Journal of Posthumanism
2025
Volume: 5, No: 6, pp. 3988–4010
ISSN: 2634-3576 (Print) | ISSN 2634-3584 (Online)
posthumanism.co.uk

DOI: https://doi.org/10.63332/joph.v5i6.2570

Shaping the Investment Decision of Young Investors in China: Behavioural Factors and Effect of Trust

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Abstract

*Purpose – The objective of this study is to explore the key elements influencing decision- making processes among young individuals in China. The selected factors are emotional intelligence, herd behaviour, overconfidence, accounting information and financial literacy. In addition, this study aims to examine whether trust acts as a mediating factor between these factors and investment decision making. Methodology – This study employed an online survey questionnaire distributed to young investors in Shenzhen aged between 30 and 42 years. The questions were modified from prior studies, and responses were collected through a 5-point Likert-type scale. G*Power was employed for calculating the minimum sample size, resulting in at least 500 useable responses. A total of 507 surveys was distributed, of which 504 responses were utilised. For data analysis, PLS-SEM was employed in this study as it is suitable for handling complex model and exploratory research. Findings – All the variables are supported. Emotional intelligence, accounting information and financial literacy are positively correlated, whereas herd behaviour and overconfidence are negatively correlated. In addition, trust acts as a positive mediating factor in these relationships, except in the case of herd behaviour and overconfidence. Practical implications – Retail and corporate investors can be aware of their behavioural biases and control their emotions to make rational decisions. The government can foster a better understanding of investor behaviour and formulate the necessary policies to stimulate and stabilise the economy.*

Keywords: *Emotional Intelligence, Herd Behaviour, Overconfidence, Accounting Information, Financial Literacy, Trust, Investment Decision.*

Introduction

Many young people in China have leapt heavily into stock trading in October 2024 despite the challenging economy. This surge follows the largest stimulus package by the Chinese government to revive its economy. A package worth approximately 7.5 trillion CNY (1 trillion USD) was announced which included two 800 billion CNY (100 billion USD) facilities for the stock markets. This announcement triggered the biggest market rally in nearly two decades, according to Tobin and Liu (2024).

After the announcement, various securities firms in China reported many new trading accounts opened by young investors aged below 35 years. A Shenzhen-based securities company noted that more than 30% of the new accounts fell under this category, and another firm in Shanghai

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observed that new accounts surged threefold compared to the corresponding period in past years. Furthermore, young investors are technologically savvy, and trading apps such as Futu and Xueqiu provide them with easy access to trading and enable them to share news and tips on online platforms and social media. Many analysts have concluded that young investors tend to follow the crowd, be overconfident and lack experience and financial literacy. They favoured technology stocks but have limited understanding of financial track records. Thus, this study examines the primary factors influencing investment decisions among young generation, aged between 30 and 42 years, because their behaviours heavily influence the future of the stock market (Chan, 2024).

This increase in youth investor participation takes place in the special context of Chinese socialism with Chinese characteristics. In socialism with Chinese characteristics, the state plays an active role in shaping market processes while fostering balanced growth and social harmony (Andrianov, 2023). Youth investors do not solely act according to economic incentives but are also shaped by ideologies that highlight national prosperity as well as collective and institutional trust (Selemela & Khwela, 2024). These political and societal fundamentals differentiate investor behaviour in China from their counterparts in liberal markets.

In Shenzhen, young investors may be influenced by multiple factors when making decisions. Haliassos and Bertaut (1995) were among the first to investigate the reasons behind stock market participation, highlighting how risk avoidance as well as financial literacy, and access to information shape investment behaviour. Subsequently, various scholars have identified other factors, including IQ (Grinblatt et al., 2011), emotional intelligence (Webb et al., 2014), financial literacy (Van Rooij et al., 2011), social contacts (Hong et a1. 2004), and financial information (Wang et al., 2013), among others. The factors selected for this study are emotional intelligence, herd behaviour, overconfidence, accounting information and financial literacy, and the rationale for choosing these factors is explained below.

In this study, EI is selected because it often influences individual decision making, whether or not investors are aware of it (Webb et al., 2014). Many researchers have recognised that EI is more important than technical skills or IQ in influencing outcomes and judgments.

Numerous studies have focused on the emotions that people experience, how these emotions influence investors and how they can be managed. EI is crucial, but no specific study targets the young generation. Over the past two decades, herding behaviour attracted considerable research attention. Furthermore, herd behaviour is selected as the Chinese market is predominantly driven by retail investors, making it necessary to understand the extent of its influence. Overconfidence is another selected factor because many studies have shown that Chinese investors tend to exhibit overconfidence because of cultural background and the characteristics of the Chinese market. Given the huge differences between Western and Chinese culture, studying this effect is essential to understand the Chinese market better. There is a common perception that financial information in China lacks the transparency seen in other developed nations. However, significant improvements have been observed in recent years. The regulatory structure and policies governing China's equity market play a crucial role. Consequently, the importance of accounting information related to stock valuation and financial analysis has grown. An increasing number of researchers have examined the connection between stock prices and the financial data of public companies in China (Wang et al., 2013), making this factor a key area of study. Studies have shown mixed results regarding financial literacy levels in China, with some indicating low levels and others showing high levels. This factor is included specifically to determine whether financial literacy significantly impacts investment decisions. Moreover, this study seeks to investigate whether trust acts as a mediating factor between the selected factors and investors' decision-making processes.

EI and Investment Decision

EI can be considered a critical skill that encompasses recognising, comprehending and regulating one's own and other's emotions and using this understanding to guide their thinking and behaviour. Goleman (2006) categorised EI into five components:

- Self-mindfulness: the capacity of individuals to recognise their own emotions, thoughts, feelings, strengths, weaknesses and motivations. This awareness helps individuals understand what affects their decision-making process.
- Handling feelings: the skill of managing one's own actions. It involves handling pressure, managing stress and adapting to changing environments.
- Motivation: the drive that guides an individual's behaviour toward accomplishing goals.
- Empathy: the ability to experience what other people feel emotionally.
- Social aptitude: the ability to get along and communicate with other individuals in social interactions.

Many researchers have recognised that EI is more important than technical skills or IQ in influencing outcomes and judgments. Numerous studies have focused on the types of emotions people experience, how these emotions influence investors and how they can be managed. Deldin and Levin (1986) and Goodell et al. (2023) showed that a positive mood leads investors to choose riskier assets, whereas a negative mood has the opposite effect. Lahav and Meer (2020) studied the financial market, where investors' moods were induced and measured before trading, and they concluded that a positive mood leads to lower risk taking. Parrott (2017) and Olson (2006) also concluded that when moods are positive, perceived risk is reduced. This collective individual mood can turn into a positive social mood, thereby increasing trust and potential gains. Hence, this research proposes hypothesis as follows:

Hypothesis 1: Emotional intelligence significantly influences investment decision-making.

Herd Behaviour and Investment Decision

Herd behaviour describes an investor's inclination to copy the behaviour of others and not rely on their own analysis and opinions. Haritha and Uchil (2020) suggests that herd behaviour can be influenced by three awareness factors:

1. Media Awareness: Media and publicity play an important role in disseminating stock market information to investors and can influence their emotions when making investment decision. Zhang et al. (2018) highlighted that stock price fluctuations are significantly impacted by social media activity. A correlation exists between share price increases and favourable news and greater media coverage, whether in traditional newspapers or on social media. Another possible cause is speculative mentality. Investors tend to invest in rising stocks to make short-term profits, relying on media publicity and market commentary instead of adopting a long- term investment strategy.
2. Social interaction between relatives, family members, and friends enables individuals to communicate, transfer information, and affect each other's choices (Akhtar et al., 2017).

Literature has proven that inexperienced investors or less financially literate individuals will tend to imitate the choices of other investors.

Nofsinger (2005) found that social group interaction is capable of developing positive or negative collective attitudes and therefore affects the decision process of individuals. His model shows the social mood cycle, which includes phases from an increasing mood such as optimism, peaking at a positive mood such as trust and then declining to pessimism and negative social moods such as fear and depression. His studies, supported by Goodell et al. (2023), showed that stock market movement is high when the social mood is high and vice versa.

3. Advocate recommendation: According to Shiller and Pound (1989), expert recommendations highly influence trading behaviour. The main cause of herd behaviour is incomplete information. Different investors have varying levels of access to accurate, timely and effective data. Institutional investors have better access to talent, technology, and capital compared to individual investors. Hence, individual investors tend to follow the buying patterns of institutions.

Herding behaviour tend to exist in underdeveloped markets; however, its extent depends on the composition of investors. If the majority of investors are individuals with low financial literacy levels, then herding behaviour is expected to be higher. Hence, this research proposes hypothesis as follows:

Hypothesis 2: Herd behaviour significantly influences investment decision-making.

Overconfidence and Investment Decision

Overconfidence is a common psychological trait where people have a false belief in their own abilities and think that their chances of success is higher than reality. Overconfidence tends to occur predominantly among male investors, young investors and those with small investment portfolio. Overconfidence can induce investors to think that their decision-making skills are superior and believe that they can outperform the market. Evans (2006) showed that the negative effect of investor overconfidence leads to wrong decision making and higher trading volumes with less impressive performance.

Overconfidence may contribute to an increase in trading volume. Retail investors buy and sell more often because they do not rely on market information (Daniel & Hirshleifer, 2015). Investors who are encouraged by their past success are less risk adverse and are inclined to take more risks, thereby trading more frequently in riskier stocks (Griffin et.al, 2007). Excessive overconfidence among investors tend to create market bubbles which lead to higher trading volume and greater mispricing of share prices (Michailova & Schmidt, 2016). Studies about the relationship between overconfidence and return on portfolio have mixed results. Some research suggests that overconfident investors may generate higher returns (Benos, 1998). Others argue they may achieve less returns because they rely on gut instinct rather than rational judgement, and excessive trading may reduce their profits (Barber & Odean, 2002). Zhang et al. (2015) found that the correlation between trading volume and gain is negative, indicating that as trading volume increases, the gain decreases. In this respect, the following hypothesis is developed:

Hypothesis 3: Overconfidence significantly influences investment decision-making.

Accounting Information and Investment Decision

Accounting information plays a crucial role in shaping investment decisions. Key indicators such as profitability, share price, past performance, expected corporate earnings, capital increases, expected stock split, dividend policy and bonus are influential in the decision-making process. Accounting information informs the market about the business performance and financial status of companies. Several academic studies have also shown that financial performance, such as expected or actual earnings, directly affects the share prices (Shakespeare, 2020; Arifha et al., 2019).

Suryani (2016) showed that financial information leads to confidence and intention to invest. It is also a key indicator for analyse investment portfolios. Sultana and Pardhasaradhi (2012) similarly identified accounting information as the most critical factor influencing investors' decisions and behaviours in India (Khoufi, 2021). Hence, the following hypothesis is formed:

Hypothesis 4: Accounting information significantly influences investment decision-making.

Financial Literacy and Investment Decision

Financial literacy refers to a structured approach aimed at improving an individual's capability in personal finance management. This knowledge encompasses saving, spending and investing (Lusardi & Messy 2023; Arianti, 2018). Financial literacy is higher among individuals who are more educated, have higher incomes, male and belong to the younger generation because they generally receive better education in China. Research investigating relationship between financial literacy and decision-making has produced mixed findings. While some research suggests that individuals with higher financial literacy tend to make more well-reasoned and impartial choices, other research indicates that it may negatively impact confidence levels. Takeda et al. (2013) and Inghelbrecht and Tedde (2024) found that lower financial literacy among investors is linked to higher overconfidence, increased risk tolerance, and more irrational investment behaviour. On the other hand, Sezer and Demir (2015) stated that financial literacy does not significantly impact investors' behavioural biases. Therefore, this study develops the hypothesis below to analyse this relationship.

Hypothesis 5: Financial literacy significantly influences investment decision making.

Trust and Investment Decision

Trust refers to the willingness to place confidence in and rely on a counterparty, believing in their reliability. From a financial investment perspective, trust in the financial market is crucial, as it signifies confidence in the regulatory framework and financial institutions' ability to meet their commitments (Van Der Cruijsen et al., 2021). It also influences stock market participation. Jaffer et al. (2014) indicated that higher trust levels lead to increased participation, which then leads to overall economic growth. Qiu et al. (2020) found that individuals with lower trust in the economy and society are less inclined to engage in financial markets. In Chinese socialist society, trust is both economic and ideological in nature, it is about trust in market institutions as well as in the ability of the state to provide economic and social stability (Wu et al., 2024). This broader conception of trust, shaped by collectivist values and state-led governance, is central to understanding investor behaviour in China. Therefore, the following hypothesis is developed:

Hypothesis 6: Trust significantly influences investment decision making.

Antecedents of Trust

Christie et al. (2015) examined the correlation between emotional intelligence (EI) and trust within the context of leadership. However, limited research links EI to trust and investment decision-making. Thus, the following hypothesis is developed to better understand this relationship:

Hypothesis 7: Emotional intelligence significantly influences trust.

According to Gong et al. (2019), trust and subjective norms are interdependent. Trust is fundamental in herd behaviour. Studies have shown that the longer the relationships of individuals within their social circles, the higher their level of trust (Chen, 2021). In this regard, the following hypothesis is developed:

Hypothesis 8: Herd behaviour significantly influences trust.

Bruhn (2019) studied the relationship between heuristics and trust. One may outsource their decision making to someone they trust, especially if they need to make quick decisions in complex situations such as financial investments. McCannon et al. (2015) showed that overconfidence leads individuals to trust their own ability and ignore the reality surrounding them when it comes to investing, so they tend to make sub-optimal investment decisions. However, research on the correlation between overconfidence and trust remains limited, especially in decision-making contexts. Below is the proposed hypothesis to examine this relationship:

Hypothesis 9: Overconfidence significantly influences trust.

From a financial investment perspective, trust in the financial market is essential. It signifies confidence in the financial regulatory system and institutions, ensuring their reliability and ability to meet obligations (Van Der Cruijsen et al., 2021). Investing in stocks is not solely based on evaluating profits and returns but also depends on trust in data accuracy and the fairness of the financial system. For example, the fall of Enron is due to fraudulent financial reporting which led to an overvaluation of its stock and subsequently its collapse (Guiso et al., 2008). Thus, we suggest to investigate this relationship through the hypothesis below:

Hypothesis 10: Accounting information significant influences trust.

Studies have demonstrated that financial literacy is essential, f signifies confidence in markets (Adil et al., 2022). A direct correlation exists between trust and individual literacy (Lee & Kim, 2020). Improved financial education regarding stock markets can help mitigate the negative impact of mistrust, as highlighted by Guiso et al. (2008). Therefore, it is believed that greater financial literacy strengthens confidence in financial institutions, which subsequently boosts individuals' willingness to trade stocks (Georgarakos & Pasini, 2011). Given this discussion, the hypothesis below is formed:

Hypothesis 11: Financial literacy significantly influences trust.

Mediator

Given the nature of trust, it can also act as a mediator that connects predictor and outcome variables.(Preacher & Hayes, 2008). In principle, the role of a mediator is vital in behavioural science studies. Behavioural studies have often demonstrated that a particular exogenous variable explains variability in an endogenous variable. Therefore, mediation occurs when an influencing factor impacts an outcome variable through an intermediary, which serves as the mediator. Regarding investment decisions, trust is expected to function as a mediator by improving the investment decision-making process (Bruhn, 2019). Although trust possesses all the characteristics of a mediator variable, its effect on investment decision making is relatively unexplored, thus necessitating further investigation. This is particularly pertinent within a socialist state where trust goes along with ideological conceptions of the state, institutional trustworthiness, and collective economic interests. Therefore, trust and investments bear strong relationships in that as trust among investors increases, their likelihood of making investments also increases (Adil et al., 2023). Within this research, the following hypotheses are proposed in an attempt to test trust as a mediator:

Hypothesis 12: Trust mediates Emotional Intelligence and Investment Decision Relationship

Hypothesis 13: Trust mediates Herd Behaviour and Investment Decision Relationship
Hypothesis 14: Trust mediates Overconfidence and Investment Decision Relationship

Hypothesis 15: Trust mediates Accounting Information and Investment Decision Relationship

Hypothesis 16: Trust mediates Financial Literacy and Investment Decision Relationship

Methodology

Conceptual framework for this study is shown in Figure 3.1.This study employed self-administered questionnaires. The questions used are modified from prior studies, and the responses are collected using a 5-point Likert-type scale. The data were gathered from young investors aged between 30 and 42 years and analysed using PLS-SEM.

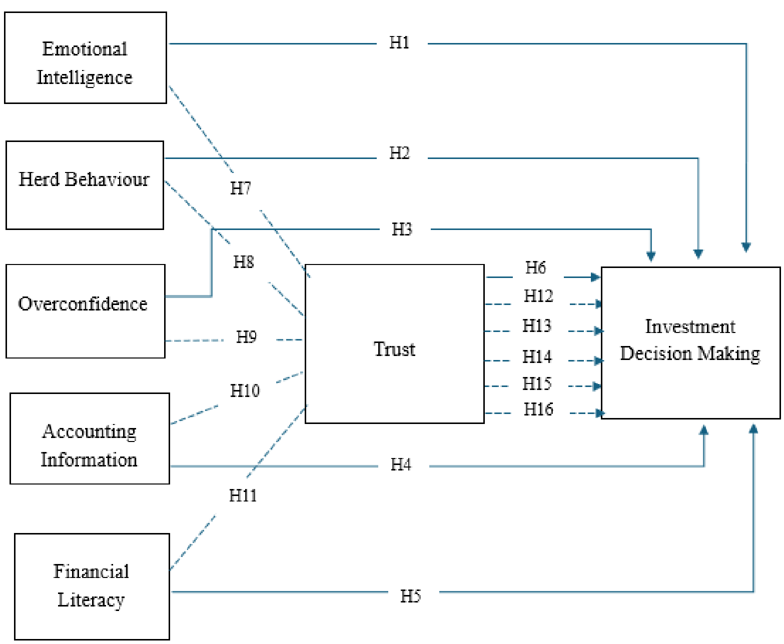

Figure 3.1: Conceptual Framework

Data Collection

Primary data were collected by distributing the online survey using Microsoft Outlook Form, targeting individuals through screening questions. The online method was selected because young investors are well-versed in the internet, making it a more efficient way to collect data. Secondary data were also used for literature review and gain a better understanding of the underlying theories and concepts.

Data Analysis

A total of 507 responses were collected, of which three were eliminated because of failure to meet the eligibility criteria. The remaining 504 responses were subjected to a thorough screening and cleansing procedure to verify their accuracy and reliability.

Multivariate Normality

Multivariate normality violations can lead to biased parameter estimates, inaccurate standard errors and misleading statistical inferences (Kline, 2015). Although PLS-SEM does not rely on normality, assessing it is advised because gaining insight into the data distribution can contribute to strengthening model robustness and assist in determining whether data transformations or other analytical strategies may be advantageous (Hair et al., 2017).

WebPower, an online tool for conducting advanced statistical analysis, was employed to confirm multivariate normality. Mardia's test of multivariate skewness and kurtosis is commonly applied when evaluating multivariate normality. Skewness assesses the symmetry of the distribution, whereas kurtosis evaluates the distribution's tails compared with a normal distribution (Mardia, 1970). According to widely accepted standards, skewness between ±2 and kurtosis values between ±7 are considered acceptable indicators of univariate normality (Hatem et al., 2020; Byrne, 2010).

In the current analysis, the results from WebPower, with a sample size of 504 and seven variables, showed significant deviations from normality. The analysis of univariate skewness values exhibited a range from -0.084 to 0.199, generally aligning with acceptable limits. However, the kurtosis values exhibited a range extending from -0.878 to -1.104, which signifies a considerable divergence from the accepted threshold. Additionally, Mardia's multivariate normality test confirmed the deviation from normality, with skewness ($z = 144.17$, $p < 0.001$) and kurtosis ($z = -4.80$, $p < 0.001$), resulting in the rejection of the null hypothesis of multivariate normality.

Therefore, SmartPLS was used in this study because of its ability to handle complex models with small to medium sample sizes and non-normal data, making it ideal when traditional structural equation modelling (SEM) methods require multivariate normality (Hair et al., 2017). PLS-SEM is particularly useful for exploratory research focused on predicting and identifying key drivers (Ringle et al., 2015). Given the significant deviations from normality found in the WebPower analysis, SmartPLS was chosen for its flexibility in handling non-normal data whilst enabling robust model testing.

Common Method Bias (CMB)

This study collected data for independent and dependent variables using a single method. Consequently, the observed relationships between variables may be inflated or distorted, leading to inaccurate results (Podsakoff et al., 2003). Therefore, the marker variable (MV) approach was used to assess the CMB. The presence of CMB can be confirmed based on the path coefficients output and their p-value. A low path coefficient (e.g. less than 0.10) indicates a weak relationship between the variables (Hair et al., 2017). According to Chin, Thatcher and Wright (2012), if the p value is more than 0.05, CMB is likely not present in the model because the MV does not influence the relationship between variables. Besides, R^2 value was observed to assess the effect of MV in the model.

To assess CMB using the MV approach, SmartPLS version 4.1.0.8 was employed. A marker variable, a variable that is theoretically not related to this study, was identified and added to the proposed model. Based on the path coefficients result, a weak relationship exists between the MV and dependent variable (investment decision), with a p-value of more than 0.05. The result also shows a weak relationship between the MV and mediator variable (trust), with a p-value of more than 0.05. Furthermore, by comparing R^2 values from both models (without and with MV), the R^2 changes insignificantly for the endogenous construct from 0.329 (without MV) to 0.330 (with MV). These outcomes suggest that CMB is not present in the proposed model for this study.

Model with Marker Variable		
	Path coefficients	**P values**
Accounting → Decision	0.142	0.002
Accounting → Trust	0.168	0.001
Behaviour → Decision	-0.114	0.012
Behaviour → Trust	-0.144	0.002
Emotion → Decision	0.149	0.001
Emotion → Trust	0.213	0
Finance → Decision	0.11	0.01
Finance → Trust	0.157	0
Marker → Decision	0.038	0.42
Marker → Trust	0.021	0.643
Trust → Decision	0.19	0
Confidence → Decision	-0.106	0.027
Confidence → Trust	-0.102	0.022

Table 3.1: Results of Path Coefficients and P-values

Results

This section reports the findings of respondents' profiles based on their demographic characteristics, such as gender, age, ethnicity, qualification, employment status, experience in share investment and income. The distribution and demographic details are shown in the table below. A total of 504 respondents participated in this survey, and all of them are Chinese. In terms of gender, female respondents are 273, and male respondents are 231, and majority are aged 30 to 42 years. Most of them had completed ta Bachelor's degree (57.9 percent), followed by a Master's degree (32.9 percent), whereas only 9.1 percent had completed a diploma. When asked about their experience in share investment, most of them had 5 to 10 years of experience (41.9 percent), whereas only 6.7 percent had less than 1 year experience. Finally, regarding annual income, most of the respondents reported an annual income ranging from 100,000–200,000 RMB which is equivalent to 60,000–120,000 RMB.

Demographic Questions	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
Ethnicity	Chinese	504	100
Highest Qualification	Diploma	46	9.1
	Bachelor's Degree	292	57.9
	Master's Degree	166	32.9
Employment Status	Employed	504	100
Experience in Share Investing	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
Annual Income	Less than 100,000 RMB	89	17.7
	100,000–200,000 RMB	151	30
	200,001–300,000 RMB	68	13.5
	300,001–400,000 RMB	116	23
	400,001–500,000 RMB	56	11.1
	More than 500,000 RMB	24	4.8

Table 3.2: The Distribution and Demographic

Measurement Model

The measurement model is applied to measure construct variables by assessing the correlation between the respective observed variables and the underlying latent constructs. This is carried out to make the measurements reliable and valid (Ramayah et al., 2018). One of the key areas of the evaluation of the measurement model is assessing indicator reliability, internal consistency, convergent validity, and discriminant validity (Hair et al., 2022).

Construct	Items	Indicator Reliability (Outer Loadings) > 0.7	Internal Consistency Reliability (CR) > 0.7	Convergent Validity (AVE) >0.5
Investment Decision Making	ID1	0.823		
	ID2	0.828	0.895	0.682
	ID3	0.822		
	ID4	0.83		
Trust	T1	0.842		
	T2	0.844		
	T3	0.832	0.919	0.693
	T4	0.817		
	T5	0.827		
Emotional Intelligence	EI1	0.824		
	EI2	0.825	0.897	0.686
	EI3	0.834		
	EI4	0.83		
Herd Behaviour	HB1	0.803		
	HB2	0.836	0.899	0.69
	HB3	0.85		
	HB4	0.832		
Overconfidence	OC1	0.845		
	OC2	0.835	0.905	0.705
	OC3	0.86		
	OC4	0.818		
Accounting Information	AI1	0.85		
	AI2	0.822	0.904	0.702
	AI3	0.84		
	AI4	0.839		
Financial Literacy	FL1	0.841		
	FL2	0.834	0.901	0.695
	FL3	0.832		
	FL4	0.828		

Table 3.3: Results of Indicator Reliability, Internal Consistency Reliability, and Convergent Validity (AVE)

Indicator Reliability

Outer loadings are utilised to evaluate measurement reliability in the reflective measurement model. The measurement item is considered reliable when outer loadings are 0.70 or higher, while values between 0.40 and 0.70 are deemed acceptable with theoretical support (Hair et al., 2010). However, for loadings below 0.40, Hair et al. (2017) recommend eliminating the measurement item to enhance composite consistency. SmartPLS is applied here to analyse the loadings for the measurement model. As presented in the table below, all item loadings met the required threshold of 0.70. Therefore, all items for each construct are retained.

Internal Consistency Reliability

This research evaluated consistency reliability using SmartPLS to confirm the measurement model. As stated by Hair et al. (2017), a consistency reliability range of 0.70 to 0.90 is deemed satisfactory to good. The table below illustrates that each construct included in this study met the minimum requirement of 0.70, with values ranging between 0.895 and 0.919. Therefore, all constructs in this research exhibit a satisfactory level of reliability.

Convergent Validity

Base on table 3.3, average extracted variance (AVE) for each construct surpassed the required minimum of 0.5. As noted by Hair, Babin, and Kr (2017), along with Hair, Sarstedt, and Ringle (2022), we need to ensure that each construct accounts for at least 50% of the designated indicator's variation to achieve satisfactory convergent validity, meaning the AVE should be at least 0.50.

Cross-Loadings

The table below shows the results of cross-loadings. All indicators are strongly associated with their respective constructs, as proven by cross-loading values exceeding 0.10.

	AI	EI	FL	HB	ID	OC	T
AI1	**0.85**	0.319	0.368	-0.379	0.339	-0.356	0.357
AI2	**0.822**	0.276	0.29	-0.311	0.325	-0.311	0.323
AI3	**0.84**	0.33	0.314	-0.353	0.352	-0.375	0.339
AI4	**0.839**	0.319	0.319	-0.352	0.357	-0.328	0.353
EI1	0.336	**0.824**	0.376	-0.315	0.342	-0.34	0.344
EI2	0.31	**0.825**	0.308	-0.291	0.35	-0.284	0.345
EI3	0.303	**0.834**	0.325	-0.291	0.338	-0.273	0.384
EI4	0.281	**0.83**	0.327	-0.302	0.324	-0.326	0.344
FL1	0.314	0.315	**0.841**	-0.31	0.314	-0.314	0.36
FL2	0.317	0.304	**0.834**	-0.294	0.319	-0.307	0.33
FL3	0.343	0.387	**0.832**	-0.267	0.307	-0.317	0.307
FL4	0.315	0.343	**0.828**	-0.251	0.319	-0.289	0.314
HB1	-0.307	-0.275	-0.321	**0.803**	-0.336	0.342	-0.307
HB2	-0.358	-0.317	-0.271	**0.836**	-0.314	0.341	-0.327
HB3	-0.372	-0.333	-0.276	**0.85**	-0.344	0.377	-0.341
HB4	-0.348	-0.272	-0.249	**0.832**	-0.272	0.309	-0.308
ID1	0.368	0.356	0.307	-0.317	**0.823**	-0.318	0.375
ID2	0.362	0.333	0.338	-0.341	**0.828**	-0.332	0.358
ID3	0.316	0.353	0.293	-0.294	**0.822**	-0.295	0.383
ID4	0.305	0.305	0.308	-0.31	**0.83**	-0.302	0.335
OC1	-0.327	-0.31	-0.302	0.34	-0.335	**0.845**	-0.309
OC2	-0.328	-0.289	-0.339	0.362	-0.285	**0.835**	-0.304
OC3	-0.374	-0.303	-0.293	0.346	-0.329	**0.86**	-0.307
OC4	-0.344	-0.334	-0.304	0.343	-0.32	**0.818**	-0.314
T1	0.34	0.347	0.341	-0.307	0.386	**-0.322**	0.842
T2	0.356	0.384	0.355	-0.331	0.388	-0.3	**0.844**
T3	0.349	0.374	0.306	-0.307	0.387	-0.29	**0.832**
T4	0.338	0.309	0.286	-0.342	0.333	-0.32	**0.817**
T5	0.321	0.365	0.348	-0.325	0.333	-0.298	**0.827**

Table 3.4: Results of Cross-loading

Heterotrait–Monotrait (HTMT) Ratio of Correlations

This study utilises the Heterotrait-Monotrait Ratio of Correlations (HTMT) to evaluate discriminant validity by measuring the ratio of correlations between and within constructs. The researchers suggested that the HTMT ratio should be below a maximum of 0.9. Besides, Franke and Sarstedt (2019) also proposed that if the HTMT bootstrapping confidence interval does not include 1, it can be inferred that the constructs exhibit adequate discriminant validity. The table below shows all the constructs in this study are less than 0.90, which means the respondents were able to understand the distinctiveness of the 7 reflective constructs.

	AI	HB	ID	EI	FL	T	OC
AI							
HB	0.487						
ID	0.479	0.449					
EI	0.435	0.425	0.482				
FL	0.450	0.394	0.444	0.476			
T	0.468	0.445	0.506	0.492	0.45		
OC	0.476	0.482	0.442	0.432	0.43	0.42	

Table 3.5: Results of Heterotrait-monotrait (HTMT) ratio of correlations

Structural Model Estimation

After confirming that the measurement model meets the necessary conditions, the next phase involves assessing how well the model predicts one or more target constructs through the structural model. In PLS-SEM, this evaluation follows six key steps (Hair et al., 2017).

To begin, collinearity is examined to ensure that the regression results remain unbiased, using variance inflation factor (VIF) values as a diagnostic measure. Next, the significance and strength of relationships between variables are determined by examining path coefficients as well as t-values and p-values (Hair, Page & Brunsveld, 2020). The third step is to calculate the coefficient of determination (R^2), indicating the percentage of variation in the dependent variable explained by independent variables. (Menard, 2000). Next, the effect size of predictor variables is assessed to determine their overall influence on endogenous variables, including mediators and dependent constructs, through the f^2 value.

After determining effect sizes, the predictive relevance (Q^2) is examined to evaluate the model's ability to predict future or unseen data (Liengaard et al., 2021). PLS-Predict technique is applied as the last step in structural model evaluation. This method utilizes a holdout sample-based procedure to generate forecasts at both the item and conceptual levels, allowing for case-level assessments.

Collinearity Issues

The existence of collinearity issues can be detected when VIF values is greater than or equal to 5 (Hair, Ringle, & Sarstedt, 2011). The results of the VIF values are presented in the table 3.6. In this study, collinearity is not a concern since all VIF values are below the threshold of 5, ranging from 1.360 to 1.464.

Hypothesis	**Relationship**	**VIF**
H1	Accounting Information → Investment Decision	1.464
H2	Emotional Intelligence → Investment Decision	1.426
H3	Financial Literacy → Investment Decision	1.392
H4	Herd Behaviour → Investment Decision	1.417

H5	Over Confidence → Investment Decision	1.418
H6	Trust → Investment Decision	1.461
H7	Accounting Information → Trust	1.422
H8	Emotional Intelligence → Trust	1.36
H9	Financial Literacy → Trust	1.356
H10	Herd Behaviour → Trust	1.386
H11	Over Confidence → Trust	1.403

Table 3.6: Results of Collinearity Issues

Path Coefficients and Significance

In the case of PLS-SEM, data normality is not required (Jannoo et al., 2014). While strict normality of data is not mandatory, deviations from normality can lead to inflated standard errors and consequently elevate the risk of Type 1 errors (Ramayah et al., 2018). Hence, bootstrapping technique was employed in this study.

Bootstrapping involves repeatedly resampling the original data with replacement to generate and estimate statistical significance (Hindley, 2017). This approach is crucial for hypothesis evaluation, as it calculates relevant statistics from each bootstrap sample. After verifying the significance of indicator loadings, the study examines the path coefficients. These values typically range from -1 to +1, where coefficients closer to -1 indicate a strong negative relationship, whereas those approaching +1 suggest a strong positive relationship (Hair et al., 2017).

Table below shows the outcomes regarding significance and strength of path coefficients. Among all the independent variables, emotional intelligence (EI = 0.149) has the strongest influence on investment decision, the dependent variable, followed by accounting information (AI = 0.143), herd behaviour (HB = -0.114), financial literacy (FL = 0.109) and overconfidence (OC = -0.107). However, two independent variables, HB and OC, negatively affect investment decision.

In addition to that, bootstrapping technique was used to determine the significance level for each relationship in the model, and the t-values and p-values based on it are listed in the respective table. For a path to be significant at 5% level, its t-value must be more than 1.96 and its p-value must be less than 0.05 (Browne, 2010). Consequently, all Hypotheses from H1 to H11 are confirmed.

Hypothesis	Relationship	Path Coefficient (β)	Std Error	t-value	p-value	Decision	BCI LL	BCI UL	f^2	Effect Size
H1	Emotional Intelligence → Investment Decision	0.149	0.046	3.268	0.001	Supported	0.059	0.237	0.023	Small
H2	Herd Behaviour → Investment Decision	-0.114	0.045	2.52	0.012	Supported	-0.203	-0.025	0.014	None
H3	Over Confidence → Investment Decision	-0.107	0.048	2.22	0.026	Supported	-0.203	-0.013	0.012	None
H4	Accounting Information → Investment Decision	0.143	0.046	3.073	0.002	Supported	0.051	0.232	0.021	Small
H5	Financial Literacy → Investment Decision	0.109	0.043	2.543	0.011	Supported	0.023	0.192	0.013	None
H6	Trust → Investment Decision	0.191	0.046	4.168	0	Supported	0.099	0.281	0.037	Small
H7	Emotional Intelligence → Trust	0.213	0.042	5.119	0	Supported	0.126	0.291	0.049	Small
H8	Herd Behaviour → Trust	-0.145	0.048	3.035	0.002	Supported	-0.236	-0.053	0.022	Small
H9	Over Confidence → Trust	-0.103	0.045	2.304	0.021	Supported	-0.191	-0.015	0.011	None
H10	Accounting Information → Trust	0.168	0.049	3.438	0.001	Supported	0.071	0.261	0.029	Small
H11	Financial Literacy → Trust	0.157	0.042	3.777	0	Supported	0.073	0.237	0.026	Small

Table 3.7: Results of Path Coefficient

Mediation Analysis

Trust (T) is incorporated as an intermediary variable within the research model proposed for this study. Five hypotheses were formulated to examine the effect of trust in the association between accounting information, emotional intelligence (EI), financial literacy, herd behaviour, overconfidence, and investment decisions. In this study, the bias-adjusted bootstrapping technique was used to evaluate the mediation effect. This approach provides precise estimates of indirect effects by correcting for potential biases found in conventional methods, ensuring a more balanced approach to hypothesis testing (Tibbe & Montoya, 2022). A statistically significant mediation occurs when the confidence interval excludes zero (Preacher & Hayes, 2008).

As shown in the table below, trust (T) serves as a significant mediator for all variables. Two negative relationships, H15 and H16, demonstrate that individuals' investment decisions are negatively influenced by herd behavior (β = -0.028, p = 0.019, 95% CI [-0.054, -0.008]) as well as overconfidence (β = -0.020, p = 0.046, 95% CI [-0.041, -0.002]) through trust.

Hypothesis	Relationship	Std Beta (β)	Std Error	t-value	p-value	Decision	BCI LL	BCI UL
H12	**EI → T → ID**	0.041	0.013	3.090	0.002	Supported	0.018	0.069
H13	**HB → T → ID**	-0.028	0.012	2.342	0.019	Supported	-0.054	-0.008
H14	**OC → T → ID**	-0.02	0.01	1.999	0.046	Supported	-0.041	-0.002
H15	**AI → T → ID**	0.032	0.012	2.705	0.007	Supported	0.012	0.058
H16	**FL → T → ID**	0.03	0.011	2.838	0.005	Supported	0.011	0.052

Table 3.8: Results of Mediation

Conclusion and Discussion

This study emphasizes the important influence of emotional intelligence on investment decisions, demonstrating that despite its moderate effect size ($\beta = 0.149$, $p = 0.001$, $f^2 = .023$), its influence remains crucial. Emotional intelligence helps investors manage emotions, leading to more rational financial choices and mitigating panic-driven selloffs, particularly in fast-paced markets like Shenzhen. Previous research supports this connection, emphasizing that emotionally intelligent investors are less likely to succumb to speculative trading or social media-induced herd behaviour. Additionally, financial literacy significantly impacts investment decisions ($\beta = 0.109$, $p = 0.011$), with financially literate individuals making more informed and diversified investments. Trust also plays a key role in shaping investor behaviour, as evidenced by its strong positive correlation with accounting information ($\beta = 0.168$, $p = 0.001$). High-quality financial reporting reduces information asymmetry, fostering investor confidence and enabling sound financial decisions. However, concerns remain about financial transparency in China, as instances of corporate fraud have undermined trust, necessitating stricter corporate governance and financial disclosure regulations.

On the other hand, the study also establishes the negative effects of herd behaviour and overconfidence on investment decisions. Herding significantly influences investment behaviour ($t = 2.52$, $p = 0.012$), with investors often mirroring market trends rather than conducting independent research. This tendency is exacerbated during volatile market periods, leading to excessive speculation and increased instability. Institutional investors, while generally more fundamentals- based, may also exhibit herding behaviour in times of policy uncertainty. Overconfidence negatively impacts investment decisions ($\beta = -0.107$, $p = 0.026$) by leading investors to overestimate their market knowledge, resulting in higher transaction costs and suboptimal decisions. The study finds that trust mediates the relationship between emotional intelligence, herd behaviour, overconfidence, and financial literacy with investment decisions. Overconfidence and herding reduce trust, thereby worsening investment choices, while emotional intelligence and financial literacy enhance trust, fostering better financial decision-making. These findings reinforce the behavioural finance perspective, illustrating that investment decisions are influenced not just by rational analysis but also by psychological and social factors. In addition, their behavioural dynamics exist within Chinese socialism's ideology. The state-guided economic outcome coupled with collective welfare creates a special investment context. The younger generation and even more so institutional investors tend to receive financial signals through an ideology-based trust in institutions and trust in long-term growth in the country. The context itself lends explanation as to why trust is not just an intermediary in behavioural finance but also an expression of underlying societal values based on Chinese socialism's governance. Future research might explore how ideological trust in socialist or collectivist societies affects behavioural finance models differently from those in liberal capitalist markets, offering new directions in cross-cultural investment psychology.

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