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Investment decision-making of young retail investors: A behavioural study from China

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Abstract

This study investigates the informational and behavioural determinants of young retail investors' investment decisions in China, a high-fintech penetration market with policy-driven volatility and strong collectivist traditions. Drawing on the Theory of Planned Behaviour (TPB) and Behavioural Finance Theory (BFT), this study tests the role of emotional intelligence, herd behaviour, overconfidence, accounting information, and financial knowledge. A quantitative, cross-sectional research design was employed with 504 young investors via an online platform. Multiple linear regression analysis reveals that emotional intelligence, accounting information, and financial knowledge have positive impacts on investment decisions and that herd behaviour and overconfidence have significant adverse effects. The study identifies the double-edged sword of fintech: online platforms enhance access to financial information and tools but reinforce behavioural biases through social influence and horizon problems. The findings have implications for the design of targeted financial education programmes and behaviour-based and policy reforms by organizations such as the China Securities Regulatory Commission (CSRC). The study has limitations in its urban and digitally connected sample and in its cross-sectional design. Future research should explore the role of trust in mediating the effects between informational and behavioural factors and should undertake longitudinal analyses and cross-country comparisons to extend the research on behavioural finance in developing markets.

Keywords: Behavioral finance, China, Investment decision-making, Risk perception, Young retail investors.

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1. Introduction

1.1. The Stock Market in China

The Chinese stock market, anchored by the Shanghai (SSE) and Shenzhen (SZSE) Stock Exchanges, has grown into the world's second-largest equity market by trading volume [1]. Unlike Western markets dominated by institutional investors, China's market is uniquely retail-driven, with over 200 individual investors accounting for the majority of trading activity. Recent trends indicate a growing participation of younger investors, with nearly half of new accounts opened by individuals under 30 [2, 3]. This demographic's participation surged with fintech democratisation, for example, platforms like EastMoney, Tencent-backed Futu, and social trading app Snowball (Xueqiu) have simplified stock access, enabling speculative trading akin to "gamified investing" [4]. However, this growth has been accompanied by pronounced volatility. State-led regulatory interventions, such as the 2021 reforms targeting the technology sector and the 2023 restrictions on gaming industries, alongside retail investor-driven speculative bubbles like the artificial intelligence stock frenzy of 2023, reveal systemic vulnerabilities within the market. These dynamics are further amplified by cultural influences. Younger investors, shaped by guanxi (a cultural emphasis on relationship-driven trust) and active engagement in online communities, frequently prioritise collective social consensus over rigorous fundamental analysis [5]. This is exemplified by the rise of stock influencer livestreams on Douyin (TikTok) and Bilibili, in which financial information is often mixed with entertainment, triggering short-term bursts of trading activity [6].

1.2. Problem Statement

Despite fintech's democratisation of investment, young Chinese investors remain vulnerable to cognitive biases shaped by collectivist norms and online herd behaviour. For example, "herd investing" (qún tǐ tóu zī), fuelled by WeChat investment groups and Reddit-style forums on Xueqiu, frequently overrides rational analysis, resulting in speculative losses [7]. A survey conducted by Organisation for Economic Co-operation and Development in 2020 showed that overconfidence persists, with 62% of Chinese investors believing they could 'beat the market,' despite having low financial literacy [8]. This study addresses knowledge gaps regarding how China's sociocultural environment, which is typified by rapid digitisation, state-media rhetoric, for instance, "self-reliance" in technology, and informal information networks, affects the dynamics of emotional intelligence, herd behaviour, overconfidence, financial literacy, and the use of accounting information.

1.3. Research Objectives

1. To determine whether emotional intelligence significantly influences the investment decisions of young Chinese investors.
2. To assess the statistical relationship between herd behaviour and investment decisions in a collectivist and fintech-integrated market environment.
3. To evaluate the extent to which overconfidence affects investment-related decision-making among retail investors in China.
4. To investigate the predictive effect of accounting information, particularly as accessed through fintech platforms, on investors' decision-making processes.
5. To analyse the effect of financial literacy on investment decisions and its moderating role in reducing behavioural bias among young investors.

2. Literature Review

2.1. Theoretical Framework

This study draws on two theories to explain investor behaviour, they are the Theory of Planned Behaviour (TPB) and Behavioural Finance Theory (BFT).

2.1.1. Theory of Planned Behaviour (TPB)

Ajzen [9] provides a robust framework for explaining investment intentions by using three pillars of attitudes, subjective norms, and perceived behavioural control. Attitudes in China's stock market, or an individual's evaluation of investment outcomes, are developed under the double dynamic of nationalistic optimism and distrust of institutional transparency. Young investors, for instance, hold ambivalent attitudes towards risk, being drawn to high-reward "concept stocks" cultivated by state media but dreading losses that would undermine familial financial security. Meanwhile, subjective norms strongly prescribe investment attitudes in China's collectivist culture. Peer pressure via social media apps such as WeChat compels investors to adhere to the majority view [10]. Additionally, family pressures centred on financial security encourage risk-free investments in state-backed assets with minimal reliance on independent analysis [11]. Lastly, Investors' perceived behavioural control is severely eroded under China's mercurial regulatory environment, as evidenced by sudden cryptocurrency trading bans and strict margin restrictions. Such arbitrary policy reversals destroy investors' perceptions of control over making their own decisions in financial markets [12]. Thus, the majority of investors rely on informal networks and financial opinion leaders on platforms such as Snowball (Xueqiu) for guidance [13]. Additionally, such factors demonstrate how TPB's universal constructs are distinctively mediated by China's sociocultural context and policy-driven markets.

While TPB has been widely used in health, education, and consumer behaviour studies, this research makes a novel theoretical contribution by adapting TPB to the unique behavioural dynamics of Chinese retail investors. By mapping the TPB components, attitude, subjective norm, and perceived behavioural control, to specific behavioural and informational constructs (i.e., emotional intelligence, herd behaviour, overconfidence, accounting information, and financial literacy), the study expands TPB's applicability to a non-traditional domain: behavioural finance in emerging Asian markets. It further shows how digital platforms and collectivist culture reinforce subjective norms and influence perceived control, thereby enriching TPB's cross-cultural relevance and flexibility in modelling financial behaviour.

2.1.2. Behavioural Finance Theory (BFT)

BFT describes how psychological biases and irrationalities impair decision-making in financial markets, a process evident in China's retail-driven stock market. Unlike Western markets, China's amateur retail investors are overconfident, encouraged by state media narratives of "technological self-reliance" and survivorship bias from viral success stories of "stock gods," such as Lin Yuan's mythologised trades. Overconfidence bias by Chinese investors has been noted in recent studies [14]. Furthermore, herd behaviour is institutionalised on social media sites like Snowball and Douyin, where speculative frenzy is affirmed by key opinion leaders, creating feedback loops like those in pre-crash bubbles in markets like real estate. The influence of social media on herding behaviour among investors has been studied, with an emphasis on the part played by these sites in amplifying speculative trends [15]. On top of these biases comes China's unique policy-driven volatility: sudden regulatory surprise and limited access to international markets enhance investors' reliance on social proof and short-term speculation. For instance, the tendency to chase "policy lottery" stocks reflects a combination of overconfidence in state-favoured sectors and herd-driven fear of missing out (FOMO). The impact of this type of policy change on investor behaviour has been examined in recent studies [12]. By situating these biases within China's regulatory and digital landscape, this study grounds the general precepts of behavioural finance in the idiosyncrasies of its "sǎn hù" (retail investor) culture, offering new perspectives on how collectivism, distrust of formal data, and fintech democratisation combine to produce investment irrationalities.

This study contributes to BFT by contextualising its core constructs, such as overconfidence, herd behaviour, and emotional bias, within the unique socio-cultural and policy-driven environment of China's retail investment landscape. Unlike most prior behavioural finance literature which focuses on Western institutional investors, this research highlights how digital platforms (e.g., Douyin, Snowball), collectivist social norms, and volatile regulatory interventions create a distinctive behavioural ecosystem. By integrating financial literacy and accounting information as informational moderators, the study refines the understanding of how behavioural biases operate under fintech-enabled conditions. This deepens BFT's explanatory power in underrepresented markets and adds a cultural dimension that has often been neglected in behavioural models.

2.2. Key Constructs in the Chinese Context

2.2.1. Emotional Intelligence (EI)

Emotional intelligence (EI) refers to an investor's ability to regulate emotions, resist impulsive decisions, and maintain rationality during market fluctuations. In China, EI holds particular importance due to the market's susceptibility to policy-driven volatility, such as abrupt regulatory crackdowns, and social media-driven sentiment swings [16]. During the 2021 tech sector selloff triggered by antitrust reforms, for instance, investors with high EI were less likely to engage in panic selling compared to their low-EI counterparts [12, 17]. Culturally, EI aligns with Confucian values of self-restraint and long-term orientation, which help mitigate the allure of speculative "get-rich-quick" schemes prevalent on platforms like Douyin [18]. However, the impact of EI is moderated by financial literacy. Even emotionally intelligent investors who lack financial education may make suboptimal decisions due to overreliance on social proof [19].

2.2.2. Herd Behaviour

Herd behaviour in China is deeply rooted in collectivist norms and amplified by digital ecosystems. Retail investors frequently mimic trades promoted on WeChat groups, Xueqiu forums, or fintech apps like Snowball, where features such as "copy trading" institutionalise herd dynamics [20]. Comparative studies highlight that herd behaviour is more pronounced in the stock market of China compared to Western markets, primarily due to the dominance of retail investors and high sensitivity to informal sources of information, especially during periods of market uncertainty [21-23]. Found that exposure to social media significantly affects family investment in China, as investors prefer to follow general investment opinions and trends posted on social media, confirming herd behaviour particularly among less financially educated families. This behaviour is further intensified by policy uncertainty. Sudden regulatory shifts, including the 2023 restrictions on online brokerages, undermine confidence in independent analysis and drive investors toward crowdsourced strategies [24].

2.2.3. Overconfidence

Overconfidence manifests in excessive trading, poor diversification, and unwarranted faith in market-timing abilities [25, 26]. In China, this bias is culturally reinforced by myths of resilience, such as "rising against the odds" [27] and survivorship bias from viral success stories of "stock gods" like Lin Yuan [28]. A study conducted by Sommer and McCoy [29] found that male investors will more probably exhibit investment overconfidence, with considerably higher subjective confidence and higher trading activity compared to female investors. Moreover, fintech platforms, especially through smartphone-based trading apps, exacerbate overconfidence and self-control problems by increasing investor attention to short-term returns and making spontaneous trading more convenient, thereby reinforcing behavioural biases and financial vulnerability [30]. Furthermore, in post-pandemic China, psychological biases like overconfidence have played an important role in shaping individual investors' decisions, which has created higher exposure in risky sectors [31].

2.2.4. Accounting Information

Young Chinese investors have an ambivalent attitude towards accounting information. While distrust of formal corporate disclosures persists, particularly in the wake of scandals such as the Luckin Coffee fraud [32] they increasingly accept fintech platforms that simplify financial information [14]. Platforms such as EastMoney and Snowball condense complex corporate reports into readable metrics such as earnings ratios and cash flow visualisations, enabling investors to negotiate opaque disclosures [33]. This distrust-augmentation dilemma is partly addressed by AI-driven innovations. For example, platforms such as DeepSeek use machine learning to generate predictive analytics such as risk scores, which have been linked to reduced speculative trading as users prioritise data-driven approaches [34]. Culturally, younger traders will often combine AI-driven insights with social media trends, such as forums on algorithmically backed stocks on Xueqiu [35]. This reflects how accounting information is reinterpreted through China's evolving digital landscape.

2.2.5. Financial Literacy

Data from the 2017 China Household Finance Survey demonstrates that rural residents possess substantially lower financial knowledge levels, as represented by their ability to respond correctly to only 33% of basic and 20.8% of advanced financial literacy questions, alluding to the persistence of educational disparities documented in the literature [36]. Low literacy correlates with susceptibility to Ponzi schemes, such as the 2020 Ezubao scandal, and speculative crypto trading [37]. In response to concerns over speculative and impulsive trading, the China Securities Regulatory Commission (CSRC) has introduced state-sponsored programs such as the "National Investor Education Month" that are designed to raise financial literacy and foster more informed investment on the part of retail investors, particularly in the urban regions [38]. Financially literate investors are also more likely to align strategies with national policies (e.g., "dual circulation"), mitigating exposure to geopolitical risks [38]. Cultural factors play a role as the Confucian emphasis on *education* and *thrift* improves literacy in older cohorts [39] while younger investors prioritise fintech-driven "learning by doing" [15].

2.2.6. Investment Decision-Making

Investment decision-making in China is influenced by a complex interplay between classical financial theories, behavioural influences, and institutional forces. Du and Zhou [40] survey classical investment valuation methods, including Net Present Value (NPV), Internal Rate of Return (IRR), and the Capital Asset Pricing Model (CAPM), that remain foundational frameworks for firms evaluating strategic investments, anchoring critical decisions in quantitative rigor. However, these logical frameworks provide little attention to the current situation of Chinese investors, for whom social and psychological factors are present. Yuan and DuraiPandi [41] for instance, find Chinese investors displaying common behavioural biases such as overconfidence, herding, and loss aversion, driven by socio-cultural norms, economic volatility, and the dynamic regulatory environment. From the firm level, Zhang and Zheng [42] investigate the investment attitudes of Chinese non-financial firms, showing the cumulative effects of external market pressures and internal firm factors on investment. Colonnelli, et al. [43] on the other hand, investigate the role of government-affiliated investors, finding Chinese firms reluctant to negotiate with politically connected partners for fear of losing strategic control. Collectively, these papers establish that Chinese investment decisions are not finance-driven but also by institutional context and behavioural tendencies.

3. Methodology

3.1. Research Framework and Hypotheses Development

Theory of Planned Behaviour (TPB) provides a formal framework for the examination of the influence of attitudes, subjective norms, and perceived control on intention and action. Behavioural Finance Theory, on the other hand, offers insights into the psychological and cognitive biases that divert investors from rational economic behaviour. The two theories complement one another when examining the stock investment decision-making of Chinese young investors.

The conceptual framework integrates five key predictors: emotional intelligence, herd behaviour, overconfidence, accounting information, and financial literacy, each representing behavioural or informational dimensions relevant to China's dynamic retail investment landscape.

3.2. Conceptual Framework

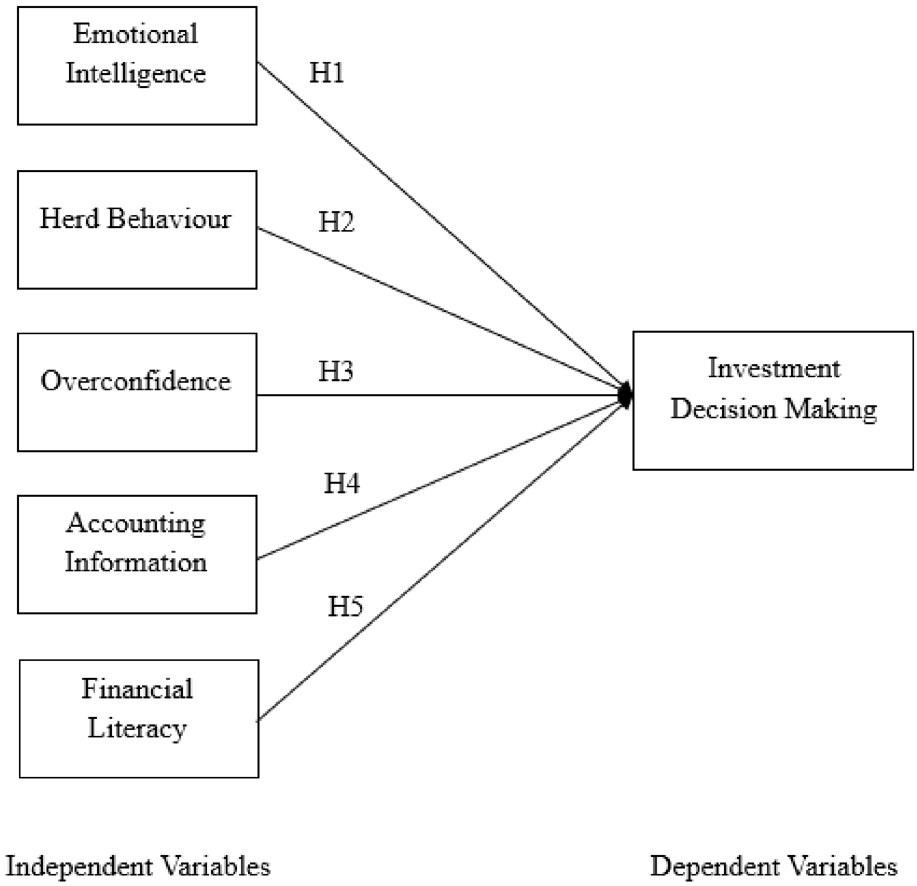

Figure 1.
Conceptual framework proposed for this study.

3.3. Research Hypotheses

Based on the framework and grounded in the Chinese investor context, the following hypotheses are proposed:

$H_{1:}$ Emotional intelligence has a significant positive effect on investment decision-making among young retail investors in China.

$H_{2:}$ Herd behaviour has a significant negative effect on investment decision-making among young retail investors in China.

$H_{3:}$ Overconfidence has a significant negative effect on investment decision-making among young retail investors in China.

$H_{4:}$ Accounting information usage has a significant positive effect on investment decision-making among young retail investors in China.

$H_{5:}$ Financial literacy has a significant positive effect on investment decision-making among young retail investors in China.

These hypotheses reflect the view that while emotional regulation, financial knowledge, and access to information enhance investment decisions, behavioural biases such as herding and overconfidence tend to undermine them, especially in China's speculative and tech-driven market environment.

3.4. Research Design

This study employs a quantitative, cross-sectional survey design to empirically test the proposed relationships. A structured online questionnaire is developed and distributed to capture the perceptions, knowledge, and behaviours of young stock investors in China.

3.5. Population and Sampling Method

The target population consisted of young Chinese investors who had participated in stock trading within the past year. A purposive sampling approach was utilised, with data collected through www.wjx.cn, a well-known survey platform in China recognised for its efficacy in recruiting digitally engaged cohorts. The final sample comprised 504 valid responses, exceeding conventional thresholds for ensuring statistical reliability in quantitative survey research [44]. Nevertheless, the sampling methodology may exhibit inherent limitations as the online platforms like www.wjx.cn predominantly attract urban, technology-proficient demographics, potentially underrepresenting rural populations and individuals with limited digital access.

3.6. Data Analysis

IBM SPSS Statistics (Version 28) was employed in this study for data analysis purpose, with two primary analytical approaches employed. First, descriptive statistics were calculated to summarise respondents' demographic profiles (e.g., age, gender, education, income, investment tenure) and central tendencies across all variables, ensuring a comprehensive overview of the dataset [45]. Second, multiple linear regression (MLR) analysis was performed to assess the predictive effects of five independent variables which are emotional intelligence, herd behaviour, overconfidence, accounting information, and financial literacy, on investment decision-making. This method enabled quantification of both the magnitude and statistical significance of variable relationships [46].

Prior to regression modelling, diagnostic tests were conducted to validate key assumptions, including normality, linearity, homoscedasticity, and multicollinearity. The latter was assessed using Variance Inflation Factor (VIF) and Tolerance indices, with all VIF values below 5.0 confirming the absence of problematic collinearity [47]. These steps align with methodological best practices for ensuring regression model robustness and interpretability [48].

4. Findings

4.1 Normality of Residuals

The assumption of residual normality was evaluated through visual inspection of a standardised residual histogram, refer to Figure 2. As depicted in the graphical analysis, the residuals approximate a normal distribution, characterised by a symmetrical, unimodal bell-shaped curve centred at zero. The observed distribution aligns closely with the superimposed theoretical normal curve, exhibiting negligible skewness ($|\text{skewness}| < 1.0$) and no influential outliers [45]. Although minor deviations from normality were detected, the large sample size ($N = 504$) ensures that regression parameter estimates remain robust. This is consistent with Osborne [49], who emphasises that parametric tests generally yield reliable results under moderate non-normality when sample sizes are sufficiently large. Consequently, the normality assumption is deemed tenable, and the regression model's inferential validity is preserved [46].

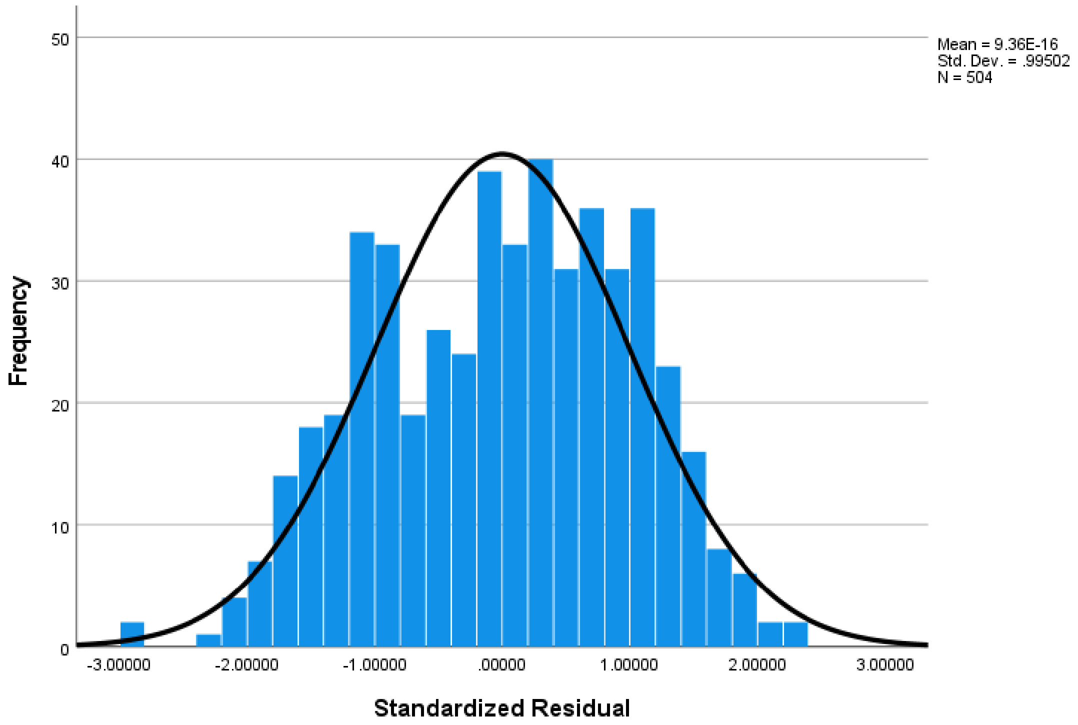

Figure 2.
Normality of Residuals.

4.2. Linearity and Homoscedasticity

To evaluate the assumptions of linearity and homoscedasticity, a scatterplot of standardised residuals against standardised predicted values was employed. Visual inspection, refers to Figure 3 revealed that residuals exhibited random dispersion around the horizontal axis (zero line), consistent with a linear association between predictors and the outcome variable [45]. While mild clustering and banding were observed, no discernible curvilinear trends (e.g., quadratic or U-shaped patterns) were detected, thereby supporting adherence to the linearity assumption [47].

Regarding homoscedasticity, the residuals demonstrated approximate homogeneity of variance across the continuum of predicted values, as evidenced by the absence of funnel-shaped or tapering dispersion [46]. Although minor fluctuations in variance were present, as is common in social science data [50] no substantial evidence of heteroscedasticity was detected.

These findings collectively suggest that both linearity and homoscedasticity assumptions were adequately satisfied, thereby upholding the inferential integrity of the regression model [48].

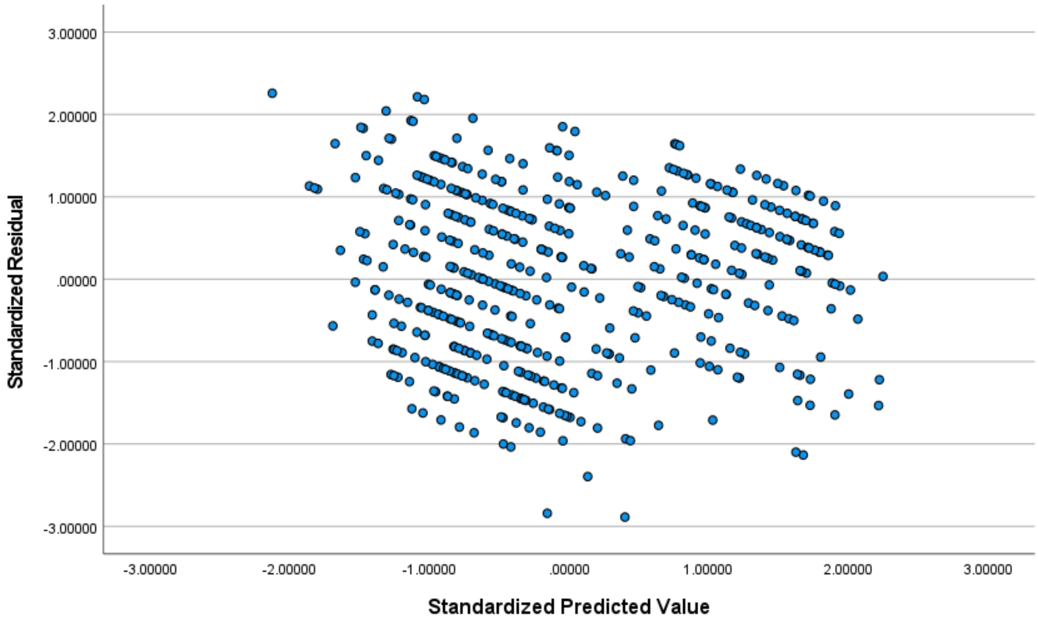

Figure 3.
Standardised residuals against standardised predicted.

4.3. Descriptive Analysis

Table 1.
Descriptive Analysis.

Demographic Data	Frequency	Percentage (%)
Gender		
Male	231	45.8
Female	273	54.2
Age		
24 - 27	90	17.9
28 - 31	152	30.2
32 - 35	133	26.4
36 - 39	88	17.5
40 - 43	41	8.1
Experience		
Less than 1 year	34	6.7
1 - 5 years	201	39.9
More than 5 - 10 years	211	41.9
More than 10 years	58	11.5

A descriptive analysis of demographic characteristics was conducted on a sample of 504 respondents. The gender distribution revealed a marginally higher proportion of female participants (54.2%) compared to males (45.8%). Age stratification demonstrated that the predominant cohort comprised individuals aged 28–31 years (30.2%), followed by those in the 32–35 (26.4%) and 24–27 (17.9%) age brackets. The 40–43 age group constituted the smallest subset, representing only 8.1% of the sample. With respect to investment experience, the majority of participants reported 1–5 years (39.9%) or 5–10 years (41.9%) of engagement in stock trading, collectively representing 81.8% of the cohort. A smaller subset possessed over a decade of experience (11.5%), while a minimal proportion (6.7%) reported less than one year of involvement. These findings suggest that the sample predominantly comprised individuals with moderately experienced to seasoned investment backgrounds, indicating a skew toward participants with substantive exposure to stock market dynamics.

4.4. Model Fit and Overall Significance

Table 2.
Model Summary.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.549[a]	0.302	0.295	0.78693

Note: a. Predictors: (Constant), FL, HB, EI, OC, AI

The model summary revealed that the explanatory variables collectively accounted for a statistically meaningful proportion of variance in the dependent variable. The R^2 coefficient of 0.302 denotes that approximately 30.2% of the variability in investment decisions is attributable to the five predictor variables. The Adjusted R^2 value (0.295) further substantiates the model's empirical robustness, confirming minimal overfitting despite the inclusion of multiple predictors.

Table 3.
ANOVA[a].

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	133.254	5	26.651	43.036	<0.001b
	Residual	308.395	498	0.619		
	Total	441.648	503			

Note:
a. Dependent Variable: ID
b. Predictors: (Constant), FL, HB, EI, OC, AI.

The ANOVA results demonstrated statistically significant explanatory power for the regression model with $F(5, 498) = 43.036$, $p < .001$. This F-ratio rejects the null hypothesis of no linear relationship between the predictors and the outcome variable, affirming that at least one independent variable exerts a significant influence on investment decision-making.

4.5. Multicollinearity Diagnostics

Table 4.
Coefficients[a].

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Volatility Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1. (Constant)	2.391	0.300		7.960	0.000		
EI	0.187	0.043	0.189	4.336	0.000	0.735	1.361
HB	-0.140	0.044	-0.141	-3.204	0.001	0.723	1.384
OC	-0.122	0.043	-0.126	-2.851	0.005	0.713	1.403
AI	0.165	0.043	0.173	3.882	0.000	0.703	1.422
FL	0.135	0.042	0.139	3.190	0.002	0.736	1.358

Note: a. Dependent Variable: ID.

Collinearity diagnostics were conducted to assess potential multicollinearity among predictors, employing Variance Inflation Factor (VIF) and Tolerance indices. Refer to Table 4, all VIF values fell within a narrow range (1.358–1.422), substantially below the conventional heuristic threshold of 5.0. Correspondingly, Tolerance metrics spanned 0.703–0.736, exceeding the conservative cutoff of 0.20. These results confirm the absence of problematic multicollinearity, as predictors demonstrated sufficient orthogonality. Consequently, each independent variable contributes distinct predictive capacity to the model, ensuring the reliability of regression coefficient interpretations. The diagnostics collectively validate the mode1's statistical rigor and adherence to Gauss-Markov assumptions, thereby supporting its analytical utility.

4.6. Multiple Linear Regression (MLR)

The regression coefficients analysis Table 4 delineated the differential impacts of predictors on investment decision-making (ID). Hypothesis 1 (H1) was substantiated, as emotional intelligence (EI) demonstrated a significant positive association with ID ($B = 0.187$, $\beta = 0.189$, $t = 4.336$, $p < .001$), corroborating recent findings that affective self-regulation enhances deliberative financial choices among digitally immersed investors [51, 52]. For H2, herd behaviour (HB) exhibited a negative effect ($B = -0.140$, $\beta = -0.141$, $t = -3.204$, $p = .001$), consistent with contemporary studies linking social media-driven conformity to speculative trading in China's retail markets (Jiang, 2020; Zhang et al., 2018). Hypothesis 3 (H3) identified overconfidence (OC) as a detrimental predictor ($B = -0.122$, $\beta = -0.126$, $t = -2.851$, $p = .005$), aligning with evidence that overestimation of analytical skills amplifies risk exposure in volatile asset classes [26, 53].

Conversely, H4 and H5 highlighted constructive influences. Accounting information (AI) positively predicted ID ($B = 0.165$, $\beta = 0.173$, $t = 3.882$, $p < .001$), resonating with research on the role of AI-driven financial disclosures in mitigating informational asymmetries in emerging economies [54, 55]. Financial literacy (FL) also showed a robust positive effect ($B = 0.135$, $\beta = 0.139$, $t = 3.190$, $p = .002$), supporting recent claims that FL fosters adaptive strategies in complex markets, particularly among Gen Z investors [56, 57]. Collinearity diagnostics confirmed the stability of the model, with variance inflation factors of below 1.5 and tolerance levels of above 0.7, following conservative multicollinearity standards [46].

Together, these results emphasise the dynamic interaction of information availability, cognitive capabilities, and behavioural tendencies on decision-making within the evolving digital finance context of China.

5. Conclusion

This study contributes considerably to the existing body of literature on the influence of emotional intelligence, herd behaviour, overconfidence, financial literacy, and accounting information on investment decision-making by young Chinese retail investors operating in a rapidly evolving, policy-driven, and culturally distinct market.

Theoretically, this study advances two major frameworks: the Theory of Planned Behaviour (TPB) and Behavioural Finance Theory (BFT). In relation to TPB, the research demonstrates how the theory's core constructs, attitude, subjective norms, and perceived behavioural control, can be contextually adapted using culturally relevant psychological and informational variables such as emotional intelligence (attitude), herd behaviour and overconfidence (subjective norms), and financial literacy and accounting information (perceived control). In doing so, it expands TPB beyond its conventional domains and shows its explanatory capacity in high-volatility, fintech-dominated investment environments such as China's. This contextual integration offers a novel application of TPB to financial decision-making and highlights its flexibility in culturally distinct, policy-sensitive markets.

With respect to Behavioural Finance Theory, this study contributes by grounding established behavioural constructs within China's unique retail-driven and technologically saturated environment. It provides empirical evidence that the manifestation of biases such as overconfidence and herding is mediated by digital ecosystems, collectivist cultural values, and regulatory unpredictability, factors often overlooked in Western-centric behavioural finance research. Furthermore, by including informational factors like accounting data and financial literacy, the study adds depth to the behavioural finance framework, suggesting that investor irrationality is not only psychological but also conditioned by knowledge access, trust, and data interpretability.

From a practical perspective, besides adding to the literature on behavioural finance, the work is relevant since it enlightens the necessity of financially advanced but behaviourally responsive and culturally attuned education programmes for young investors, who dominate China's retail market. By demonstrating the influence of emotional intelligence and financial literacy on the tempering of speculative behaviours, the findings present practical insights for policymakers, especially the China Securities Regulatory Commission (CSRC), as they further refine their interventions and promote long-term investment behaviours via the National Financial Literacy Plan 2026. Equally, the study equips fintech developers and educators with an empirical foundation for designing AI-powered tools and educational modules that enhance investor resilience amid market volatility.

However, the contributions must be interpreted within the limitations of the study. The purposive sampling strategy, which largely captured urban, digitally proficient investors, raises questions about the applicability of the findings to rural or less technologically integrated populations. Furthermore, the cross-sectional design constrains causal inference and limits the ability to trace how behavioural patterns evolve in response to market cycles or regulatory changes. Future research should adopt longitudinal and mixed-method approaches, incorporate more demographically and geographically diverse samples, and explore the mediating or moderating role of trust, a pivotal yet under-examined construct, in shaping investor behaviour. Comparative studies across individualistic and collectivist societies would also offer valuable insights into how cultural and institutional configurations condition the interplay between financial literacy, behavioural biases, and technological adoption, thereby deepening both theoretical and practical understandings of investment decision-making in global financial markets.

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