Personality and behavioural factors as predictors of investment intention in the Croatian stock market

Marija Vuković✉, Snježana Pivac, Karmen Vrhar Šušnjara
University of Split, Croatia

Abstract: This research examines the role of personality traits and appropriate behavioural factors in individual investors' decisions. The research was carried out using a survey analysis among 310 Croatian stock market investors. PLS-SEM (Partial least squares structural equation modelling) results offer evidence that investors' stability positively influences their emotions, overconfidence, loss aversion and investment decisions, while plasticity affects their overconfidence and loss aversion. Overconfidence, emotions and loss aversion positively affect investment decisions. These decisions positively impact investment performance, satisfaction and further investment intention. Understanding investors' behaviour may improve investment decisions and future investment intention, while also helping financial advisors design more suitable portfolios and strategies. Comparative analysis could further confirm broader behavioural patterns in the stock market.

Keywords: behavioural factors, investment decision, personality, financial market, investment intention

Introduction

According to economic theory in the traditional sense, the main determinant of a successful investment is risk (Fama, 1970; Markowitz, 1959), considering that individuals are perfectly rational when making investment decisions. According to traditional finance, the rational Homo economicus applies unlimited data processing power based on all available information (Bhoj, 2019). He makes financial decisions to maximise his returns and holds preferences well-described by standard expected utility theory. Numerous empirical studies have confirmed financial market anomalies and various factors influencing individual behaviour (Kübilay & Bayrakdaroğlu, 2016; Malyshenko et al., 2019; Wong, 2021). This is especially relevant in Central and Eastern European markets, which are shaped by structural differences, economic changes, and lower predictability in less developed market environments (Ligocká, 2023). More recent models recognise highly error-prone financial environments and, emotionally, error-prone Homo sapiens influenced by various behavioural factors

✉ Assistant Professor, University of Split, Faculty of Economics, Business and Tourism, Croatia, e-mail: marija.vukovic@efst.hr.

HOW TO CITE: Vuković, M., Pivac, S., & Vrhar Šušnjara, K. (2026). Personality and behavioural factors as predictors of investment intention in the Croatian stock market. *Eastern Journal of European Studies, 17*(01), 37-59. https://doi.org/10.47743/ejes-2026-0102

(Bhoj, 2019). Behavioural finance is a psychology-based theory that aims to identify characteristics and psychological processes influencing investors' intentions and decisions (Che Hassan et al., 2023; Dolfin et al., 2017; Kumar & Goyal, 2016; Luong & Thu Ha, 2011). The growing integration of psychology and other social sciences into economics has increased the importance of behavioural finance, making it a "revolutionary trend" (Shiller, 2015; Thaler, 2015).

The significant influence of personality traits on individual behaviour has been confirmed (Ferreira-Schenk et al., 2021; Jurevičiene & Ivanova, 2013). Investors' decisions are shaped by behavioural factors, and the most frequently analysed are heuristics (mostly tested through overconfidence), prospect theory (mostly tested through loss aversion), herd behaviour and emotions (Vuković & Pivac, 2024).

This research examines investment predictors in the Croatian financial market. Studying behavioural factors in Croatia is relevant because its financial market has structural features that may strengthen non-fundamental investor behaviour. Although classification varies across index providers, Croatia is commonly analysed as a frontier market (FTSE Russell, 2025; MSCI, 2026). Such markets are typically characterised by lower liquidity, thinner trading activity, and greater structural constraints than more developed markets (Matek & Galić, 2024; Minović, 2012), increasing the influence of subjective beliefs and behavioural factors on investment decisions. This is consistent with evidence from European stock markets showing stronger herding behaviour in frontier markets, linked to lower liquidity, stability, and transparency (Bogdan et al., 2022). Evidence for Croatia also points to volatility clustering and sensitivity to external market signals, suggesting that investor reactions may be more strongly shaped by uncertainty and informational spillovers (Jošić et al., 2021). Financial literacy is also relevant, as recent official evidence indicates that, despite improvement, further progress is needed in Croatia, particularly in financial behaviour (Croatian National Bank, 2023). Accordingly, Croatia provides a relevant context for examining behavioural factors and their links with personality traits, investment decisions, performance, and investment intention among individual investors.

Using survey data from 310 Croatian investors and partial least squares structural equation modelling (PLS-SEM), the study shows that the higher-order traits stability and plasticity act as key exogenous predictors (DeYoung, 2006; Erdle et al., 2010). Stability positively influences emotions, overconfidence, loss aversion, and investment decisions, whereas plasticity mainly affects overconfidence and loss aversion. This is consistent with research showing that personality traits shape behavioural patterns and risk perceptions in financial decision-making (Ahmad, 2020; Thuy & Ngoc, 2021). Behavioural factors such as overconfidence, emotions, and loss aversion also positively contribute to long-term investment decision-making, which is strongly linked to satisfaction with investment performance and further investment intention (Alshamy, 2019; Luong & Thu Ha, 2011; Qasim et al., 2019; Statman, 2017; Trang & Tho, 2017). Overall, the findings support a sequence from personality traits to behavioural factors, decision-making, and future market participation (Cao et al., 2021; Sashikala & Chitramani, 2018).

The remainder of the paper is structured as follows. Section 1 provides a theoretical background on personality traits, behavioural factors, and investment-related outcomes, followed by the development of research questions and hypotheses. Subsequent sections present the data and methodology, empirical results, discussion and conclusions.

1. Behavioural factors - theoretical background

1.1. Personality characteristics

Many studies have confirmed that personality traits significantly affect financial decisions and individuals' economic status. The most accepted personality model is the Big Five, which includes extraversion, openness, agreeableness, conscientiousness, and neuroticism (Charles & Kasilingam, 2016; De Bortoli et al., 2019; DeYoung, 2010; John & Srivastava, 1999; Vuković & Pivac, 2024). In decision-making, openness is associated with flexibility, long-term investments, and successful financial decisions, while conscientiousness is linked to safer, long-term investing due to greater organisation and self-discipline (Aren & Nayman Hamamci, 2020; Lin, 2011; Nga & Ken Yien, 2013; Statman, 2017; Yadav & Narayanan, 2021). Agreeableness is associated with greater reliance on market trends and information, which may result in herding behaviour and lower overconfidence (Aren & Nayman Hamamci, 2020; Lin, 2011; Nga & Ken Yien, 2013; Yadav & Narayanan, 2021). Tauni et al. (2020) found that all personality traits positively affect investment performance except neuroticism, which shows a negative relationship (Lai, 2019).

The Big Five personality model is the most widely used, with some studies proposing that its traits can be summarised by two higher-order factors: stability (alpha) and plasticity (beta) (Erdle et al., 2010; DeYoung, 2010, 2006; Blackburn et al., 2004). Stability includes conscientiousness, agreeableness, and low neuroticism, reflecting the tendency to maintain emotional, social, and motivational balance (DeYoung, 2006). Plasticity is marked by higher extraversion and openness, indicating social expressiveness and openness to new experiences (DeYoung, 2006).

The higher-order Big Two framework, comprising stability and plasticity, offers theoretical advantages over the traditional Big Five in analysing investment behaviour. By reducing traits to two broader dimensions, it provides a more parsimonious framework while retaining strong explanatory power (DeYoung, 2006; Erdle et al., 2010). Stability reflects emotional regulation and long-term goal orientation, whereas plasticity captures adaptability and openness to new information under uncertainty (DeYoung, 2006). The framework also supports the analysis of indirect effects, whereby personality traits shape behavioural factors that influence investment decisions and intentions (Kahneman, 2013; Thaler, 2015). This approach is particularly suitable for frontier markets such as Croatia, where higher uncertainty and lower market efficiency make broad dispositional traits more informative than narrower personality distinctions.

1.2. Overconfidence, herding, prospect theory and emotions

Investors often face complex information and make decisions quickly under uncertainty. As a result, they rely on heuristics such as representativeness, overconfidence, anchoring, availability, and the gambler's fallacy (Kahneman, 2013; Khan et al., 2017; Luong & Thu Ha, 2011; Raut et al., 2020). Overconfidence is among the most common factors in financial markets and reflects the gap between actual and perceived knowledge (Kahneman, 2013; Kübilay & Bayrakdaroğlu, 2016; Mikołajek-Gocejna, 2017; Raut et al., 2020; Vuković, 2022). While a modest degree of overconfidence may support innovation and decisive action, excessive overconfidence can hinder investor learning and lead to less reliable decisions (Bernardo & Welch, 2001; Fahim et al., 2019; Zhang & Zheng, 2015). At the same time, some studies report a positive association between overconfidence and investment performance (Alquraan et al., 2016; Bakar & Yi, 2016; Luong & Thu Ha, 2011; Qasim et al., 2019).

Herding behaviour is common in financial markets, particularly less developed ones, and refers to investors copying others rather than relying on their own knowledge and information. Investors often imitate others to avoid the effort of gathering information, not because others' decisions are necessarily optimal (Qasim et al., 2019; Raut et al., 2020). In stock markets, similar judgments and actions may also arise because investors react to the same market signals and information (Shiller, 2015). Findings on the effect of herding on investment decisions are mixed, with some studies reporting a positive effect (Qasim et al., 2019; Rekha, 2020) and others a negative or insignificant one (Bakar & Yi, 2016; Mahanthe & Sugathadasa, 2018; Rahman & Gan, 2020; Vuković, 2022).

Prospect theory explains behaviour in situations involving potential gains and losses. Individuals perceive losses as more painful than equivalent gains, and their judgments are shaped more by changes in wealth than by absolute wealth levels. As a result, investors may become more willing to take risks when facing certain losses (Kahneman, 2013; Malkiel, 2019; Thaler, 2015). Differences in the perception of gains and losses may therefore negatively affect investment performance (Luong & Thu Ha, 2011). At the same time, some studies report that risk aversion positively influences investment decisions (Alshamy, 2019), while higher perceived risk has been linked to greater satisfaction with stock performance (Trang & Tho, 2017). Risk-averse investors are also often viewed as more rational and logical (Qureshi et al., 2012), suggesting that prospect theory elements can shape investment decisions.

Emotions cannot realistically be excluded from investment decisions, as they complement intellect. Negative emotions, such as sadness, fear, and regret, significantly decrease the likelihood of market participation (Statman, 2017), whereas positive emotions enhance investment decision-making (Ackert et al., 2003; Statman, 2014). Positive emotions, including optimism, happiness, and hope, motivate investors and may lead to better decisions and further gains.

Behavioural characteristics not only shape investor behaviour and decision-making in financial markets but also influence one another. Extraverted investors are more likely to exhibit herding and overconfidence (Ahmad, 2020). Some studies, however, suggest that extraversion is linked to overconfidence rather than herding behaviour (Aren & Nayman Hamamci, 2020; Lin, 2011; Nga & Ken Yien, 2013; Yadav & Narayanan, 2021). Conscientiousness has likewise been associated with overconfidence, while neuroticism has been linked to herding behaviour (Ahmad, 2020).

Personality traits also influence risk aversion. It decreases with higher agreeableness and openness, whereas extraversion, neuroticism, and conscientiousness are positively related to it (Thuy & Ngoc, 2021). Neuroticism is associated with negative emotions, while low self-confidence may increase reliance on others' advice and, in turn, herding behaviour (Aren & Nayman Hamamci, 2020; Fossum & Feldman Barrett, 2000; Lin, 2011; Nga & Ken Yien, 2013; Yadav & Narayanan, 2021). By contrast, extraversion and agreeableness are linked to more positive emotions (Fossum & Feldman Barrett, 2000; Komulainen et al., 2014; Reisenzein et al., 2020; Zhu et al., 2023). Emotional intelligence also appears to mediate the relationship between conscientiousness, openness, extraversion, and decision-making styles (El Othman et al., 2020).

1.3. Investment decision, investment performance and investment intention

Investment decisions often require choosing between short-term and long-term options. Speculative investors are generally associated with short-term, higher-risk investments, whereas true investors favour long-term investing as a form of risk management and return enhancement (Khan et al., 2021). Graham (2003) distinguished true investment from speculation by arguing that only long-term trading qualifies as investment. Consistent with this view, sound investment decisions are linked to long-term benefits, while a "get-rich-quick" mindset tends to direct investors toward high-risk stocks and short-term profits (Graham, 2003; Malkiel, 2019). Long-term investments generate cash flows and capital growth over years or decades, whereas speculators expect gains within days or weeks (Malkiel, 2019).

The importance of investor psychology is widely emphasised, as risk depends less on the investment itself than on the investor's understanding, self-assessment, and profile (Graham, 2003). Subjective norms also matter for stock market participation, while past behaviour indirectly affects investor intentions through attitudes (Raut, 2020). Heuristics, prospect theory, market factors, and herding have also been shown to positively affect investment decision-making and investment success (Cao et al., 2021). Because investment decisions affect both profit and personal satisfaction, investor satisfaction is often treated as an indicator of investment performance, alongside returns relative to expectations (Luong & Thu Ha, 2011; Trang & Tho, 2017). Higher satisfaction is associated with greater investment efficiency. Prospect and herding factors influence short-term investment intentions, whereas heuristics and market factors are more important for long-term intentions (Sashikala & Chitramani, 2018). Long-term investment intentions are also shaped by personality traits, particularly extraversion and openness to experience, as well as willingness to take risks (Ferreira-Schenk & Dickason-Koekemoer, 2023). Investment intention significantly affects stock market participation (Yang et al., 2021), while perceived risk affects investment performance directly and intentions indirectly through performance (Trang & Tho, 2017). These findings confirm the close link between behavioural characteristics and investor decision-making in financial markets.

According to the literature review, the research goal has been translated into five research questions (RQ), which are as follows:

RQ1. Do personality traits influence behavioural factors?

RQ2. Do personality traits have an impact on long-term investment decisions?

RQ3. How do behavioural factors affect long-term investment decisions?

RQ4. Do long-term investment decisions affect satisfaction with investment performance?

RQ5. Does satisfaction with investment performance have an impact on further investment intention?

2. Data and methodology

Data were collected through an online survey conducted between May 31 and July 7, 2021, and developed based on prior research (Charles & Kasilingam, 2016; John & Srivastava, 1999; Lin, 2011; Luong & Thu Ha, 2011; Nugraha & Rahadi, 2021; Rekha, 2020; Trang & Tho, 2017; Waweru et al., 2008). The survey covered the respondents' socio-demographic characteristics and included items measuring the variables in the research model. Responses were measured on a 5-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). The items captured the Big Two personality traits, behavioural patterns, investment preferences, satisfaction, and intention. The target population comprised investors in the Croatian financial market. As investors' names and contact details were not publicly available due to General Data Protection Regulation (Regulation (EU) 2016/679 of the European Parliament and of the Council) requirements, the survey was distributed online with the support of investment companies. The final sample consisted of 310 investors.

To answer the research questions, partial least squares structural equation modelling (PLS-SEM) was applied. The analysis examined the effects of the Big

Two personality traits on behavioural factors and investment decisions, followed by the effects of investment decisions on performance and of performance on future investment intention. Because all variables in the model are latent constructs that cannot be measured directly, PLS-SEM was considered an appropriate method. The model has not previously been tested in this form, indicating the exploratory nature of the research. According to methodological guidelines, PLS-SEM is suitable when the assumption of multivariate normality is not met, especially in complex models using quasi-metric measured variables (Hair et al., 2017; Sarstedt et al., 2023; Vuković, 2024). This was the case in the present study. Data analysis was conducted using SPSS 23 and SmartPLS 4 (Ringle et al., 2022).

Table 1 presents all survey items and their corresponding codes used in the analysis. Mean and standard deviation values indicate that investors are generally neutral toward heuristics, prospect theory behaviour, and emotions, and are not strongly prone to herding behaviour. Both plasticity and stability are present at moderate to high levels, with stability more pronounced than plasticity. Investors generally prefer long-term investments, report slightly positive investment performance, and show high investment intention.

Table 1. Items in the model

Code	Item	Source	Mean	SD
H1	"I believe that my skills and knowledge of stock market can help me to outperform the market."	Luong & Thu Ha (2011), Lin (2011)	2.95	1.124
H2	"I rely on my previous experiences in the market for my next investment."		3.74	1.009
H3	"I am sure that I can make the correct investment decision."		3.18	0.979
H4	"I think market trend is often consistent with my perspectives."		2.98	0.859
H5	"I always refer the investing profit to my successful investment strategy."		2.85	0.933
H6	"I am normally able to anticipate the end of good or poor market returns."		2.71	1.033
PT1	"I tend to treat each element of my investment portfolio separately."	Waweru et al. (2008), Luong & Thu Ha (2011), Rekha (2020)	3.16	1.081
PT2	"I prefer the long-term security of my funds over short-term monetary gains."		3.62	1.069
PT3	"I have been investing in stocks with higher security from the beginning."		3.38	1.026
HERD1	"I would invest in stocks by following my friend's recommendation."	Lin (2011), Rekha (2020)	2.45	0.996
HERD2	"I follow what my advisor suggests while investing."		2.81	1.115

HERD3	"I follow the other investors' advice while buying stocks, as I do not have proper knowledge."		2.64	1.049
EM1	"I am very much thrilled to invest during the booming or recovery stage of the market."	Charles and Kasilingam (2016)	3.36	1.082
EM2	"My positive outlook encourages me to invest in the market."		3.47	1.122
EM3	"I am looking forward to my next opportunity to invest after a deep fall in the market."		3.41	1.131
PL1	"I am full of energy."	John and Srivastava (1999)	3.53	0.930
PL2	"I generate a lot of enthusiasm."		3.46	0.919
PL3	"I have an assertive personality."		3.81	0.909
PL4	"I am ingenious, a deep thinker."		3.05	1.002
PL5	"I have an active imagination."		3.61	0.895
PL6	"I am inventive."		3.48	0.913
STAB1	"I do a thorough job."		3.84	0.891
STAB2	"I like to cooperate with others."		3.65	0.954
STAB3	"I am relaxed and handle stress well."		3.49	1.042
STAB4	"I remain calm in tense situations."		3.51	1.010
STAB5	"I am a reliable worker."		4.18	0.795
STAB6	"I persevere until the task is finished."		3.97	0.872
STAB7	"I do things efficiently."		3.83	0.850
STAB8	"I make plans and follow through with them."		3.75	0.893
STAB9	"I am helpful and unselfish with others."		3.73	0.937
STAB10	"I am generally trusting."		4.15	0.801
ID1	"I allot funds that will produce long-term benefits."	Rekha (2020)	3.95	0.951
ID2	"I regularly review, compare and take instant decision on my investment performance."		3.82	0.887
ID3	"I do market research before taking any short-term investment"		3.79	0.977
ID4	"I allot more funds for the long term than the short term."		3.71	1.052
IP1	"The return rate of my recent stock investment meets my expectations."	Luong & Thu Ha (2011), Trang & Tho (2017)	3.44	0.949
IP2	"My rate of return is equal to or higher than the return on most other stocks."		3.09	0.901
IP3	"I feel satisfied with my investment decisions in the last year, considering buying stocks."		3.35	0.999
IP4	"I feel satisfied with my investment decisions in the last year, considering selling stocks."		3.09	1.118
INT1	"I intend to engage in stock investment in the near future."	Nugraha & Rahadi (2021)	4.05	1.075
INT2	"I will recommend others to invest in the stock market."		3.21	1.269

INT3	"I will continue to invest in the stock market."	4.12	1.042
INT4	"I can stand the inconvenience caused by stock investment."	3.73	1.146

Source: authors' representation according to Nugraha & Rahadi (2021), Rekha (2020), Trang & Tho (2017), Charles & Kasilingam (2016), Lin (2011), Luong & Thu Ha (2011), Waweru et al. (2008), John & Srivastava (1999).

Potential common method bias (CMB), which is often associated with self-administered questionnaires, was assessed. CMB refers to measurement error caused by the measurement method rather than by actual causal relationships in the model (Kock, 2015; Min et al., 2016), and it may inflate variable relationships through systematic error (Conway & Lance, 2010; Podsakoff et al., 2003). A full collinearity test with a random variable was used to examine CMB (Kock & Lynn, 2012). As shown in Table 2, all variance inflation factors (VIFs) were below 3.3, indicating no CMB or collinearity concerns in the model (Kock, 2015; Kock & Lynn, 2012).

Table 2. Assessment of CMB using full collinearity VIFs

	VIF
EM	1.161
HERD	1.214
HEU	1.628
ID	1.996
INT	1.961
IP	1.595
PL	1.333
PT	1.376
STAB	1.523

Source: authors' representation

3. Results and discussion

The model comprises nine constructs. The Big Two personality traits, stability (STAB) and plasticity (PL), are exogenous, while behavioural factors - heuristics (HEU), prospect theory (PT), herding (HERD), and emotions (EM) - together with investment decision (ID), investment performance (IP), and investment intention (INT), are endogenous constructs.

The first step in PLS-SEM is testing the outer (measurement) model. First, convergent validity and reliability were analysed. Table 3 reports the outer loadings, average variance extracted (AVE), composite reliability, and Cronbach's alpha. Outer loadings were high for all items, resulting in AVE values above 0.5 for all constructs, indicating that each construct explains more than 50% of the variance in its indicators (Hair et al., 2017; Vuković, 2024; Vuković & Pivac, 2021). Composite reliability values also exceeded the recommended threshold of 0.70. Cronbach's alpha values were generally within the acceptable 0.60–0.90 range, except EM, which showed a slightly lower value. This may reflect Cronbach's alpha sensitivity to the number of items and its conservative nature, which can underestimate internal consistency reliability (Gefen et al., 2000; Hair et al., 2017). For this reason, composite reliability was also considered and showed satisfactory values for all constructs (Hair et al., 2017; Sarstedt et al., 2017).

Convergent validity and reliability are both supported, meaning that all items represent their constructs well. These results are consistent with prior behavioural finance studies using PLS-SEM, confirming the robustness of similar measurement models when analysing psychological and behavioural constructs simultaneously (Hair et al., 2017; Sarstedt et al., 2023).

Table 3. Analysis of construct validity and reliability

	Outer loading	AVE	Composite reliability	Cronbach's alpha
Heuristics (HEU)				
H1	0.764	0.519	0.865	0.816
H2	0.679			
H3	0.797			
H4	0.742			
H5	0.702			
H6	0.624			
Prospect theory (PT)				
PT1	0.648	0.558	0.789	0.607
PT2	0.840			
PT3	0.741			
Herding (HERD)				
HERD1	0.455	0.568	0.785	0.690
HERD2	0.770			
HERD3	0.952			
Emotions (EM)				
EM1	0.729	0.526	0.766	0.561
EM2	0.607			
EM3	0.823			
Plasticity (PL)				
PL1	0.754	0.510	0.861	0.807
PL2	0.738			
PL3	0.786			
PL4	0.609			
PL5	0.665			
PL6	0.716			
Stability (STAB)				
STAB1	0.749	0.512	0.913	0.893
STAB2	0.650			

STAB3	0.634			
STAB4	0.674			
STAB5	0.767			
STAB6	0.725			
STAB7	0.717			
STAB8	0.720			
STAB9	0.700			
STAB10	0.805			
Investment decision (ID)				
ID1	0.788	0.580	0.846	0.757
ID2	0.813			
ID3	0.754			
ID4	0.684			
Investment performance (IP)				
IP1	0.885	0.690	0.899	0.849
IP2	0.784			
IP3	0.864			
IP4	0.784			
Investment intention (INT)				
INT1	0.904	0.716	0.909	0.865
INT2	0.760			
INT3	0.899			
INT4	0.813			

Source: authors' representation

Discriminant validity was assessed using the heterotrait-monotrait ratio (HTMT), which tests whether the constructs are empirically distinct. According to the literature, HTMT values should be below 0.85 (Hair et al., 2017; Henseler et al., 2015; Sarstedt et al., 2023). As shown in Table 4, all values met this criterion, confirming discriminant validity. This confirms that the conceptual distinctions between personality traits, behavioural factors, and investment-related outcomes are empirically valid, aligning with earlier studies that treat these constructs as theoretically and empirically separable (Kumar & Goyal, 2016; Vuković & Pivac, 2024).

Table 4. HTMT Ratio for construct discriminant validity

	EM	HERD	HEU	ID	INT	IP	PL	PT	STAB
EM									
HERD	0.395								
HEU	0.475	0.157							
ID	0.545	0.152	0.497						
INT	0.683	0.349	0.557	0.704					

IP	0.392	0.301	0.636	0.622	0.645			
PL	0.428	0.107	0.542	0.447	0.410	0.455		
PT	0.375	0.360	0.297	0.673	0.241	0.299	0.205	
STAB	0.478	0.134	0.448	0.581	0.491	0.515	0.725	0.440

Source: authors' representation

The research questions were addressed by observing the structural (inner) model relationships and testing their significance through the bootstrapping procedure. Table 5 displays these results.

Table 5. Structural model coefficients with significance testing

	Path coefficient	t-value	p-value
EM → ID	0.191	3.633	0.000
HERD → ID	-0.115	1.542	0.123
HEU → ID	0.146	2.556	0.011
ID → IP	0.510	11.214	0.000
IP → INT	0.555	13.067	0.000
PL → EM	0.136	1.600	0.110
PL → HERD	0.100	0.875	0.382
PL → HEU	0.326	5.293	0.000
PL → ID	0.106	1.548	0.122
PL → PT	-0.180	2.404	0.016
PT → ID	0.366	6.512	0.000
STAB → EM	0.274	3.874	0.000
STAB → HERD	-0.157	1.339	0.181
STAB → HEU	0.200	2.993	0.003
STAB → ID	0.154	2.166	0.030
STAB → PT	0.449	6.429	0.000

Source: authors' representation

Firstly, the impact of the Big Two personality traits on other factors was examined. Plasticity significantly affects only overconfidence ($\beta = 0.326$, $p < 0.001$) and prospect theory ($\beta = -0.180$, $p = 0.016$), suggesting that individuals high in extraversion and openness are more prone to overconfidence in financial markets. This is consistent with prior research linking extraversion and openness to greater confidence and risk-taking tendencies (Ahmad, 2020; Yadav & Narayanan, 2021). At the same time, such individuals appear less prone to behaviour associated with prospect theory, which aligns with evidence that openness reduces risk aversion (Thuy & Ngoc, 2021). However, the absence of a significant relationship between plasticity and herding or emotions contrasts with studies suggesting that extraverted individuals are more socially influenced (Ahmad, 2020). One possible explanation lies in the Croatian frontier market context, where limited participation and information asymmetry may reduce social imitation compared to more developed markets.

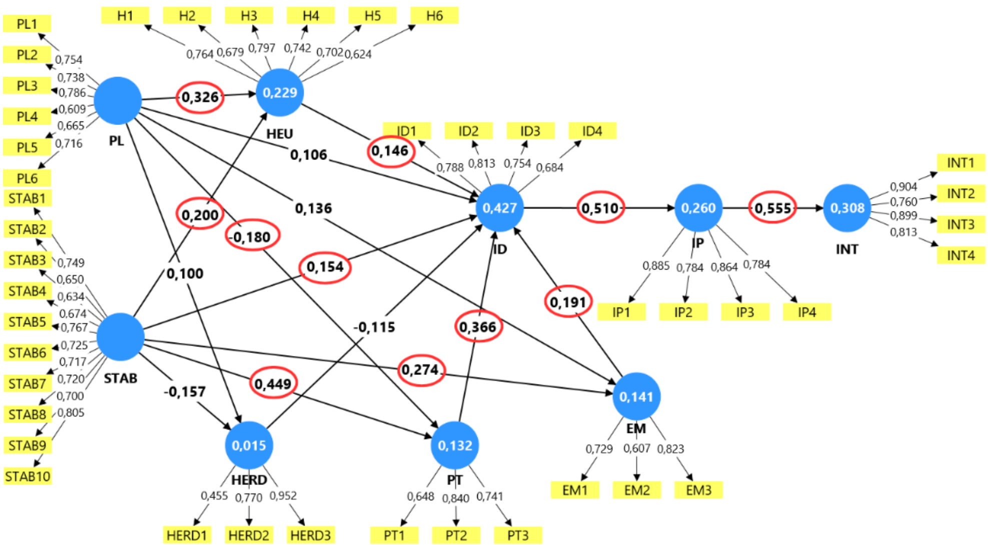
Stability significantly influences all behavioural patterns except herding. Its impact on emotions is positive (β=0.274, p<0.001), implying that conscientious, reliable, collaborative, calm, and emotionally stable investors tend to show more positive emotions in their investment activities. This is consistent with prior findings linking emotional stability and conscientiousness to positive emotional regulation (Komulainen et al., 2014; Fossum & Feldman Barrett, 2000). Furthermore, these investors are significantly more prone to overconfidence bias (β=0.200, p=0.003), supporting earlier evidence that conscientious individuals may overestimate their abilities due to structured decision-making approaches (Ahmad, 2020). They also prefer secure investments over risky ones (β=0.449, p<0.001), which is consistent with studies linking conscientiousness and risk aversion (Thuy & Ngoc, 2021). Finally, the stability significantly affects investment decisions (β=0.154, p=0.030). These findings indicate that conscientious, reliable and stable investors are more prone to perform detailed research and analysis of investment options, often choosing long-term investments, confirming earlier work emphasising disciplined and long-term behaviour among such individuals (Aren & Nayman Hamamci, 2020; Statman, 2017).

Among behavioural factors, only herding does not significantly affect investment decisions. This is largely consistent with previous research by Vuković and Pivac (2024), on which this extended model is based. While some studies report a significant positive influence of herding on investment decisions (Qasim et al., 2019), others find weak or insignificant effects (Bakar & Yi, 2016; Rahman & Gan, 2020), which supports the present findings. A possible explanation lies in the increasing availability of financial information and individual learning, which may reduce reliance on collective behaviour, particularly among more experienced investors. Emotions positively impact investment decisions (β=0.191, p<0.001), suggesting that optimistic investors more often make long-term investments. Overconfidence also has a positive effect (β = 0.146, p = 0.011), indicating that investors with greater confidence in their knowledge and abilities tend to make more long-term investment decisions. This is consistent with studies showing that moderate overconfidence can encourage active investment behaviour, although it contrasts with research emphasising its negative effects through biased judgment (Kahneman, 2013; Qasim et al., 2019). Similarly, behaviour according to prospect theory positively affects investment decisions (β=0.366, p<0.001). Measured by loss aversion and mental accounting, it suggests that investors who prioritise security in their investments are more likely to make more long-term investment decisions, consistent with findings that risk-averse individuals prefer safer, long-term strategies (Alshamy, 2019; Trang & Tho, 2017).

Investment decision significantly positively affects investment performance satisfaction ($\beta=0.510$, $p<0.001$), indicating that investors who prefer long-term investments are more satisfied with their trading decisions and returns. This supports classical investment principles advocating long-term strategies (Graham, 2003; Malkiel, 2019), as well as behavioural studies linking decision quality to perceived performance (Luong & Thu Ha, 2011). Lastly, investment performance significantly positively impacts investment intention ($\beta=0.555$, $p<0.001$), suggesting that investors who are more satisfied with their returns and stock trading decisions are more likely to continue investing and recommend stock market participation to others. This is consistent with prior research showing that performance satisfaction is a key driver of future investment participation (Trang & Tho, 2017; Yang et al., 2021).

Figure 1 presents the path diagram, including path coefficient estimates, outer loadings, and coefficients of determination (R^2) for the endogenous constructs. For the key target construct, investment intention, the model shows high in-sample predictive power, explaining 30.8% of the variance in INT ($R^2 = 0.308$) (Ringle et al., 2014).

Figure 1. Path diagram with estimated coefficients (significant paths circled red)



Source: authors' representation according to SmartPLS 4

PLS-SEM focuses on both explanation and prediction (Hair et al., 2011, 2017; Sarstedt et al., 2023; Vuković, 2024). Accordingly, in addition to in-sample predictive power, the model's out-of-sample predictive power was assessed using the PLS Predict procedure for the key endogenous construct (Hair et al., 2017; Shmueli et al., 2019). The results are shown in Table 6.

Table 6. Assessment of out-of-sample predictive power using PLS Predict

Item	Q^2predict	PLS-SEM_RMSE	LM_RMSE
INT1	0.067	1.040	1.054
INT2	0.055	1.236	1.211
INT3	0.066	1.010	1.014
INT4	0.091	1.095	0.935

Source: authors' representation

All Q^2 predict values were positive, indicating lower prediction errors in the PLS model than in the naïve benchmark linear model (LM). Predictive power was further assessed by comparing RMSE values between the PLS-SEM and LM models. Since the PLS-SEM model showed lower RMSE values in most cases, it demonstrates medium predictive power (Shmueli et al., 2019). This suggests that the model adequately captures relationships between constructs and supports its applicability in future research and across different data samples.

The predictive performance also supports integrating personality traits and behavioural factors in explaining investment intention, consistent with behavioural finance literature (Shiller, 2015; Thaler, 2015).

These findings should be interpreted cautiously given the timing of data collection. As the survey was conducted in 2021, the model does not reflect the subsequent growth of AI-enabled financial advisory services, digital investment platforms, and generative AI tools. Recent studies suggest that these developments are reshaping how retail investors process financial information and may therefore influence how behavioural factors affect investment decision-making (He et al., 2025; Zhu et al., 2024).

Conclusions

This research examines the impact of personality traits and selected behavioural factors on stock investment among Croatian financial market investors. The study focuses on the higher-order personality traits of stability and plasticity, as well as overconfidence, prospect theory, herding, and emotions. It analyses how these factors relate to investment decisions, performance, and ultimately investment intention. Based on survey data from 310 investors, the analysis uses partial least squares structural equation modelling (PLS-SEM). The results indicate high in-sample and medium out-of-sample predictive power.

The results identify the Big Two personality traits, stability and plasticity, as exogenous constructs, while behavioural factors, investment decisions, performance, and intention are endogenous. The findings show that stability significantly and positively affects emotions, overconfidence, loss aversion, and investment decisions, suggesting that more organised and emotionally stable individuals may better understand market dynamics and favour long-term investing. Plasticity affects only overconfidence and loss aversion, but may still help investors recognise opportunities consistent with long-term goals. These findings highlight the importance of aligning investment strategies with investors’ psychological profiles to support more tailored and effective decision-making. Overconfidence, emotions, and loss aversion positively influence investment decisions, particularly the preference for long-term investments. Although often viewed as irrational, such behavioural factors may, at moderate levels, support market participation and sustained engagement. Overconfidence can encourage more active trading and positively affect investment decisions, while prospect theory elements are linked to perceptions of financial security. Loss aversion may strengthen the preference for long-term investments as safer options with higher profit potential, while positive emotions may improve motivation and investment decisions. These decisions increase satisfaction with investment performance, as investors who make more informed long-term decisions tend to report greater satisfaction with returns and trading outcomes. Finally, investment performance positively influences further investment intention, suggesting that satisfied investors are more likely to start or continue investing in the stock market. This underscores the importance of positive investment experiences in sustaining long-term market participation and investor engagement.

This research contributes to behavioural finance by examining the relatively underexplored Croatian financial market. The results are broadly consistent with prior studies and propose a comprehensive model in which behavioural factors influence investment intention, while the Big Two personality traits act as key predictors of investment decisions, performance, and intention. The findings suggest that incorporating behavioural insights into investment frameworks may improve decision quality and strengthen long-term participation, especially in less developed or frontier markets.

The findings may guide future research on similar models and broader behavioural patterns in financial market decision-making. They may also help investors better recognise their behavioural tendencies, while advisors and brokers may use these insights to design portfolios and strategies suited to investors’ needs. In particular, behavioural profiling and stronger financial literacy may improve independent decision-making and reduce reliance on collective market signals.

The study has several limitations. The model could be expanded by incorporating relevant market indicators and additional dimensions of behavioural factors. Because investor behaviour may change over time, future research could examine these relationships across periods and contexts. Another limitation is that the study does not explicitly capture the recent technological transformation of financial markets. AI increasingly influences financial advisory services, information processing, and broader financial system functions, meaning that the investor decision environment today may differ from that at the time of the survey (Aldasoro et al., 2025; Zhu et al., 2024). Future studies could test whether the identified relationships remain robust in a more AI-shaped market environment.

References

Ackert, L. F., Church, B. K., & Deaves, R. (2003). Emotion and Financial Markets. *Economic Review, Federal Reserve Bank of Atlanta*, *88(Q2)*, 33-41.

Ahmad, F. (2020). Personality traits as predictor of cognitive biases: moderating role of risk-attitude. *Qualitative Research in Financial Markets*, *12*(4), 465-484. https://doi.org/10.1108/QRFM-10-2019-0123

Aldasoro, I., Gambacorta, L., Korinek, A., Shreeti, V., & Stein, M. (2025). Intelligent financial system: How AI is transforming finance. *Journal of Financial Stability*, *81*, 101472. https://doi.org/10.1016/j.jfs.2025.101472

Alquraan, T., Alqisie, A., & Al Shorafa, A. (2016). Do Behavioral Factors Influence Stock Investment Decisions of Indidivudal Investors? (Evidences from Saudi Stock Market). *American International Journal of Contemporary Research*, *6*(3), 159-169.

Alshamy, S. A. (2019). Factors Affecting Investment Decision Making: Moderating Role of Investors Characteristics. *The Journal of Social Sciences Research*, *5*(4), 965-974.

Aren, S., & Nayman Hamamci, H. (2020). Relationship between risk aversion, risky investment intention, investment choices: Impact of personality traits and emotion. *Kybernetes*, *49*(11), 2651-2682. https://doi.org/10.1108/K-07-2019-0455

Bakar, S., & Yi, A. N. C. (2016). The Impact of Psychological Factors on Investors' Decision Making in Malaysian Stock Market: A Case of Klang Valley and Pahang. *Procedia Economics and Finance*, *35*, 319-328. https://doi.org/10.1016/S2212-5671(16)00040-X

Bernardo, A. E., & Welch, I. (2001). On the evolution of overconfidence and entrepreneurs. *Journal of Economics & Management Strategy*, *10*(3), 301-330. https://doi.org/10.1111/j.1430-9134.2001.00301.x

Bhoj, J. (2019). A study of origin and history of behaviour finance with special reference to India. *International Journal of Research and Development*, *4*(11), 144-155. https://eprajournals.com/IJSR/article/1817/

Blackburn, R., Renwick, S. J. D., Donnelly, J. P., & Logan, C. (2004). Big Five or Big Two? Superordinate factors in the NEO Five Factor Inventory and the Antisocial Personality Questionnaire. *Personality and Individual Differences*, *37*(5), 957-970. https://doi.org/10.1016/j.paid.2003.10.017

Bogdan, S., Šuštar, N., & Olgić Draženović, B. (2022). Herding behavior in developed, emerging, and frontier European stock markets during COVID-19 pandemic. *Journal of Risk and Financial Management*, *15*(9), 400. https://doi.org/10.3390/jrfm15090400

Cao, M. M., Nguyen, N. T., & Tran, T. T. (2021). Behavioral factors on individual investors' decision making and investment performance: A survey from the Vietnam Stock Market. *The Journal of Asian Finance, Economics and Business*, *8*(3), 845-853. https://doi.org/10.13106/jafeb.2021.vol8.no3.0845

Charles, A., & Kasilingam, R. (2016). Impact of selected behavioural bias factors on investment decisions of equity investors. *ICTACT Journal on Management Studies, 2*(2), 297-311. https://doi.org/10.21917/ijms.2016.0041

Che Hassan, N., Abdul-Rahman, A., Mohd Amin, S.I., & Ab Hamid, S.N. (2023). Investment Intention and Decision Making: A Systematic Literature Review and Future Research Agenda. *Sustainability*, *15*, 3949. https://doi.org/10.3390/su15053949

Conway, J. M., & Lance, C. E. (2010). What reviewers should expect from authors regarding common method bias in organizational research. *Journal of Business and Psychology*, *25*(3), 325–334. https://doi.org/10.1007/s10869-010-9181-6

Croatian National Bank. (2023, December 14). *Financial knowledge in Croatia above OECD average with a continued trend of improving overall financial literacy*. Croatian National Bank. https://www.hnb.hr/en/-/financial-knowledge-in-croatia-above-oecd-average-with-a-continued-trend-of-improving-overall-financial-literacy

De Bortoli, D., da Costa, N. Jr., Goulart, M., & Campara, J. (2019). Personality traits and investor profile analysis: A behavioral finance study. *PloS one, 14*(3), e0214062. https://doi.org/10.1371/journal.pone.0214062

DeYoung, C. G. (2006). Higher-Order Factors of the Big Five in a Multi-Informant Sample. *Journal of Personality and Social Psychology, 91*(6), 1138-1151. https://doi.org/10.1037/0022-3514.91.6.1138

DeYoung, C. G. (2010). Toward a Theory of the Big Five. *Psychological Inquiry, 21*(1), 26-33. https://doi.org/10.1080/10478401003648674

Dolfin, M., Leonida, L., & Outada, N. (2017). Modeling Human Behavior in Economics and Social Science. *Physics of Life Reviews, 22-23*, 1-21. https://doi.org/10.1016/j.plrev.2017.06.026

El Othman, R., El Othman, R., Hallit, R., Obeid S., & Hallit S. (2020). Personality traits, emotional intelligence and decision-making styles in Lebanese universities medical students. *BMC Psychology, 8*, 46. https://doi.org/10.1186/s40359-020-00406-4

Erdle, S., Irwing, P., Rushton, J. P., & Park, J. (2010). The general factor of personality and its relation to self-esteem in 628,640 internet respondents. *Personality and Individual Differences, 48*(3), 343-346. https://doi.org/10.1016/j.paid.2009.09.004

Fahim, F., Ali, A., Khan, A.M., & Khan, A.R. (2019). Impact of overconfidence on investor's investment decision: moderating role of risk perception and religiosity-A survey of Pakistan stock exchange. *JISR-MSSE, 17*(2), 85-96.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance, 25*(2), 383-417. https://www.jstor.org/stable/2325486

Ferreira-Schenk S., Dickason-Koekemoer Z., & Shah N. H. (2021). Factors Influencing Individuals Short-term Investment Intentions, *International Journal of Economics and Financial Issues, 11*(4), 73-81. https://doi.org/10.32479/ijefi.11449

Ferreira-Schenk S., & Dickason-Koekemoer, Z. (2023). Analysing the Factors Affecting the Long-term Investment Intention of Investors. *International Journal of*

Economics and Financial Issues, *13*(1), 112–120. https://doi.org/10.32479/ijefi.13640

Fossum T.A., & Feldman Barrett L. (2000). Distinguishing Evaluation From Description in the Personality-Emotion Relationship. *Personality and Social Psychology Bulletin*, *26*(6), 669-679. https://doi.org/10.1177/0146167200268003

FTSE Russell. (2025, October). *FTSE equity country classification matrix*. FTSE Russell. https://www.lseg.com/content/dam/ftse-russell/en_us/documents/country-classification/matrix-of-markets.pdf

Gefen, D., Straub, D. & Boudreau, M.C. (2000). Structural equation modeling and regression: Guidelines for research practice. *Communications of the Association for Information Systems*, *4*(1), 1-79. https://doi.org/10.17705/1CAIS.00407

General Data Protection Regulation. (2018). *Regulation (EU) 2016/679 of the European Parliament and of the Council*. https://gdpr-info.eu/

Graham, B. (2003). *The Intelligent Investor*. HarperBusiness.

Hair, J. F., Hult, G. T. M., Ringle, C. M. & Sarstedt, M. (2017). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* (2nd ed.). Sage Publications.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing theory and Practice*, *19*(2), 139-152. https://doi.org/10.2753/MTP1069-6679190202

He, H. H., Jones, L., Lu, Y., & Gepp, A. (2025). Technology-enabled innovations in financial markets and retail investors: A systematic literature review. *Journal of Accounting Literature*. https://doi.org/10.1108/JAL-11-2024-0331

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the academy of marketing science*, *43*(1), 115-135. https://doi.org/10.1007/s11747-014-0403-8

John, O. P., & Srivastava, S. (1999). The Big Five Trait taxonomy: History, measurement, and theoretical perspectives. In L.A. Pervin & O.P. John (Eds.), *Handbook of personality: Theory and research* (pp. 102-138). Guilford Press.

Jošić, H., Žmuk, B., & Kovač, V. (2021). Modeling stock market volatility in Croatia: A reappraisal. *Ekonomski vjesnik/Econviews*, *34*(2), 431–442.

Jurevičiene, D. & Ivanova, O. (2013). Behavioural Finance: Theory and Survey. *Mokslas – Lietuvos ateitis/Science – Future of Lithuania*, *5*(1), 53-58. https://doi.org/10.3846/mla.2013.07

Kahneman, D. (2013). *Thinking, Fast and Slow*. Farrar, Straus and Giroux.

Khan, H. H., Naz, I., Qureshi, F., & Ghafoor, A. (2017). Heuristics and stock buying decision: Evidence from Malaysian and Pakistani stock markets. *Borsa Istanbul Review*, *17*(2), 97-110. https://doi.org/10.1016/j.bir.2016.12.002

Khan, I., Afeef, M., Jan, S., & Ihsan, A. (2021). The impact of heuristic biases on investors' investment decision in Pakistan stock market: moderating role of long term orientation. *Qualitative Research in Financial Markets. 13(2)*, 252-274. https://doi.org/10.1108/QRFM-03-2020-0028

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration*, *11*(4), 1-10. https://doi.org/10.4018/ijec.2015100101

Kock, N., & Lynn, G.S. (2012). Lateral Collinearity and Misleading Results in Variance-Based SEM: An Illustration and Recommendations. *Journal of the Association for Information Systems*, *13*(7), 546-580. https://doi.org/10.17705/1jais.00302

Komulainen E., Meskanen K., Lipsanen J., Lahti J.M., Jylhä P., Melartin T., Wichers M., Isometsä E., & Ekelund J. (2014). The Effect of Personality on Daily Life Emotional Processes. *PLOS ONE*, *9*(10), 1-9. https://doi.org/10.1371/journal.pone.0110907

Kübilay, B., & Bayrakdaroğlu, A. (2016). An Empirical Research on Investor Biases in Financial Decision-Making, Financial Risk Tolerance and Financial Personality. *International Journal of Financial Research*, *7*(2), 171-182. https://doi.org/10.5430/ijfr.v7n2p171

Kumar, S. & Goyal, N. (2016). Evidence on rationality and behavioural biases in investment decision making. *Qualitative Research in Financial Markets*, *8*(4), 270-287. https://doi.org/10.1108/QRFM-05-2016-0016

Lai, C. P. (2019). Personality Traits and Stock Investment of Individuals. *Sustainability, 11*(19*)*, 54–74. https://doi.org/10.3390/su11195474

Ligocká, M. (2023). The relationship between macroeconomic variables and stock market indices: Evidence from Central and Eastern European countries. *Eastern Journal of European Studies*, *14*(2), 76–107. https://doi.org/10.47743/ejes-2023-0204

Lin, H-W. (2011). Elucidating rational investment decisions and behavioral biases: Evidence from the Taiwanese stock market. *African Journal of Business Management*, *5*(5), 1630-1641. https://doi.org/10.5897/AJBM10.474

Luong, L. P., & Thu Ha, D. T. (2011). *Behavioral Factors Influencing Individual Investors' Decision-Making and Performance: A Survey at the Ho Chi Minh Stock Exchange*. [Unpublished Master's Thesis]. Umea School of Business.

Mahanthe, J. W., & Sugathadasa, D. D. (2018). The Impact of Behavioural Factors on Investment Decision Making in Colombo Stock Exchange. *The International Journal of Business & Management*, *6*(8), 199-207.

Malkiel, G. B. (2019). *A Random Walk Down Wall Street: The Time-Tested Strategy for Successful Investing*. W.W. Norton.

Malyshenko, K., Malyshenko, V., Ponomareva, E. Y., & Anashkina, M. (2019). Analysis of the stock market anomalies in the context of changing the information paradigm. *Eastern Journal of European Studies*, *10*(1), 239–270.

Markowitz, H. M. (1959). *Portfolio Selection: Efficient Diversification of Investment*. Yale University Press.

Matek, P.-P., & Galić, M. (2024). The impact of designated market-makers on liquidity in frontier markets: Evidence from Zagreb and Ljubljana Stock Exchanges. *Zbornik* *radova Ekonomskog fakulteta u Rijeci*, *42*(1), 95–124. https://doi.org/10.18045/zbefri.2024.1.95

Mikołajek-Gocejna, M. (2017). Heuristic. Psychological Aspects of Decision-Making on Capital Market – Literature Review. *Finanse, Rynki Finansowe, Ubezpieczenia*, *90*, 51-65. https://doi.org/10.18276/frfu.2017.90-05

Min, H., Park, J., & Kim, H. J. (2016). Common method bias in hospitality research: A critical review of literature and an empirical study. *International Journal of Hospitality Management*, *56*, 126-135. https://doi.org/10.1016/j.ijhm.2016.04.010

Minovic J. Z. (2012). Liquidity of the Croatian Stock Market: An Empirical Analysis. *Economic Research*, *25*(3), 776-802. https://doi.org/10.1080/1331677X.2012.11517533

MSCI. (2026). *MSCI Croatia Index (USD) factsheet*. https://www.msci.com/indexes/index/136635

Nga, J. K. H., & Ken Yien, L. (2013). The influence of personality trait and demographics on financial decision making among Generation Y. *Young Consumers*, *14*(3), 230-243. https://doi.org/10.1108/YC-11-2012-00325

Nugraha, B. A., & Rahadi, R. A. (2021). Analysis of young generations toward stock investment intention: A preliminary study in an emerging market. *Journal of Accounting and Investment*, *22*(1), 80-103. https://doi.org/10.18196/jai.v22i1.9606

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of applied psychology*, *88*(5), 879-903. https://doi.org/10.1037/0021-9010.88.5.879

Qasim, M., Hussain, R., Mehboob, I., & Arshad, M. (2019). Impact of herding behavior and overconfidence bias on investors' decision-making in Pakistan. *Accounting, 5(2)*, 81-90.

Qureshi, S. A., Rehman, K. U., & Hunjra, A. I. (2012). Factors Affecting Investment Decision Making of Equity Fund Managers. *Wulfenia Journal*, *19*(10), 280-291.

Rahman, M., & Gan, S. S. (2020). Generation Y investment decision: an analysis using behavioural factors. *Managerial Finance*, *46*(8), 1023-1041. https://doi.org/10.1108/MF-10-2018-0534

Raut, R. K., Das, N., & Mishra, R. (2020). Behaviour of Individual Investors in Stock Market Trading: Evidence from India. *Global Business Review*, *21*(3), 818-833. https://doi.org/10.1177/0972150918778915

Raut, R.K. (2020). Past behaviour, financial literacy and investment decision-making process of individual investors, *International Journal of Emerging Markets*, *15*(6), 1243-1263. https://doi.org/10.1108/IJOEM-07-2018-0379

Reisenzein, R., Hildebrandt, A., & Weber, H. (2020). Personality and emotion. In P. J. Corr & G. Matthews (Eds.), *The Cambridge handbook of personality psychology* (pp. 81–100). Cambridge University Press.

Rekha, D. M. (2020). Determinants of behavioral finance influencing investment decisions with respect to income: A study on investment in the equity market. *International Journal of Advanced Science and Technology, 29(8)*, 5015-5028.

Ringle, C. M., Wende, S., Becker, J.-M. (2022). *SmartPLS 4*. SmartPLS GmbH. http://www.smartpls.com.

Ringle, C., Silva, D., & Bido, D. (2014). Structural Equation Modeling with the Smartpls. *Brazilian Journal of Marketing*, *13*(2), 56-73. https://doi.org/10.5585/remark.v13i2.2717

Sarstedt, M., Hair, J. F., & Ringle, C. M. (2023). "PLS-SEM: Indeed a silver bullet"– retrospective observations and recent advances. *Journal of marketing theory and practice*, *31*(3), 261-275. https://doi.org/10.1080/10696679.2022.2056488

Sarstedt, M., Ringle, C. M. & Hair, J. F. (2017). Partial least squares structural equation modeling. In Homburg, C., Klarmann, M. & Vomberg, A. E. (Eds.), *Handbook of market research* (pp. 1-40). Springer International Publishing. https://doi.org/10.1007/978-3-319-05542-8_15-1

Sashikala V., & Chitramani, P. (2018). The Impact of Behavioural Factors on Investment Intention of Equity Investors. *Asian Journal of Management*, *9*(1), 183-189. https://doi.org/10.5958/2321-5763.2018.00028.8

Shiller, R. J. (2015). *Irrational Exuberance* (3rd ed.). Princeton University Press.

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. *European Journal of Marketing*, 53, 2322-2347. https://doi.org/10.1108/EJM-02-2019-0189

Statman, M. (2014). Behavioral finance: Finance with normal people. *Borsa Istanbul Review*, *14*, 65-73. https://doi.org/10.1016/j.bir.2014.03.001

Statman, M. (2017). *Finance for normal people: How Investors and Markets Behave*. Oxford University Press.

Tauni, M. Z., Yousaf, S., & Ahsan, T. (2020). Investor-advisor Big Five personality similarity and stock trading performance. *Journal of Business Research, 109*, 49-63. https://doi.org/10.1016/j.jbusres.2019.11.047

Thaler, R. H. (2015). *Misbehaving: The making of behavioral economics.* W.W. Norton & Co.

Thuy T. T. T., & Ngoc V. T. N. (2021). A Behavioral Finance Study: Effect of Personal Characteristics on Risk Preferences and Investment Decisions of Vietnamese Investors. In *Proceedings of the International Conference on Emerging Challenges: Business Transformation and Circular Economy (ICECH 2021), Advances in Economics, Business and Management Research*, *196*, 571-580.

Trang P.T.M., & Tho N.H. (2017). Perceived Risk, Investment Performance and Intentions in Emerging Stock Markets. *International Journal of Economics and Financial Issues*, *7*(1), 269-278. https://izlik.org/JA46GF98BG

Vuković, M. (2022). Personality as a predictor of students' heuristic and herding biases in determining their predispositions for long-term investment decisions. *Proceedings of the 77th International Scientific Conference on Economic and Social Development, online, January 27*, 53-62.

Vuković, M. (2024). CB-SEM vs PLS-SEM comparison in estimating the predictors of investment intention. *Croatian Operational Research Review*, *15*(2), 131-144. https://doi.org/10.17535/crorr.2024.0011

Vuković, M., & Pivac, S. (2021). Does financial behavior mediate the relationship between self-control and financial security? *Croatian Operational Research Review*, *12*(1), 27-36. https://doi.org/10.17535/crorr.2021.0003

Vuković, M., & Pivac, S. (2024). The impact of behavioral factors on investment decisions and investment performance in Croatian stock market. *Managerial Finance*, *50*(2), 349-366. https://doi.org/10.1108/MF-01-2023-0068

Waweru, N. M., Munyoki, E., & Uliana, E. (2008). The effects of behavioral factors in investment decision-making: a survey of institutional investors operating at the Nairobi Stock Exchange. *International Journal of Business and Emerging Markets, 1*(1), 24-41. https://doi.org/10.1504/IJBEM.2008.019243

Wong, W.-K. (2021). Editorial statement and research ideas for behavioral financial economics in the emerging market. *International Journal of Emerging Markets*, *16(5),* 946-951. https://doi.org/10.1108/IJOEM-07-2021-991

Yadav, A., & Narayanan, G. B. (2021). Do personality personality traits predict biasdness while making investment decisions? *International Journal of Accounting & Finance Review*, *6*(1), 19-33. https://orcid.org/0000-0001-9628-8173

Yang, M., Mamun, A. A., Mohiuddin, M., Al-Shami, S. S. A., & Zainol, N. R. (2021). Predicting stock market investment intention and behavior among Malaysian working adults using partial least squares structural equation modeling. *Mathematics*, *9*(8), 873. https://doi.org/10.3390/math9080873

Zhang, Y., & Zheng, X. (2015). A Study Of The Investment Behavior Based On Behavioral Finance. *European Journal of Business and Economics*, *10*(1), 1-5.

Zhu, H., Vigren, O., & Söderberg, I.-L. (2024). Implementing artificial intelligence empowered financial advisory services: A literature review and critical research agenda. *Journal of Business Research*, *174*, 114494. https://doi.org/10.1016/j.jbusres.2023.114494

Zhu Z., Qin S., Dodd A., & Conti M. (2023). Understanding the relationships between emotion regulation strategies and Big Five personality traits for supporting effective emotion regulation tools/interventions design. *Advanced Design Research*, *1*(1), 38-49. https://doi.org/10.1016/j.ijadr.2023.06.001