Advances in Management & Applied Economics, Vol. 16, No. 5, 2026, 65-87
ISSN: 1792-7544 (print version), 1792-7552(online)
https://doi.org/10.47260/amae/1654
Scientific Press International Limited

The Social Genesis of Overconfidence: How Social Capital and Risk Tolerance Shape Investor Decisions

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Abstract

This study investigates whether social capital functions as a key antecedent of investor overconfidence and evaluates the mediating role of risk tolerance within this relationship. Using survey data from 425 investors and structural equation modeling, the analysis shows that social capital is positively associated with overconfidence, that risk tolerance also exhibits a positive relationship with overconfidence, and that risk tolerance partially mediates the influence of social capital on overconfidence. These findings highlight how investors' relational resources shape risk attitudes and cognitive biases, extending behavioral finance research by offering a socially embedded explanation of overconfidence formation. The results further provide practical implications for financial advisors, platform designers, and policymakers seeking to mitigate socially driven overconfidence and excessive risk-taking through targeted education and intervention strategies.

JEL classification numbers: D91, G41.
Keywords: Social capital, Risk tolerance, Overconfidence, Behavioral finance, Investor psychology.

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Article Info: *Received:* May 14, 2026. *Revised*: May 30, 2026.
Published online: June 5, 2026.

1. Introduction

1.1 Research background

Overconfidence has long been recognized as one of the most pervasive behavioral biases in financial decision-making (e.g., Barber and Odean, 2001; Gervais and Odean, 2001; Singh et al., 2024). This tendency for individuals to overestimate their knowledge, information precision, and control over outcomes (Gervais and Odean, 2001) frequently leads to detrimental behaviors such as excessive trading, under-diversification, and suboptimal asset allocation (Barber and Odean, 2001; Glaser and Weber, 2007). Various perceived behavioral factors significantly influence such decisions across different market contexts (Shahzad et al., 2024). While substantial literature has explored overconfidence consequences, and some research has considered factors like investor sophistication in mitigating behavioral biases (Feng and Seasholes, 2005), the antecedents have received less attention. Understanding these antecedents, particularly broader social contexts and psychological mechanisms in shaping cognitive distortions, becomes critical in an era of rapid financial transformation where 'viral' information significantly impacts choices (Rehman et al., 2024).

Recent advances in behavioral finance have moved beyond purely cognitive models to incorporate social context influence, encompassing studies on herding behavior, social learning, and peer effects in investment decisions (Bursztyn et al., 2014; Shiller, 2015). Within this landscape, social capital—defined as resources embedded within social networks, including trust, shared norms, and information access (Nahapiet and Ghoshal, 1998)—is posited to play a significant role. It shapes investor behavior by influencing information dissemination and risk assessment, supported by evidence on how social networks influence household financial decisions (Jiang et al., 2022a). Despite its explanatory power, social capital remains underexplored as a direct determinant of behavioral biases like overconfidence. The potential "darker side" of social capital—its capacity to create echo chambers, reinforce ill-informed confidence, or amplify existing biases—deserves examination within behavioral finance, especially given online investment communities' proliferation where investor attention can be significantly influenced (Reichenbach and Walther, 2024).

Concurrently, risk tolerance has emerged as a key psychological trait influencing information processing and uncertainty responses. Higher risk tolerance levels are often positively associated with financial risk-taking and self-perceived investment competence (Grable and Lytton, 1999; Raheja and Dhiman, 2021). This study posits that social capital may influence investor overconfidence not only directly but also indirectly through its effect on risk tolerance. Understanding this psychological mediation mechanism is paramount for navigating modern investment complexities; this aligns with broader findings where psychological constructs like risk perception mediate behavioral factors' effects on decisions (Almansour et al., 2023a).

1.2 Motivation and research gap

While financial literature has extensively documented overconfidence's behavioral consequences, the underlying mechanisms driving its emergence, particularly socio-psychological roots, remain inadequately understood. Addressing this gap is crucial for academic advancement—even as recent reviews synthesize findings on its causes (Singh et al., 2024)—and for informing strategic responses within a transforming financial industry. This study's motivation stems from several critical lacunae in existing literature.

Current research predominantly conceptualizes overconfidence from an individual-level psychological perspective, often neglecting social networks and relational resources' (i.e., social capital) formative role in shaping investor cognition. Even when factors like investor experience are considered (Feng and Seasholes, 2005), the pervasive influence of investor social embeddedness—significantly amplified by modern communication technologies and social media dynamics (Reichenbach and Walther, 2024)—remains a critical, yet underexplored, dimension impacting market dynamics.

Furthermore, while social capital has been investigated regarding information diffusion and financial decisions broadly (Jiang et al., 2022a), its direct or mediated relationship with specific behavioral biases such as overconfidence remains empirically underdeveloped. This leaves a void in understanding how social structures translate into individual cognitive biases with potential systemic implications.

Compounding these gaps, risk tolerance's mediating role in the social capital-overconfidence relationship, although theorized in behavioral finance (e.g., risk tolerance-overconfidence links explored by Raheja and Dhiman, 2021, and related mechanisms like risk perception mediation identified elsewhere, Almansour et al., 2023b), lacks sufficient empirical testing within frameworks incorporating social capital as an antecedent. Uncovering this pathway is key to designing effective interventions and advisory frameworks.

Given that risk tolerance critically determines investment decisions and may be shaped by social interactions and social capital-derived resources, understanding its mediating effect promises deeper insights into overconfidence bias formation. By systematically addressing these gaps, this study contributes to behavioral finance literature by offering a socially embedded and psychologically mediated framework explaining overconfidence emergence, providing foundational insights for strategic decision-making in evolving investment contexts.

1.3 Research objectives and questions

To illuminate the social genesis of overconfidence and its implications for investor decision-making within a transforming financial industry, this paper examines the social and psychological antecedents of this bias through social capital theory. The study determines whether social capital positively influences investor overconfidence and explores if risk tolerance mediates this relationship. By addressing these inquiries, the study develops a theory-driven explanation for how

social structures and personal risk preferences interact to shape biased financial decision-making, contributing to understanding the social underpinnings of overconfidence and informing strategic responses to behavioral challenges.

2. Literature review and research hypotheses

2.1 Social capital: theoretical foundations and financial implications

2.1.1 Theoretical foundation: social capital theory

Social capital theory provides the theoretical foundation for understanding how relational resources influence individual behavior. Coleman (1988) conceptualized social capital as a functional entity that facilitates certain actions within social structures, emphasizing its role in fostering information channels, establishing norms, and shaping authority relations. Bourdieu (1984) defined social capital as "the aggregate of the actual or potential resources which are linked to possession of a durable network of more or less institutionalized relationships of mutual acquaintance and recognition."

Nahapiet and Ghoshal (1998) offered a key development by identifying three distinct but interrelated dimensions: the structural dimension (network ties and configuration), the relational dimension (trust, norms, and obligations), and the cognitive dimension (shared codes and language). This multidimensional framework is particularly relevant for financial contexts, where information asymmetries, trust relationships, and shared understanding of market dynamics play crucial roles in investment decision-making.

The mechanisms through which social capital operates in financial contexts include facilitating information acquisition through network connections (Granovetter, 1973), shaping risk perceptions through social influence (Cialdini and Goldstein, 2004), and reinforcing beliefs through social validation processes (Festinger, 1957). These mechanisms collectively suggest that social capital can fundamentally alter how individuals perceive, process, and act upon financial information.

2.1.2 Social capital in digital investment ecosystems

The digital transformation of financial markets has significantly evolved our understanding of social capital. Traditional face-to-face networks have been supplemented or replaced by digital communities, social media platforms, and online investment forums (Zeng and Tao, 2024). This evolution has amplified both the reach and speed of social influence while potentially altering the quality of social capital formation.

Digital platforms create "networked publics" where investment-related information spreads rapidly across vast networks of loosely connected individuals (Boyd, 2011). The traditional gatekeeping functions of strong, trusted ties may be circumvented by the viral nature of digital information transmission (Reichenbach and Walther, 2024). Additionally, how investors allocate attention on social media—a process influenced by cognitive biases—further shapes their engagement with socially transmitted information.

2.1.3 Social capital's link to overconfidence

While traditionally viewed as beneficial for cooperation and resource mobilization (Nahapiet and Ghoshal, 1998), social capital in financial decision-making reveals a more complex character. Strong social ties may provide access to valuable information and foster collective wisdom. However, dense or homogenous networks can create echo chambers, exert conformity pressures, and enable the spread of biased information (Shiller, 2015; Bursztyn et al., 2014).

Evidence from China demonstrates that social networks significantly affect household financial decisions (Jiang et al., 2022b). Building on these considerations, this study posits that social capital significantly influences the development of investor overconfidence.

2.2 Investor overconfidence: a pervasive behavioral bias

Overconfidence stands as one of the most extensively documented behavioral biases in finance (Barber and Odean, 2001; Gervais and Odean, 2001; Singh et al., 2024). It refers to unwarranted faith in one's intuitive reasoning and judgments, leading individuals to overestimate the precision of their knowledge and perceived control over future events (Gervais and Odean, 2001). In investment contexts, overconfidence manifests in excessive trading, risk underestimation, poor diversification, and attributing successes to skill while blaming failures on external factors (Barber and Odean, 2001; Glaser and Weber, 2007).

While cognitive heuristics and individual traits have been primary explanatory foci, the influence of an investor's social environment remains less explored. If social capital provides a heightened sense of informational advantage or consistent social validation, it might foster an inflated sense of predictive abilities. This reasoning leads to our first hypothesis:

Hypothesis 1 (H1): Social capital is positively associated with investor overconfidence.

Rationale for H1: Investors with higher social capital have access to more information channels and frequent investment-related social interactions (Nahapiet and Ghoshal, 1998; Jiang et al., 2022b). This exposure, particularly in reinforcing social media environments (Reichenbach and Walther, 2024), could cultivate perceived enhancement of knowledge or insight. If shared information is predominantly confirmatory or optimistic, it may bolster belief in judgment soundness, leading to overconfidence. Furthermore, trust in strong social ties might predispose investors to uncritically accept network-sourced information, solidifying potentially biased convictions.

2.2.1 Alternative perspectives

While our framework emphasizes social capital's potential to enhance overconfidence, alternative perspectives warrant consideration. Hong et al. (2004) argue that social interactions can reduce biases by exposing individuals to diverse viewpoints. Networks with weak ties and structural holes may provide non-redundant information that challenges beliefs (Burt, 2005). However, dense networks of strong, homogenous ties likely create echo chambers that reinforce biases (Sunstein, 2001). This study hypothesizes a positive main effect while acknowledging these nuances for future investigation.

2.3 Risk tolerance: a key psychological trait

Risk tolerance—the degree of uncertainty individuals willingly accept in financial decisions pursuing higher returns (Grable and Lytton, 1999)—is a fundamental psychological trait significantly influencing investment choices and financial behavior (Shahzad et al., 2024). Individuals with higher risk tolerance typically invest in riskier assets and demonstrate different information processing patterns.

The relationship between risk tolerance and overconfidence is gaining academic interest. Higher risk tolerance may correlate with greater overconfidence because it enables discounting negative feedback and maintaining optimism in uncertain situations. Almansour et al. (2023a) found risk perception mediating between behavioral factors and investment decisions, highlighting risk-related constructs' centrality.

Hypothesis 2 (H2): Risk tolerance is positively associated with investor overconfidence.

Rationale for H2: Higher risk tolerance investors may be psychologically predisposed to downplay downsides and focus on optimistic scenarios (Grable and Lytton, 1999). This optimistic framing contributes to overestimating ability to achieve favorable results—a hallmark of overconfidence (Gervais and Odean, 2001). Greater willingness for risk-taking leads to broader investment experiences. If attribution biases cause overemphasis on successful episodes while downplaying failures, this reinforces overconfident beliefs (Barber and Odean, 2001).

2.4 The mediating role of risk tolerance

2.4.1 Conceptualizing the mediation pathway

Building upon direct links between social capital and overconfidence, and between risk tolerance and overconfidence, this study proposes risk tolerance as a crucial intermediary mechanism. Resources, information, and social validation from investor social networks may directly impact confidence while significantly shaping fundamental risk attitudes, which then affect overconfidence levels.

2.4.2 Psychological mechanisms underlying risk tolerance mediation

Several interconnected psychological mechanisms underpin risk tolerance's mediating role. First, social capital provides access to information and advice from trusted network members (Nahapiet and Ghoshal, 1998), altering risk perceptions. Positively framed information from credible ties may downplay potential downsides (Kahneman and Tversky, 1979), enhancing perceived understanding and control, thereby increasing risk tolerance.

Second, investors observe and learn from others' behaviors within their networks (Bandura, 1977; Bursztyn et al., 2014). If risk-taking is prevalent or celebrated within social circles, these norms become internalized (Cialdini and Goldstein, 2004). Evidence from China demonstrates social networks significantly affect household financial decisions and risk asset holdings (Jiang et al., 2022b), underscoring social learning's power.

Third, witnessing network peers achieve success through risk-taking generates vicarious reinforcement (Bandura, 1977). Such observations instill beliefs that risks are manageable and rewarding, bolstering confidence in navigating similar risks and elevating risk tolerance.

Finally, affective states spread through social networks (Shiller, 2015). Prevailing optimism about market opportunities can be contagious, lowering perceived threats associated with risk-taking and fostering adventurous attitudes.

Hypothesis 3 (H3): Risk tolerance mediates the positive relationship between social capital and investor overconfidence.

Rationale for H3: This study posits a causal chain where social capital provides resources, information, or validation that enhances willingness to take financial risks, increasing risk tolerance (Grable and Lytton, 1999). This elevated tolerance serves as a psychological foundation for building overconfident beliefs about investment capabilities (Gervais and Odean, 2001). Thus, social capital's impact on overconfidence operates not solely directly but significantly through its effect on fundamental risk orientation.

2.5 Empirical evidence and synthesis

Empirical literature on social capital's influence on investor behavior presents a complex picture. Studies on peer effects generally support that social interactions significantly influence financial choices (Bursztyn et al., 2014), though effects vary across contexts. Evidence from China indicates social networks facilitate household financial market participation and increase risk asset holding (Jiang et al., 2022a). However, relationships are nuanced—peer effects depend on group characteristics and prior experiences (Kaustia and Knüpfer, 2012), and social interactions can lead to both beneficial information sharing and harmful herding (Pool et al., 2008).

Digital interactions further complicate this landscape, as online platforms may amplify social influence while challenging information quality (Zeng and Tao, 2024;

Reichenbach and Walther, 2024). While studies support psychological mediation mechanisms via risk perception (Almansour et al., 2023b), direct empirical tests of risk tolerance mediating between social capital and overconfidence remain scarce, representing a significant gap this study addresses.

2.6 Conceptual Integration and Study Positioning

This study contributes to behavioral finance literature by proposing and testing a socially embedded framework for understanding overconfidence formation. Unlike previous research focusing primarily on individual-level cognitive processes (Singh et al., 2024), our approach recognizes that investor psychology is fundamentally shaped by social context and relational resources (Nahapiet and Ghoshal, 1998).

The theoretical integration of social capital theory with behavioral finance represents a novel contribution extending beyond traditional bounded rationality models. By incorporating risk tolerance as a mediating mechanism, we provide a more nuanced understanding of how social factors translate into cognitive biases. This positioning is particularly relevant in the current digital investment landscape (Zeng and Tao, 2024; Reichenbach and Walther, 2024), offering both theoretical advancement and practical insights for understanding investor behavior in rapidly evolving financial markets.

3. Research method

This chapter outlines the methodological approach adopted to examine the relationships among social capital, risk tolerance, and investor overconfidence. The discussion details the research design and framework, the procedures for data collection and sample characteristics, the operationalization and measurement of key constructs, considerations for measurement validation, and the data analysis strategy.

3.1 Research design and framework

The study employs a cross-sectional survey design to investigate the proposed relationships. Investor overconfidence is conceptualized as the dependent variable, with social capital serving as the independent variable, and risk tolerance acting as a mediating variable in this dynamic. In addition to these core constructs, gender and investment experience were included as control variables hypothesized to directly influence investor overconfidence. Other demographic factors (age, marital status, occupation, educational level, and self-reported risk appetite) were also collected; this information was utilized for descriptive profiling of the sample and for supplementary analyses. The research framework, which builds upon the theoretical foundations established in the preceding literature review (see Chapter II), is visually presented in Figure 1.

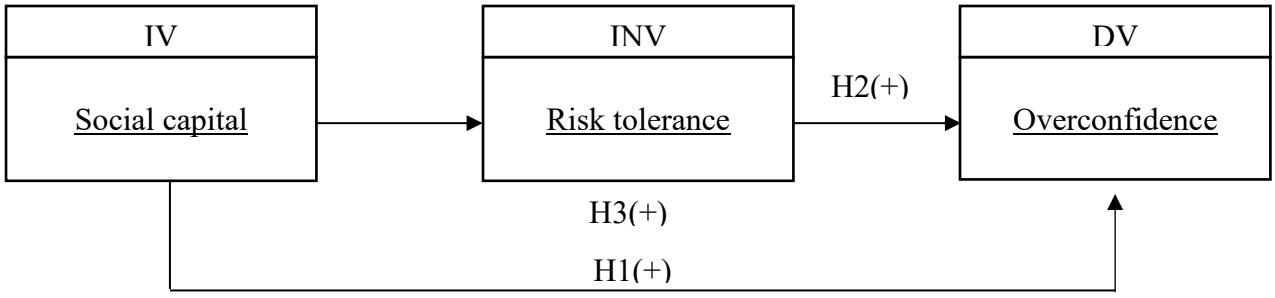

Figure 1: Research Framework

3.2 Data collection and sample

To assess the proposed relationships within the general investing public, a structured questionnaire was distributed online to reach a broad segment of investors. This yielded 448 initial responses. After screening to remove invalid or incomplete responses (n=23), the final sample comprised 425 valid questionnaires, resulting in an effective availability ratio of 94.86%.

To address potential common method bias, procedural remedies were employed during questionnaire design and data collection, including ensuring respondent anonymity and providing clear item wording to reduce misinterpretation (Podsakoff et al., 2003). Statistical checks, such as Harman's single-factor test, were conducted post-collection and are detailed in Chapter IV.

3.3 Measurement of key constructs

The core constructs of social capital, risk tolerance, and investor overconfidence were measured using multi-item scales, primarily employing a 5-point Likert-type response format (1 = strongly disagree; 5 = strongly agree), adapted from or informed by established literature.

3.3.1 Social capital

Acknowledging the context of the original study in Taiwan, the social capital measure was initially informed by the work of Jen et al. (2010), which itself drew upon foundational concepts from Burt (1984) and Krackhardt and Hansen (1993) concerning interpersonal advisory networks, trust networks, and relationship networks. For this English-language manuscript targeting an international audience, the conceptualization aligns with the widely recognized multidimensional framework of social capital by Nahapiet and Ghoshal (1998), encompassing structural, relational, and cognitive aspects. The items used in this study were carefully translated and adapted to ensure semantic equivalence and capture these dimensions within the Taiwanese investor context. An example item is: "I have a good network of contacts who can provide useful information regarding investments." The full set of adapted items and their reliability indices (Cronbach's $\alpha = 0.848$ in this study) are provided in Appendix A.

3.3.2 Risk tolerance

Risk tolerance, operationally defined as the willingness to bear uncertainty in investment decisions (Grable, 2008), was measured using a set of five items selected and adapted from the FinaMetrica Risk Profiling System, a tool widely used in financial advisory and research for assessing investor risk preferences. While the full FinaMetrica instrument consists of 25 items (FinaMetrica Pty Ltd., 2014), we selected five items deemed most relevant to the present study's objectives, focusing on general risk propensity, comparative risk preference, and responses to hypothetical risk scenarios. This selection was guided by both the need for content coverage pertinent to our research questions and consideration of prior reliability evidence for similar adapted scales (see Corter and Chen, 2006a; 2006b). Each item was rated on a 5-point Likert scale. An example item is: "In comparison with others, to what degree do you consider yourself willing to bear the risks of wealth management?" The five-item scale demonstrated good reliability in the current study (Cronbach's $\alpha = 0.824$). The full English wording of the five items used in this study is provided in Appendix B for transparency and replication purposes.

3.3.3 Investor overconfidence

Investor overconfidence was measured using the scale developed by Fogel et al. (2006a; 2006b), which has been validated in prior behavioral finance studies and is well-aligned with our operational definition of overconfidence as the tendency to overestimate one's investment skill and attribute success internally (consistent with Daniel et al., 1998). The scale comprises six items (the full English wording is provided in Appendix C), each rated on a 5-point Likert scale. An example item is: "I attribute returns primarily to my own successful investment strategies." This instrument was selected for its concise structure, established empirical reliability, and demonstrated suitability for use with general investor samples in behavioral finance research. The Cronbach's alpha for the overconfidence scale in our sample was 0.846, indicating good internal consistency.

Following the measurement of these primary constructs, two key variables, gender and investment experience, were operationalized for inclusion as control variables in the structural model. Gender was recorded as a dichotomous variable (e.g., 0 = Male, 1 = Female). Investment experience was assessed based on the number of years the respondent reported having been actively investing, subsequently categorized (e.g., Under 3 years, 4-6 years, 7-9 years, Over 10 years) and coded appropriately for statistical analysis. In addition to these control variables, other demographic information—including age (categorized), marital status, occupation, educational level, and self-assessed risk appetite (e.g., risk-loving, risk-neutral, risk-averse)—was collected. This latter set of information was utilized primarily for describing the sample and for exploring potential group differences through supplementary analyses.

3.4 Measurement validation

The psychometric properties of the measurement scales were rigorously assessed as part of the PLS-SEM analysis (detailed in Chapter IV), focusing on indicator reliability, internal consistency, convergent validity, and discriminant validity. Given that the social capital scale involved adaptation from an instrument originally developed in a different linguistic context (Jen et al., 2010), particular attention was paid to its performance in the current sample. Although a formal translation-back-translation procedure involving multiple bilingual experts as recommended by Van de Vijver and Hambleton (1996) was not fully documented as part of the original data collection for the Chinese survey, the items were carefully translated for this English manuscript, and their empirical performance was evaluated. The scales for risk tolerance and overconfidence were adapted from established English-language instruments. A comprehensive measurement model evaluation, including the assessment of factor loadings, Cronbach's alpha, composite reliability (CR), Average Variance Extracted (AVE), and discriminant validity criteria (e.g., Fornell-Larcker criterion, HTMT ratios), was conducted to ensure that all selected and adapted scales functioned reliably and validly for measuring the intended constructs in this study.

3.5 Data analysis strategy

The data were analyzed using several statistical techniques. Initially, descriptive statistics were generated for all demographic variables and key constructs to provide sample characteristics and response distributions. Reliability analyses (Cronbach's alpha) were conducted for each multi-item scale to assess internal consistency, as reported in section 3.3. The core hypotheses were tested using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS software. PLS-SEM was chosen for its suitability in handling complex path models, robust performance with non-normally distributed data, and effectiveness in predictive research settings (Hair et al., 2017; Hair et al., 2019). The PLS-SEM analysis followed a two-step approach: first, evaluating the measurement model to confirm construct reliability and validity (convergent and discriminant); second, assessing the structural model to examine hypothesized path coefficients, their statistical significance (via bootstrapping with 5,000 resamples), and the model's explanatory power (R^2 values). The mediating effect of risk tolerance (H3) was tested using bootstrapping to establish indirect effect significance.

4. Empirical results

4.1 Sample characteristics

The data were collected from individual investors (N=425). Personal data analyses encompassed gender, marital status, occupation, age, investment experience, educational level, and self-assessed risk preference. The sample comprised predominantly females (64.7%), with 41.6% aged between 36-45 years. Most respondents held university/college degrees (50.8%) or graduate degrees (37.2%),

with 32.7% having over 10 years of investment experience. Regarding risk appetite, the majority identified as risk-neutral (54.8%), while risk-loving (22.4%) and risk-averse (22.8%) investors were well-represented. Detailed distributions are presented in Table 1.

Table 1: Description of Research Samples

Item	Option		Effective percentage	Accumulated percentage
Gender	Male	150	35.3%	35.3%
	Female	275	64.7%	100%
Marital status	Married	290	68.2%	68.2%
	Single	135	31.8%	100%
Occupation	Military, public office or teacher	178	41.9%	41.9%
	Service industry	53	12.5%	54.4%
	Information industry	17	4.0%	58.4%
	Financial industry	28	6.6%	64.9%
	Corporate executives	2	.5%	65.4%
	Freelance	27	6.4%	71.8%
	Housewife	26	6.1%	77.9%
	Student	18	4.2%	82.1%
	Retired	23	5.4%	87.5%
	Others	53	12.5%	100%
Age	under 25 years old	23	5.4%	5.4%
	26 to 35 years old	65	15.3%	20.7%
	36 to 45 years old	177	41.6%	62.4%
	46 to 55 years old	92	21.6%	84%
	56 to 65 years old	39	9.2%	93.2%
	Above 66 years old	29	6.8%	100%
Investment and wealth management	Under 3 years	163	38.4%	38.4%
	4 to 6 years	77	18.1%	56.5%
	7to 9 years	46	10.8%	67.3%
	Over 10years	139	32.7%	100%
Educational level	Below junior high school (inclusive)	5	1.2%	1.2%
	Senior high school	46	10.8%	12%
	University and College	216	50.8%	62.8%
	Graduate school and above	158	37.2%	100%
Risk appetite	Risk-loving	95	22.4%	22.4%
	Risk-neutral	233	54.8%	77.2%
	Risk-aversion	97	22.8%	100%

4.2 Measurement model evaluation

Prior to examining the hypothesized structural relationships, a thorough assessment of the measurement model was conducted to ensure the reliability and validity of the constructs: social capital, risk tolerance, and overconfidence. This evaluation involved an analysis of convergent validity and discriminant validity using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS software V3.0.

Convergent validity, indicating the extent to which multiple indicators designed to measure the same construct agree, was an initial focus. This was evaluated by examining standardized factor loadings, Cronbach's alpha values, composite reliability (CR), and the average variance extracted (AVE) for each construct. Following established criteria (Fornell and Larcker, 1981; Hair et al., 2017), convergent validity is supported when factor loadings exceed 0.70 (or >0.50 if CR and AVE are strong), Cronbach's alpha and CR values exceed 0.70, and AVE values are 0.50 or higher. The results, summarized in Table 2, demonstrate strong scale performance. For social capital, while its AVE was 0.461, approaching the 0.50 threshold, its CR value was a robust 0.882, and all factor loadings were above 0.50 and statistically significant (t-values > 1.96), supporting its acceptability. Both risk tolerance (AVE = 0.587, CR = 0.876) and overconfidence (AVE = 0.567, CR = 0.886) met all recommended thresholds, with all factor loadings being significant and above 0.50. These results collectively indicate satisfactory convergent validity for the scales utilized.

Table 2: Validity Analysis of Scales

Research variable	Item No.	Factor loading value	Variance inflation factor (VIF)	T value	Composite reliability (CR)	Average variance extracted (AVE)
Social capital	1	0.504	1.434	7.975	0.882	0.461
	2	0.554	1.317	9.578		
	3	0.727	1.882	17.182		
	4	0.752	2.184	18.034		
	5	0.578	1.923	9.642		
	6	0.554	1.880	8.949		
	7	0.805	2.678	25.097		
	8	0.823	2.977	30.823		
	9	0.728	2.105	19.586		
Risk tolerance	1	0.837	2.164	50.644	0.876	0.587
	2	0.639	1.369	14.380		
	3	0.788	2.101	28.963		
	4	0.826	2.354	34.574		
	5	0.725	1.348	24.340		
Overconfidence	1	0.634	1.380	16.091	0.886	0.567
	2	0.736	1.700	20.413		
	3	0.794	2.024	28.710		
	4	0.815	2.095	40.083		
	5	0.792	1.868	41.993		
	6	0.733	1.628	21.315		

Subsequently, discriminant validity was examined to ensure that each construct was empirically distinct from others in the model. This was assessed using the Fornell-Larcker criterion, which requires the square root of AVE for each construct to exceed its correlations with all other constructs. The results in Table 3 show the data complied with this principle, as diagonal values (square root of AVE) exceeded off-diagonal values (inter-construct correlations). Further assurance was obtained through cross-loadings analysis (Table 4), confirming all items loaded more strongly on their intended construct than on any other, with primary loadings above 0.50 and higher than cross-loadings (Hair *et al.*, 1998).

Table 3: Discriminant Validity Analysis

Dimension	Social capital	Risk tolerance	Overconfidence
Social capital	**0.679**		
Risk tolerance	0.208	**0.766**	
Overconfidence	0.290	0.660	**0.753**

Table 4: Cross-loading

Dimension	Item No.	Social capital	Risk tolerance	Overconfidence
Social capital	1	**0.504**	0.073	0.088
	2	**0.554**	0.144	0.179
	3	**0.727**	0.127	0.248
	4	**0.752**	0.150	0.261
	5	**0.578**	0.145	0.131
	6	**0.554**	0.193	0.145
	7	**0.805**	0.131	0.174
	8	**0.823**	0.123	0.216
	9	**0.728**	0.161	0.239
Risk tolerance	1	0.194	**0.837**	0.526
	2	0.170	**0.639**	0.309
	3	0.069	**0.788**	0.464
	4	0.130	**0.826**	0.509
	5	0.214	**0.725**	0.626
Overconfidence	1	0.278	0.413	**0.634**
	2	0.239	0.471	**0.736**
	3	0.162	0.490	**0.794**
	4	0.339	0.475	**0.815**
	5	0.134	0.586	**0.792**
	6	0.186	0.519	**0.733**

4.3 Structural model and hypothesis testing

Having established the adequacy of the measurement model, the structural model was evaluated to test the hypothesized relationships. The SRMR values for the saturated model (0.081) and estimated model (0.089) were both below the 0.10 threshold (Hair et al., 2017), suggesting acceptable model fit.

The core analysis involved examining path coefficients (β), representing the direction and intensity of relationships between variables. Statistical significance was determined through bootstrapping with 5,000 resamples.

Hypothesis 1, which posited a positive association between social capital and investor overconfidence, revealed a significant positive direct effect ($\beta = 0.172$, $t = 4.317$, $p < 0.001$), supporting H1. Similarly, Hypothesis 2 proposed a positive relationship between risk tolerance and investor overconfidence. The analysis yielded a strong positive path coefficient ($\beta = 0.571$, $t = 17.768$, $p < 0.001$), supporting H2. (Demographic variables such as gender ($\beta = -0.104$, $p = 0.004$) and investment experience ($\beta = 0.128$, $p = 0.001$) also showed significant associations with overconfidence in preliminary analyses, though they were not included in the final parsimonious model).

The model's predictive power was assessed using R^2 values. The model explained 48.5% of the variance in investor overconfidence ($R^2 = 0.485$), suggesting good explanatory capability. Social capital explained 4.3% of the variance in risk tolerance ($R^2 = 0.043$).

A crucial aspect was examining the mediating role of risk tolerance in the relationship between social capital and overconfidence (Hypothesis 3). The path from social capital to risk tolerance was positive and significant ($\beta = 0.208$, $t = 4.366$, $p < 0.001$). The indirect effect of social capital on overconfidence through risk tolerance was calculated as the product of path coefficients ($0.208 * 0.571 = 0.119$). The bootstrapping procedure confirmed this indirect effect was statistically significant ($p < 0.001$).

To quantify the mediation extent, the Variance Accounted For (VAF) was computed as (Indirect Effect) / (Total Effect). The total effect of social capital on overconfidence is the sum of direct (0.172) and indirect (0.119) effects, which is 0.291. Thus, VAF = 0.119 / 0.291 = 0.4089, or 40.89%. As this value falls between 20% and 80%, and the indirect effect is significant, it signifies partial mediation (Hair et al., 2017). Therefore, risk tolerance partially mediates the impact of social capital on investor overconfidence, supporting H3. The results are summarized in Table 5, and the overall path model is depicted in Figure 2.

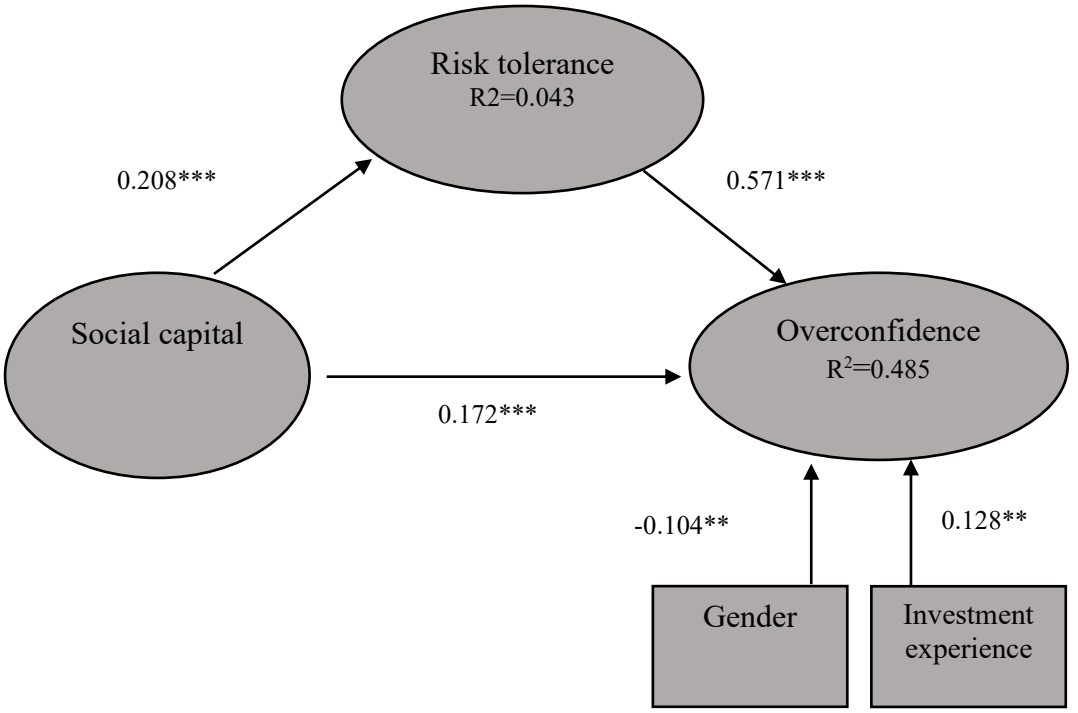

Figure 2: R^2: Path Coefficients and Predictive Power of Models

Table 5: Influential Effects of Research Variables

Latent variable	**Risk tolerance**	**Overconfidence**		
	Direct effect	Direct effect	Indirect effect	Total effect
Social capital	0.208***	0.172***	0.118	0.290
Risk tolerance		0.571***		0.571

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

5. Discussion

5.1 Interpreting the key findings: social capital, risk tolerance, and overconfidence in a transforming financial landscape

This study's empirical results offer critical insights into the socio-psychological antecedents of investor overconfidence, a behavioral bias with significant implications for financial decision-making, particularly within today's rapidly evolving financial industry. The findings related to our three central hypotheses contribute to behavioral finance theory and raise important strategic considerations for market participants, regulators, and financial service providers.

The confirmation of the first hypothesis (H1)—that investors' social capital exhibits a strikingly positive correlation to overconfidence—underscores the profound impact of social embeddedness on individual investor psychology. In an era characterized by online investment communities, social media financial influencers ("finfluencers"), and algorithmically curated information streams, the avenues through which social capital is built and leveraged are undergoing a seismic shift. While social capital can provide valuable information and support, our findings suggest its "darker side" may be increasingly salient. Investors embedded in dense or homogenous social networks might perceive their information as more exclusive or reliable than it objectively is, leading to an inflated sense of their predictive capabilities. This observation moves beyond a purely cognitive understanding of overconfidence, suggesting it is not merely an individual processing error but can be a socially constructed phenomenon. For the financial industry, this poses a strategic challenge concerning how financial service providers and platform designers can acknowledge and navigate the influence of social capital. If the very networks investors rely on contribute to overconfidence, traditional approaches to investor education and risk warnings may prove insufficient, necessitating a strategic rethink towards fostering critical information evaluation skills and promoting cognitive diversity within investors' information ecosystems.

Building on this, the study's second key finding (H2), that risk tolerance presents a remarkably positive correlation with overconfidence, resonates strongly with behavioral finance literature. Studies reveal overconfident investors often engage in more frequent trading, indicative of higher risk appetite. The process of 'learning' to be overconfident can be fueled by successful outcomes from past risk-taking endeavors, creating a cycle where risk tolerance and overconfidence may reinforce each other. This relationship gains new strategic importance when considering democratized access to complex financial products and increased emphasis on self-directed investing. Higher risk tolerance may lead individuals to engage with riskier assets, and if this concurrently fuels overconfidence, investors might underestimate the true extent of their risks. From a strategic perspective, financial advisors must recognize that assessing risk tolerance is not a static exercise. Client communication strategies need to be more nuanced, helping clients distinguish between well-calibrated willingness to bear risk and overconfident assessment of their ability to manage it.

Perhaps the most strategically significant finding is the confirmation of H3: that risk tolerance plays a partial mediating role in the positive relationship between social capital and overconfidence. This uncovers a critical socio-psychological pathway, suggesting an individual's social capital can shape their willingness to take risks, which influences their level of overconfidence. For FinTech innovators and platform providers, this finding raises questions about responsible design of user interfaces and community features. This pathway highlights a strategic imperative for the industry to consider how platform architectures and regulatory frameworks can mitigate the potential for socially amplified risk-taking and overconfidence, calling for a shift towards strategically designing environments that promote more calibrated self-assessment and prudent decision-making among investors.

5.1 Theoretical contributions and strategic implications for a transforming financial sector

The findings of this study, which illuminate the intricate relationships between social capital, risk tolerance, and investor overconfidence, offer several important contributions to behavioral finance theory and carry significant strategic implications for various stakeholders operating within the rapidly evolving financial services industry.

Theoretically, this research extends behavioral finance frontiers in key ways. It contributes a more nuanced perspective to *social capital theory within financial contexts.* Traditionally, social capital has been invoked to explain positive outcomes such as access to resources or enhanced performance. Our findings demonstrate how social capital, particularly the relational resources and information flows inherent in social networks, can also act as a conduit for, or even an amplifier of, cognitive biases like overconfidence. This "double-edged sword" aspect enriches the theory by highlighting its potential to foster not only opportunities but also vulnerabilities, particularly in environments saturated with social information and online interactions.

Furthermore, our research provides *a crucial socially-embedded view of overconfidence antecedents*. Much of the extant literature focuses on individual cognitive heuristics or demographic factors. By identifying social capital as a significant antecedent, we underscore the importance of considering an investor's relational context and the influence of social learning or peer effects when analyzing this pervasive bias, moving the discourse beyond purely intra-psychic explanations to a more holistic socio-psychological framework.

A significant theoretical refinement is offered through the *elucidation of the mediating role of risk tolerance*. The identification of risk tolerance as a partial mediator in the social capital-overconfidence nexus uncovers a psychological pathway through which social influence can translate into cognitive bias. This suggests that the impact of social networks on investor cognition involves not merely information transfer but also shifts in fundamental psychological orientations like risk attitudes, providing a more granular understanding of how

social structures can shape individual judgment and decision-making in financial markets.

These relationships carry profound strategic implications for how the financial industry adapts to investor behavior in an era of digital transformation and social network influence. There is a clear need for *rethinking investor profiling and advisory models within financial institutions.* While advisors traditionally focus on assessing risk tolerance through psychometric tools, our findings suggest a more comprehensive approach that also considers an investor's social capital structure and its potential influence on both their risk appetite and propensity for overconfidence. Strategic advisory models should evolve to incorporate discussions about the sources of an investor's financial information and the nature of their investment-related social interactions.

The proliferation of online investment platforms and social trading communities necessitates a focus on *responsible design and governance for FinTech platforms and online communities.* Our findings present a strategic imperative for innovators to consider how platform features might inadvertently amplify the link between social capital, heightened risk tolerance, and overconfidence, urging strategic choices in architecture and moderation to mitigate socially contagious biases.

For regulators and policymakers, this research underscores the importance of *evolving regulatory frameworks and investor protection* beyond traditional disclosure-based methods. If social capital significantly influences biases like overconfidence, frameworks must adapt to address challenges from digitally mediated social influence and misinformation spread, perhaps involving new guidelines for financial influencers or scrutiny of social trading platforms.

Finally, these insights call for *advancing investor education beyond mere financial literacy.* While literacy remains crucial, effective modern investor education must also encompass "social network literacy" and critical thinking skills. Investors need education on the psychological impact of their social environment on their decision-making, enhancing their ability to critically evaluate network-sourced information, recognize echo chambers, and develop calibrated self-awareness regarding their susceptibility to biases like overconfidence fueled by social capital. This represents a strategic shift towards cognitive and metacognitive skill development.

5.2 Limitations and avenues for future research

While this study provides valuable insights into the socio-psychological antecedents of investor overconfidence, several limitations open promising avenues for future research critical to understanding the evolving financial landscape.

The present research operates within methodological constraints. The cross-sectional nature of our survey data precludes definitive causal inferences between social capital, risk tolerance, and overconfidence. Longitudinal studies are needed to track these relationships over time, observing how changes in social capital structure impact risk tolerance and overconfidence levels throughout different market cycles. Such dynamic analyses would offer richer insights for predictive

modeling and intervention strategies. Another consideration pertains to self-reported data, which may be subject to common method variance or social desirability biases. Future research could benefit from incorporating objective behavioral data (e.g., actual trading records, platform engagement metrics) alongside survey measures. Furthermore, experimental designs could test the causal mechanisms proposed in our model. Finally, the formation and impact of social capital can vary significantly across different cultural settings, making cross-cultural comparative studies essential for generalizability.

Several strategic research directions emerge that can deepen understanding and inform practice. An important endeavor is the disaggregation of social capital to understand its differential impacts. Future work should distinguish different dimensions (e.g., bonding, bridging, linking; online versus offline) and investigate their distinct effects. Exploring whether diverse, bridging social capital offers more cognitive benefits compared to dense, bonding social capital that might foster echo chambers is strategically vital for designing beneficial online platforms.

As financial interactions migrate to digital platforms, a critical agenda involves investigation into the "dark side" mechanisms within these digital ecosystems. Understanding how algorithmic biases, misinformation propagation, and online influence dynamics contribute to the social construction of overconfidence is crucial for developing ethical AI and responsible platform governance.

A significant strategic challenge lies in developing and testing behavioral interventions. Future research should focus on designing interventions—whether educational, nudges within FinTech platforms, or advisory protocols—aimed at helping investors leverage social capital benefits while mitigating overconfidence inflation.

The financial landscape's continuous reshaping by robo-advisors and decentralized finance necessitates research into the interplay with emerging financial technologies. Studies should explore how these technologies interact with investors' social capital and whether they moderate or exacerbate identified effects.

Finally, the relationship between social capital, risk tolerance, and overconfidence calls for exploration of contextual moderators and long-term outcomes. Investigating moderators such as financial literacy, investor experience, or market sentiment, alongside longitudinal tracking of how socially influenced biases impact long-term financial well-being, would provide invaluable insights for theory and strategic policy formulation.

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