ES, employment status, and Inc, the household's average income bracket ([Table A1](#)). Moreover, fixed effects are included to incorporate country-specific characteristics into the model.

Against this background, SI is defined as stock market participation, referring to “the fraction of individuals who directly own stocks” ([Guiso et al., 2008](#), p. 28). It is a binary variable equal to 1 if individuals report direct investment in shares or securities through recent savings, current holding or active selection and 0 otherwise.

Next, investor attention (Atten) reflects limited cognitive resources ([Kahneman, 1973](#)), leading to reliance on low-cognitive-cost signals in information-rich settings ([Hirshleifer and Teoh, 2003](#)). In empirical finance, attention is measured through observable information-seeking behavior and interpreted as revealed attention ([Da et al., 2011](#)) and amplified by algorithmic exposure on social media ([Jang and Jun, 2025](#)). It is coded 1 if decisions were influenced by recommendations from unknown individuals (e.g. influencers) and 0 otherwise.

Along similar lines, DFL is defined as the “combination of knowledge, skills, attitudes and behaviors necessary for individuals to be aware of and safely use digital financial services and digital technologies with a view to contributing to their financial well-being” ([OECD, 2023](#), p. 7). It is measured through a principal component analysis (PCA)-based index, capturing three standardized dimensions: digital financial behavior (DFB), reflecting secure and responsible online practices; digital financial knowledge (DFK), based on correct responses to questions on digital finance and regulation, and digital financial attitude (DFA), assessing prudent and safety-oriented attitudes toward digital financial services.

4. Results

As shown in [Table 1](#), 21.4% of individuals report SI, a relatively low but adequate level for analyzing its determinants, while 17.7% report Atten, suggesting this channel already influences decisions. The descriptive statistics by country are presented in the [Supplementary file, Supplementary Table No. S1](#). Finland has the highest investment rate, whereas attention is greatest in the Philippines and Saudi Arabia, revealing opposite cross-country patterns. Potential multicollinearity was assessed using the variance inflation factor (VIF). Results in [Supplementary Table No. S2](#) report an average VIF of 1.12, well below the 4–5 threshold, indicating no multicollinearity concerns ([Li and Huang, 2025](#)).

Table 1. Descriptive statistics

Variable	Obs	Mean	Std. Dev	Min	Max
Stock investment	6,865	0.214	0.410	0	1
Investor attention	6,865	0.177	0.381	0	1
Digital financial literacy	6,865	0.000	0.699	–2.119	1.886
Digital financial behavior	6,865	2.363	0.921	0	4
Digital financial knowledge	6,865	1.581	0.924	0	3
Digital financial attitude	6,865	1.701	0.993	0	3
Gender	6,865	0.496	0.500	0	1
Age	6,865	41.968	15.171	16	80
Education	6,865	3.254	1.039	0	5
Employment status	6,865	0.661	0.473	0	1
Income	6,865	1.882	0.905	0	3

Source(s): Authors' own work

The empirical analysis begins by examining the underlying structure of DFL through PCA, indicating that the first component captures a general DFL factor across countries, but that its composition varies: behavior and attitude dominate in Saudi Arabia and Finland, while Brazil and the Philippines display more balanced contributions. The second component is consistently driven by DFK, suggesting a distinct, specialized dimension. The country-specific PCA result tables are reported in [Supplementary Table No. S3](#).

[Table 2](#) reports the marginal effects from the baseline logit specifications for SI. Focusing first on the pooled sample (Models 1–3), Atten influencers exhibit a positive, economically meaningful and highly statistically significant effect on stock market participation. In Model (1), Atten raises the probability of investing in stocks by 17.2% (Std. Err. = 0.011, $p < 0.01$). This effect remains stable and statistically significant across alternative specifications that incorporate DFL, decreasing only modestly to 15.8% in Model (2) and 12.2% in Model (3). DFL also shows a positive and statistically significant association with SI. In the pooled sample, DFL increased the probability of investing in stocks by 5.8% (Std. Err. = 0.0066, $p < 0.01$). When disaggregating DFL into its components, DFK emerges as the main driver, with a marginal effect of 6.1% ($p < 0.01$), while DFB and DFA dimensions play a comparatively smaller or statistically weaker role.

In Brazil (Models 4–6), Atten exerts a positive and statistically significant effect on SI. Specifically, the marginal effect ranges from 8.28% in Model (4) (Std. Err. = 0.0139, $p < 0.01$) to 5.33% in Model (6) (Std. Err. = 0.0132, $p < 0.01$). DFL also contributes positively, increasing the probability of SI by 4.22% ($p < 0.01$), with the effect largely driven by DFK (marginal effect = 2.68%, $p < 0.01$). In Finland (Models 7–9), Atten raises the probability of SI by 28.1% in Model (7) (Std. Err. = 0.0423, $p < 0.01$), remaining highly significant at 27.9% in Model (8) and 23.5% in Model (9). DFL is likewise economically meaningful, with a marginal effect of 10.4% ($p < 0.01$), again predominantly explained by DFK, which alone increases SI by 9.54% ($p < 0.01$). In the Philippines (Models 10–12), Atten increases the probability of SI by 18.3% in Model (10) (Std. Err. = 0.0247, $p < 0.01$), 18.4% in Model (11) and 12.5% in Model (12), remaining statistically significant throughout. DFL contributes positively as well, raising SI likelihood by 6.81% ($p < 0.01$), with both DFK (5.5%, $p < 0.01$) and behavioral components playing a secondary but supportive role. Finally, in Saudi Arabia (Models 13–15), Atten continues to exhibit a positive and statistically significant association with SI, with marginal effects ranging from 14.3% in Model (13) (Std. Err. = 0.0161, $p < 0.01$) to 4.79% in Model (15) (Std. Err. = 0.0159, $p < 0.01$). DFL remains significant across specifications, increasing SI by 3.46% ($p < 0.01$), once again driven mainly by DFK (6.5% in Model 13, $p < 0.01$).

Turning to the control variables reported in [Table 2](#), gender is positively and statistically significant across most specifications: in the pooled sample (Model 2), being male increases the probability of investing in stocks by 4.7% ($p < 0.01$), with similar effects in Brazil (7.6%), Finland (8.1%) and the Philippines (5.0%). Education is strongly associated with SI, raising investment probabilities by 7% in the pooled model and up to 10.4% in the Philippines ($p < 0.01$). Employment status also increases SI likelihood (4.8%, pooled; $p < 0.01$), while income emerges as one of the strongest predictors, with positive and significant effects across all countries. Socioeconomic factors persistently shape investment behavior, consistent with prior evidence ([Van Rooij et al., 2011](#)). Taken together, these findings provide strong empirical support for [Hypothesis 1](#), confirming that investor attention to digital financial content significantly increases SI, even after controlling for DFL and standard socioeconomic factors.

The interaction results reported in [Table 3](#) provide direct evidence on [Hypothesis 2](#), revealing substantial cross-country heterogeneity in the moderating role of DFL on the relationship between Atten and SI. In Brazil, the interaction between Atten and DFL is statistically insignificant, with or without controls, indicating that DFL raises overall SI but does not alter the effect of attention on investment decisions, consistent with Brazil's still-developing financial knowledge ([Ramalho, 2019](#)). A similar result holds for Finland, where the interaction remains insignificant across specifications, despite strong direct effects of

Table 2. Marginal effects main model

	All countries			Brazil			Finland			Philippines			Saudi Arabia		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Atten	0.172*** (0.0110)	0.158*** (0.0110)	0.122*** (0.0109)	0.0828*** (0.0139)	0.0798*** (0.0139)	0.0533*** (0.0132)	0.281*** (0.0423)	0.279*** (0.0419)	0.235*** (0.0409)	0.183*** (0.0247)	0.184*** (0.0247)	0.125*** (0.0257)	0.143*** (0.0161)	0.0997*** (0.0164)	0.0479*** (0.0159)
DFL	0.0584*** (0.0066)			0.0422*** (0.0100)			0.104*** (0.0166)			0.0681*** (0.0180)			0.0346*** (0.0111)		
Digital financial behavior		−0.00875 (0.00551)	−0.0113** (0.00529)		0.0247*** (0.0087)	0.0137 (0.0086)		−0.0370** (0.0146)	−0.0356** (0.0140)		−0.0018 (0.0130)	−0.0054 (0.0124)		−0.0152 (0.0093)	0.000805 (0.00904)
Digital financial knowledge		0.0607*** (0.00504)	0.0388*** (0.00498)		0.0268*** (0.0069)	0.0098 (0.0067)		0.0954*** (0.0117)	0.0490*** (0.0118)		0.055*** (0.0145)	0.0388*** (0.0142)		0.0650*** (0.0094)	0.0539*** (0.00888)
Digital financial attitude		0.00423 (0.00517)	0.000228 (0.00499)		−0.0044 (0.0073)	−0.0057 (0.0071)		0.0270** (0.0125)	0.0254** (0.0120)		0.0122 (0.0131)	−0.0003 (0.0130)		−0.0148 (0.0100)	−0.0128 (0.00953)
Gender			0.0472*** (0.00879)			0.0755*** (0.0126)			0.0805*** (0.0218)			0.0496** (0.0251)			−0.0163 (0.0150)
Age			−0.000664** (0.000326)			−0.0027*** (0.0005)			0.0013* (0.0007)			−0.00175* (0.0010)			0.000305 (0.000690)
Education			0.0699*** (0.00539)			0.0193*** (0.0068)			0.0876*** (0.0118)			0.104*** (0.0169)			0.139*** (0.0143)
Employment status			0.0484*** (0.0105)			0.0370** (0.0150)			0.0983*** (0.0233)			0.0813*** (0.0270)			−0.0189 (0.0279)
Income			0.0484*** (0.00489)			0.0262*** (0.0078)			0.0804*** (0.0108)			0.0149 (0.0123)			0.0777*** (0.0115)
Fixed effect	Yes	Yes	Yes	No	No	No	No	No	No	No	No	No	No	No	No
LR χ^2	1,064.48	1,133.43	1,573.89	59.54	68.64	195.98	73.82	109.43	307.08	65.86	69.47	148.16	77.7	120.50	313.23
Prob > χ^2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	6,865	6,865	6,865	2,000	2,000	2,000	1,806	1,806	1,806	1,000	1,000	1,000	2,059	2,059	2,059

Note(s): Models (1), (2), and (3) correspond to the full sample of countries. Models (4), (5), and (6) correspond to Brazil; models (7), (8), and (9) to Finland; models (10), (11), and (12) to the Philippines; and models (13), (14), and (15) to Saudi Arabia. Standard errors are in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively

Source(s): Authors' own work

Table 3. Marginal effects and the interactive role of digital financial literacy

	All countries (1)	Brazil (2)	Finland (3)	Philippines (4)	Saudi Arabia (5)	All countries (6)	Brazil (7)	Finland (8)	Philippines (9)	Saudi Arabia (10)
Atten	0.171*** (0.0110)	0.0878*** (0.0154)	0.285*** (0.0457)	0.207*** (0.0244)	0.150*** (0.0152)	0.131*** (0.0108)	0.0528*** (0.0147)	0.239*** (0.0442)	0.144*** (0.0256)	0.0800*** (0.0151)
DFL	0.0612*** (0.00758)	0.0465*** (0.0117)	0.103*** (0.0175)	0.130*** (0.0217)	0.00475 (0.0130)	0.0285*** (0.00742)	0.0128 (0.0113)	0.0461*** (0.0173)	0.0850*** (0.0213)	0.0134 (0.0126)
Attention * DFL	−0.0118 (0.0161)	−0.0168 (0.0226)	0.0148 (0.0594)	−0.192*** (0.0374)	0.0929*** (0.0236)	0.00463 (0.0153)	0.00376 (0.0224)	0.0292 (0.0569)	−0.148*** (0.0364)	0.0787*** (0.0225)
Gender						0.0485*** (0.00885)	0.0763*** (0.0126)	0.0911*** (0.0216)	0.0455* (0.0249)	−0.0280* (0.0149)
Age						−0.000730** (0.000327)	−0.00273*** (0.000473)	0.00107 (0.000767)	−0.00189** (0.000953)	0.000411 (0.000696)
Education						0.0726*** (0.00543)	0.0209*** (0.00678)	0.0924*** (0.0118)	0.0974*** (0.0168)	0.147*** (0.0146)
Employment status						0.0489*** (0.0106)	0.0384** (0.0150)	0.0961*** (0.0234)	0.0810*** (0.0268)	−0.0167 (0.0278)
Income						0.0501*** (0.00490)	0.0264*** (0.00784)	0.0833*** (0.0108)	0.00995 (0.0122)	0.0782*** (0.0115)
Fixed effect	Yes	No	No	No	No	Yes	No	No	No	No
LR χ^2	1,065.02	60.09	73.88	90.95	93.29	1,531.92	192.52	289.14	160.9	300.07
Prob > χ^2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	6,865	2,000	1,806	1,000	2,059	6,865	2,000	1,806	1,000	2,059

Note(s): Standard errors are in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively

Source(s): Authors' own work

attention and DFL, suggesting that digital competencies are already embedded in information processing in a high-literacy context (Kalmi and Ruuskanen, 2017). The Philippines exhibits a negative and statistically significant interaction effect (Model 9: $-0.148, p < 0.01$), implying that higher levels of DFL weaken the positive impact of Atten on SI. This finding aligns with national evidence documenting low overall financial literacy and less sophisticated financial behavior (Bangko Sentral ng Pilipinas, 2024). Conversely, Saudi Arabia shows a positive, significant interaction (Model 10: $0.0787, p < 0.01$), consistent with evidence linking higher financial literacy to better investment decisions (Albarrak et al., 2024).

Overall, these findings indicate that DFL does not operate as a universal buffer against digital persuasion. Instead, its moderating role is highly context-dependent and is shaped by the level and distribution of financial knowledge across countries. Consequently, Hypothesis 2 receives partial empirical support, as the direction and strength of the interaction between attention and DFL vary systematically across national settings.

4.1 Endogeneity

4.1.1 Two-stage instrumental variable regression. To address potential reverse causality, endogeneity is mitigated using an instrumental variable (IV) based on online purchasing behavior, measured on a 1–4 scale that indicates how often respondents bought goods and services online in the past 12 months. More frequent online shopping increases exposure to digital platforms where influencers are prominent, plausibly raising attention to their recommendations. Consistent with this channel, social media interactions shape purchase decisions (Ismael et al., 2025), and influencers' live-commerce demonstrations affect consumer choices (Li et al., 2025). The instrument is assessed in terms of exogeneity, relevance and strength; it should be valid, relevant and strong (Cameron and Trivedi, 2005). Table 4 reports Spearman correlations between the instrument and baseline residuals (Panel A) and between the instrument and the endogenous variable (Panel B), with p -value testing for independence. The instrument appears valid in Finland, the Philippines and Saudi Arabia, as independence from model errors cannot be rejected. It is relevant in Brazil, Finland and the Philippines, where independence from the endogenous variable is rejected, with the strongest associations in Brazil and the Philippines. In the pooled sample, the instrument correlated 15.68% with the endogenous variable, rejecting independence.

To address potential endogeneity concerns with a nonlinear dependent variable, the methodology proposed by Wooldridge (2014), known as the control function method or two-stage residual inclusion (2SRI), was applied. A central feature of this approach is that, in the second stage, the generalized residuals estimated in the first stage are included in the specification. As shown in Table 5, the IV is significantly positive for the pooled sample, indicating that individuals who purchase goods and services online are 3.8% ($p < 0.01$) more likely to pay attention to investment recommendations issued by social media influencers;

Table 4. Spearman correlations between the instrumental variable, model errors and the endogenous variable

	Brazil	Finland	Philippines	Saudi Arabia
<i>Panel A: Spearman correlations – Instrument and baseline model errors</i>				
Rho	−0.2689	−0.0280	−0.0286	0.0250
p -value	0.000	0.2347	0.3665	0.2568
<i>Panel B: Spearman correlations – Instrument and endogenous variable</i>				
Rho	0.2543	0.0950	0.3089	0.0112
p -value	0.000	0.0001	0.000	0.6115
Source(s): Authors' own work				

Table 5. Marginal effects from the two-stage residual model

	All countries		Brazil		Finland		Philippines		Saudi Arabia	
	First step	Second step	First step	Second step	First step	Second step	First step	Second step	First step	Second step
	Attention	Stock investment	Attention	Stock investment	Attention	Stock investment	Attention	Stock investment	Attention	Stock investment
I.V.	0.0380*** (0.00444)		0.0431*** (0.00708)		0.0113 (0.00717)		0.0704*** (0.0109)		0.00336 (0.0104)	
Atten		0.329*** (0.0611)		0.244*** (0.0822)		0.118 (0.269)		0.568*** (0.121)		-0.429** (0.178)
DFL	-0.0543*** (0.00622)	0.0381*** (0.00726)	0.0153 (0.0117)	0.00448 (0.0105)	-0.0265*** (0.00908)	0.0449** (0.0184)	0.00949 (0.0188)	0.0212 (0.0173)	-0.119*** (0.0119)	-0.0347 (0.0266)
Gender	-0.0655*** (0.00866)	0.0644*** (0.0101)	0.00771 (0.0139)	0.0724*** (0.0121)	-0.00713 (0.0127)	0.0908*** (0.0217)	-0.0660*** (0.0255)	0.0969*** (0.0278)	-0.178*** (0.0165)	-0.144*** (0.0409)
Age	-0.00350*** (0.000334)	-0.000177 (0.000391)	-0.00355*** (0.000518)	-0.00159*** (0.000595)	-0.00317*** (0.000441)	0.000686 (0.00123)	-0.00524*** (0.000958)	0.000722 (0.00116)	0.00183** (0.000890)	0.00162* (0.000826)
Education	0.0590*** (0.00535)	0.0562*** (0.00702)	0.0113 (0.00801)	0.0143** (0.00709)	0.00489 (0.00668)	0.0910*** (0.0124)	0.0803*** (0.0152)	0.0442** (0.0223)	0.183*** (0.0149)	0.253*** (0.0406)
Employment status	-0.00544 (0.0108)	0.0504*** (0.0106)	-0.0127 (0.0154)	0.0355*** (0.0137)	-0.00432 (0.0133)	0.0954*** (0.0238)	0.00605 (0.0275)	0.0671*** (0.0258)	-0.0655* (0.0336)	-0.0560* (0.0319)
Income	0.0198*** (0.00513)	0.0458*** (0.00512)	0.00403 (0.00941)	0.0245*** (0.00748)	0.0256*** (0.00668)	0.0867*** (0.0134)	0.00739 (0.0125)	0.00345 (0.0122)	-0.00335 (0.0128)	0.0742*** (0.0111)
Resid		-0.116*** (0.0353)		-0.109** (0.0477)		0.0593 (0.138)		-0.271*** (0.0743)		0.500*** (0.178)
Fixed effect	Yes	Yes	No	No	No	No	No	No	No	No
LR χ^2	923.35	1,164.47	179.45	156.16	112.60	244.24	165.61	120.45	438.26	188.65
Prob > χ^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations	6,865	6,865	2,000	2,000	1,806	1,806	1,000	1,000	2,059	2,059

Note(s): Standard errors are in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively

Source(s): Authors' own work

however, this effect is not statistically significant for Finland or Saudi Arabia. In the second-stage regression, the residual is significant, and Atten remains significant at the 1% level for the pooled sample, again with Finland as the exception. After 2SRI correction, social media attention still significantly affects investment decisions.

4.1.2 Propensity score matching (PSM). The propensity score matching (PSM) is used to correct selection bias that arises when individuals who receive a treatment differ systematically from those who do not (Ali and Behera, 2015). This technique allows estimating the average treatment effect by matching treated and untreated individuals with similar observable characteristics (Rosenbaum and Rubin, 1983). PSM is necessary in this study because attention to investment recommendations from influencers is not randomly assigned and may be associated with individual attributes such as gender, age, DFL or income. Propensity scores were obtained using a logit model, after which two matching methods were applied: single nearest-neighbor matching and nearest-neighbor matching with the Mahalanobis distance. As reported in Table 6 (Panels A and B), substantial differences existed between individuals who paid attention to influencer recommendations and those who did not, but these differences were considerably reduced after applying PSM, indicating that both groups became adequately balanced across observed covariates. Regarding the results, the probability of participating in the stock market reaches 32.1% (Panel A.1) among individuals who paid attention to influencers, compared with only 21.8% among those who did not: an absolute difference of 10%, significant at the 1% level. These results match baseline estimates, supporting robustness: influencer attention increases the likelihood of SI. The country-level average treatment effect on the treated estimates are presented in the Supplementary file, Supplementary Table No. S4 and Supplementary Table No. S5.

5. Discussion

5.1 Theoretical implications

The results reinforce and broaden its theoretical implications in the context of social media and DFL on SI. The evidence indicates that attention would act as a prior selection mechanism, in which signals from influencers operate as attention-grabbing events that delimit the set of investment alternatives. The findings strengthen attention-based explanations by showing that salient digital signals may function as “attention triggers” that stimulate investment activity, even when informational content is limited (Arnold *et al.*, 2022) and that attention to social media content catalyzes investment decisions (Kim and Fan, 2025).

Likewise, the results nuance the view of DFL as a universal buffer against digital persuasion, as its moderating effect is heterogeneous and context-dependent. The heterogeneity observed in the moderating role of DFL can be understood through Hofstede’s cultural dimensions (The Culture Factor Group, 2025) – particularly individualism or collectivism, uncertainty avoidance and long-term orientation, which influence how individuals process financial information and respond to attention stimuli across different national settings. In more collectivist societies, such as Brazil, the Philippines and Saudi Arabia, economic decisions tend to be more influenced by social signals, amplifying the impact of recommendations disseminated on social media. Uncertainty avoidance introduces a second mechanism: in societies with a high need for certainty, such as Brazil and Saudi Arabia, digital signals may function as cognitive shortcuts. However, while in Brazil DFL has not yet reached sufficient levels to modify this pattern, in Saudi Arabia, greater digital competencies allow attention to translate into more effective investment decisions. In the Philippines, where uncertainty avoidance is lower, increased DFL fosters a more critical evaluation of social signals, weakening the relationship between attention and investment. Finally, long-term orientation explains why DFL is integrated into the general decision-making process in Finland, whereas in countries with a short-term orientation, DFL may act both as a protective filter and as a facilitator of investment action.

Table 6. Average treatment effect on the treated

Panel A.1: Average treatment effect on the treated (ATT) using nearest-neighbor					
Variable	Treatment	Controls	Difference	S.E.	T-stat
SI	0.321	0.218	0.103	0.021	4.870
Panel A.2: Comparison of variable averages under PSM					
Variable	Matched	Treated	Control	<i>t</i>	<i>p > t</i>
DFL	Unmatched	−0.114	0.025	−6.300	0.000
	Matched	−0.114	−0.145	1.090	0.276
Gender	Unmatched	0.394	0.518	−7.920	0.000
	Matched	0.394	0.389	0.250	0.803
Age	Unmatched	35.333	43.391	−17.130	0.000
	Matched	35.333	35.859	−1.080	0.281
Education	Unmatched	3.691	3.160	16.440	0.000
	Matched	3.691	3.708	−0.520	0.602
Employment status	Unmatched	0.771	0.638	8.970	0.000
	Matched	0.771	0.762	0.530	0.597
Income	Unmatched	2.105	1.834	9.520	0.000
	Matched	2.105	2.092	0.350	0.724
Panel B.1: Average treatment effect on the treated (ATT) using nearest-neighbor matching with Mahalanobis distance					
Variable	Treated	Controls	Difference	S.E.	T-stat
SI	0.321	0.221	0.100	0.019	5.140
Panel B.2: Comparison of variable averages under PSM					
Variable	Matched	Treated	Control	<i>t</i>	<i>p > t</i>
DFL	Unmatched	−0.114	0.025	−6.300	0.000
	Matched	−0.114	−0.104	−0.370	0.712
Gender	Unmatched	0.394	0.518	−7.920	0.000
	Matched	0.394	0.394	0.000	1.000
Age	Unmatched	35.333	43.391	−17.130	0.000
	Matched	35.333	35.466	−0.280	0.780
Education	Unmatched	3.691	3.160	16.440	0.000
	Matched	3.691	3.687	0.130	0.901
Employment status	Unmatched	0.771	0.638	8.970	0.000
	Matched	0.771	0.771	0.000	1.000
Income	Unmatched	2.105	1.834	9.520	0.000
	Matched	2.105	2.104	0.020	0.981
Source(s): Authors' own work					

5.2 Managerial/policy implications

The results have direct implications for market participants and policymakers, particularly when considering the interaction between attention and social media, DFL and the cultural context. First, the positive association between attention to influencers and equity market participation suggests that influencers and platform-mediated recommendations have become established as influential channels for disseminating market signals, with potential relevance for financial inclusion and economic empowerment strategies (Mölders *et al.*, 2025). For firms operating in financial markets and digital investment platforms, these findings highlight the

need to design more responsible social media communication strategies, incorporating clear information on risks, investment horizons and potential conflicts of interest. Nevertheless, evidence showing that attention-driven dynamics can increase risk-taking and impair returns in other settings reinforces the need to complement inclusion initiatives with financial education and effective consumer protection mechanisms (Arnold *et al.*, 2022).

In this regard, recent regulatory guidance and enforcement actions emphasize that financial promotions on social media must be clear, fair and not misleading, and that influencer participation and compensation schemes should be appropriately disclosed (FCA, 2024). For individual investors, these guidelines underscore the importance of critically assessing the source, incentives and quality of information received through social media before making investment decisions. This regulatory emphasis is particularly relevant, given that the abundance of stock-related information available in financial markets makes investment decision-making especially demanding, as processing such information imposes a high cognitive load and may lead to irrational choices (Isidore and Christy, 2019).

Taken together, these findings indicate that public policies and regulatory frameworks should be context-sensitive, recognizing that DFL does not operate as a universal buffer but rather as a culturally contingent mechanism that can either amplify or attenuate the behavioral impact of social media attention on SI. Consequently, strengthening DFL, alongside more transparent digital communication practices by firms and platform design tools aimed at reducing impulsive decision-making, may contribute to a more informed, prudent and sustainable financial environment (Shunmugasundaram and Sinha, 2025).

5.3 Limitations and future research agenda

This study has limitations that also point to promising directions for future research. First, the analysis relies on cross-sectional and self-reported measures, which may introduce reporting and inference biases; longitudinal or panel designs would enable researchers to assess whether attention to social media predicts SI and longer-term investment performance. Second, the question capturing attention to influencer recommendations was only recently introduced in the OECD/INFE survey, which restricts intertemporal comparisons and the analysis of dynamic effects. Future studies could incorporate measures of attention intensity, platform specificity and content characteristics, such as sentiment, emotional tone, credibility cues or informational complexity, to identify the underlying behavioral mechanisms more precisely. In this regard, the use of machine learning and natural language processing techniques applied to large-scale social media data could substantially enrich the measurement of digital attention and allow a finer classification of informational versus persuasive content.

6. Conclusion

Consistent with its objectives, this study contributes to the behavioral finance literature by showing that individual attention to social media influencers significantly increases the likelihood of SI, reinforcing attention-based explanations of investment behavior. The heterogeneous moderating role of DFL across countries, based on differences in financial literacy levels and cultural characteristics, underscores the need to interpret digital influence within this broader context. Theoretically, the findings advance the understanding of how digital signals function as behavioral triggers and how individual competencies shape their effects, bridging digital finance and investor psychology. Practically, the results support policies that strengthen DFL and improve the oversight of financial content on social media. As these platforms become integral to retail investment decisions, effective regulation and targeted education are essential to foster informed participation and reduce behavioral risks in increasingly digital financial markets.

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Appendix

Variables used in the 2023 OECD international survey of adult financial literacy

A1.1. Stock investment (SI) variable

It was defined as a binary variable identifying individuals who met at least one of the three conditions, coded as 1 when at least one of the specified actions was performed.

- (1) QF3_7: In the past 12 months, have you been [personally] saving money in any of the following ways, whether or not you still have the money? Please don't take into account any money paid into a pension, but think about all kinds of savings, such as building up a rainy-day fund or putting money aside for a special occasion. Response: Investing in shares and securities.
- (2) QP2_12: Can you tell me whether you [personally or jointly] currently hold any of these types of products? Response: Shares and securities.
- (3) QP3_12: In the last two years, which of the following types of financial products have you chosen [Personally or jointly], whether or not you still hold them? Please do not include products that were renewed automatically. Response: Shares and securities.

A1.2. Investor attention (Atten) variable

Question QP7_6 is used: "Which of these sources of information do you feel significantly influenced your decision {about which one to take out}?" The variable takes the value of 1 if the respondent selects the option "A recommendation from people you do not know (such as social media or 'influencers')", and 0 otherwise.

A1.3. Digital financial literacy (DFL) variables and their dimensions

The DFK dimension includes three true-or-false items. Each item scores 1 for a correct answer and 0 otherwise:

- (1) QK7_4, "True or False: A digital financial contract requires the signature on a paper contract to be considered valid."
- (2) QK7_5, "True or False: The personal data that I share publicly online may be used to target me with personalized commercial or financial offers."
- (3) QK7_6, "True or False: Cryptocurrencies have the same legal tender status as banknotes and coins."

The DFB dimension includes four items. Responses are coded as 1 for the appropriate behavior and 0 otherwise:

- (1) QS2_6, "I share the passwords and PINs of my bank account with close friends."
- (2) QS2_7, "Before buying a financial product online I check if the provider is regulated in my country."
- (3) QS2_8, "I share information about my personal finances publicly online (e.g. on social media)."
- (4) QS3_13, "I regularly change the passwords on websites that I use for online shopping and personal finance."

The DFA dimension consists of three statements. Answers are scored 1 for the appropriate attitude and 0 otherwise.

- (1) QS4_1, "I think that it is safe to shop online using public Wi-Fi networks."
- (2) QS4_2, "It is important to pay attention to the security of a website before making a transaction online."
- (3) QS4_3, "I think it is not important to read the terms and conditions when buying something online."

A1.4. Gender (Gen)

Question QD1, which takes the value of 1 if the respondent identifies as male and 0 if female.

A1.5. Age

Question QD7: "How old are you?" Respondents report their age in years.

A1.6. Education (Edu) variable

Education is measured on a 0–5 scale. Level 0 indicates no formal education. Level 1 corresponds to primary education, Level 2 to lower or secondary education, and Level 3 to upper secondary or high school. Level 4 represents completed university studies (e.g. bachelor's degree), while Level 5 includes postgraduate education such as a master's or a doctorate. The variable is labeled QD9.

A1.7. Employment status (ES) variable

The variable takes values of 1 or 0, where a value of 1 is assigned to two categories: individuals who are self-employed and those who are employed for pay. Conversely, a value of 0 is assigned when the respondent is an apprentice, homemaker, seeking work (unemployed), retired, not working, not seeking work, or a student. The question label for this variable is QD10.

A1.8. Household income (Inc) variable

The variable QD13 classifies monthly household income into four categories: nonresponse, below 75% of the median, between 75 and 125% of the median, and above 125%, using country-specific thresholds. The three income ranges for each country are as follows:

Table A1. Income ranges for each country

Salary range	Saudi Arabia	Brazil	Philippines	Finland
Low (1)	Up to 7,000 Saudi riyals	Up to 2,604 reais	Up to 20,800 Philippine pesos	Up to 30,000 euros
Medium (2)	Between 7,000 and 11,000 Saudi riyals	Between 2,604 and 6,510 reais	Between 20,800 and 42,000 Philippine pesos	Between 30,000 and 50,000 euros
High (3)	11,000 Saudi riyals or more	6,510 reais or more	42,000 Philippine pesos or more	50,000 euros or more

Supplementary material

The supplementary material for this article can be found online.

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