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**Investor Herding Behaviour in a Frontier Market:
Evidence from Dar es Salaam Stock Exchange**

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Abstract: This paper examines how investors behave in the Dar es Salaam Stock Exchange (DSE), with a focus on their tendency to follow others when making investment decisions. Based on survey data from 356 investors, the study uses Partial Least Squares Structural Equation Modeling (PLS-SEM) to explore how psychological, demographic, and informational factors shape herding behaviour. The results reveal that psychological traits including risk aversion, overconfidence, and trust in peers together with the market information environment, have a strong and significant effect on herding. In contrast, demographic factors such as age, education, and income show only weak influence. In the presence of limited information and uncertainty, psychological biases have more significance, hence making the investors base their decision on the actions of other people instead of their independent analysis. Such collective behaviour creates mispricing in the market, leading to inefficiency and poor investment performance. According to the findings of the paper, information transparency and better awareness of the investors would be effective in preventing herding behaviour.

Keywords: Herding behaviour, Behavioural Finance, Frontier Markets, Investor Psychology, Dar es Salaam Stock Exchange

Introduction

Many studies around the world have confirmed that herding behaviour happens in both developed and emerging markets. Studies done in the US and Europe reveal that herd behaviour is heightened when there is financial distress and results in bubbles and crashes in the market (Duygun et al., 2021; Júnior et al., 2022). Herd behaviour among the retail investors in various Asian stock markets has also been observed in such a way that the investors follow the actions of institutional investors or market leaders and it tends to heighten volatility (Memarista & Prasetyo, 2025; Ninan et al., 2025). Recently, herding behaviour has been seen in the digital finance sector as well, such as crypto currency trading

(Bajaj & Kaur, 2025; Kyriazis, 2020; Omane-Adjepong et al., 2021). These studies show that herding is not tied to one region or one era it is a global behaviour that continues to shape both traditional and modern markets.

Yet, while global evidence is growing, herding in frontier markets is still not well understood. These markets such as those in East Africa are smaller, less liquid, and mostly driven by retail investors. Psychology becomes much more important in such an environment than the objective data due to the poor regulatory system and lack of communication (Aawaar et al., 2020; Alamsyah et al., 2023; Economou & Vassilios, 2019). Under such market conditions, people tend to be driven by market rumours, peer influence, and limited publicly available information. By contrast, in developed economies, investors may herd for professional or reputational reasons; in frontier settings, herding comes more from information scarcity and low transparency.

The Dar es Salaam Stock Exchange (DSE) illustrates the frontier market characteristics described above. The stock exchange has been in existence for quite some time since 1996 (Komba, 2020; Mwakabumbe et al., 2023) though it is still developing at a slow pace. As of 2025, the stock exchange had 28 companies listed with a market capitalization of approximately TZS 23.99 trillion (USD 9.42 billion) (African Financials, 2025). On the other hand, the trading volume is not significant with daily trading volume rarely surpassing TZS 500 million in non-trading days (African Financials, 2025). According to the research carried out by Komba (2020), there were a total of 200,000 investors registered in the stock exchange as at 2015, whereby the retail investors formed the majority while the few institutional investors performed the majority of the transactions.

Illiquidity, retail nature of investors, and information asymmetry are the factors that create serious problems for the theory of market efficiency in frontier markets (Aawaar et al., 2020; Alamsyah et al., 2023). According to Fama's definition, the price in efficient markets contains all possible information (Fama, 1970). At the same time, scarcity, timeliness, and validity of information affect negatively the price formation process. Behaviour of investors as a group can lead to deviations of prices from their true value (Banerjee, 1992; Bikhchandani et al., 1992; Shiller, 2015). It renders resource allocation inefficient and causes instability along with lowering investment (Rahaman, 2024; Auwal & Sanusi, 2018; Gupta & Avais, 2025). Thus, the influence of herding on the efficiency of frontier markets is an important topic for further research.

Evidence from neighbouring markets points in the same direction. Research done in Ghana, Nigeria, and South Africa has provided clear evidence of herd behaviour, especially during unstable market times (Aawaar et al., 2020; Mbengue et al., 2024; Ndlovu, 2024). Even though these results have been discovered, very few pieces of empirical evidence have been provided concerning what is going on in Tanzania. There have been various studies done to see how Fintech and financial literacy affect stock market participation in Tanzania (Nathanael & Ngollo, 2025). Nevertheless, little has been known about how the psychological and behavioural factors influencing the behaviour of the investors, including herding, influence decisions made by the investors. Most of the literature in this area has focused on things such as stock market returns, market efficiency, liquidity, and macroeconomic variables, but very little has been done concerning the determinants of investors' behaviour.

The aim of this study is to investigate the existence and extent of investor herding in the Dar es Salaam Stock Exchange through empirical data obtained from retail and institutional investors. Specifically, the study investigates how demographic and psychological factors influence herding behaviour and examines the implications of herding for market efficiency in Tanzania's frontier stock market. To achieve these objectives, the study is guided by the following research questions, what extent do investors at the DSE engage in herding behaviour, which demographic and psychological traits explain differences in herding tendencies, how does herding influence perceptions of market efficiency in Tanzania's stock market.

This research contributes to the literature in three ways. First, it brings behavioural finance theories to a frontier market context, demonstrating how investor biases work in settings of limited information and weak institutions. Second, unlike most previous African herding studies that rely primarily on return-dispersion measures derived from secondary market data, this study employs primary investor-level survey data analysed using PLS-SEM. This approach allows direct examination of the psychological and informational mechanisms underlying herding behaviour.

Literature Review

Theoretical Frameworks on Herding Behaviour

To understand the phenomenon of herding among investors, it is necessary to go beyond the presuppositions of traditional finance that assumes investors to be entirely rational actors who use all the information available to them in making investment decisions. The Efficient Market Hypothesis (EMH) asserts that prices of stocks in the market embody all information and investors make rational decisions in order to maximize their gains (Fama, 1970). But in reality, people do not always act rationally.

Behavioural finance explains why such behaviour is common for the financial market (Shiller, 2015). It assumes that people are emotional and social beings making decisions based on the environment around them. A prominent example of such behaviour is herding, which occurs when investors abandon their own analysis and follow the crowd. Thus, herding undermines the concept of efficient market and becomes an important explanation of the reasons for the sharp price rises or falls (Bikhchandani et al., 1992).

Although the Efficient Market Hypothesis (EMH) assumes that investors are rational and all information is reflected in prices, this assumption does not hold in practice, particularly in developing countries. In most frontier markets of Africa, information is asymmetrical and institutions are not trusted. Therefore, emotions and social aspects start playing a more significant role in decision-making. The investors' decisions are determined by fear or excitement or actions of other market participants instead of rational evaluation of the situation. Consequently, such behavioural aspects as overconfidence, loss aversion and herding become important factors affecting prices much more than real fundamental values (Bajaj & Kaur, 2025; Rahaman, 2024).

There are three approaches to explaining herding: (i) informational cascades, (ii) reputational herding, and (iii) psychological/social influence.

Informational Cascades

The Informational Cascade Theory (Banerjee, 1992; Bikhchandani et al., 1992) suggests that herding is a logical consequence of lack of information. According to this theory, people observing the behaviour of other people under the conditions of information imperfection may think that such behaviour is the result of better knowledge. Such an understanding will lead to an informational cascade effect, when an increasing number of people start acting in the same way, convincing others that the actions were right, despite contradicting the individual knowledge. However, such cascade effect will prove to be vulnerable since it is not based on the fundamentals, but rather on actions performed by other people. In the case of frontier stock markets such as DSE, with limited analysis and lagging corporate announcements, such effects will be more prevalent.

Reputational Herding

Reputational Herding Theory (Scharfstein & Stein, 1990) deals with the behaviour of professionals, namely managers of mutual funds and institutional investors. This theory claims that the reason for which managers may engage in herding is the fact that they do not consider the herd's decisions to be right, but rather they want to maintain their professional image. This theory proposes that: when a manager decides to go along with the majority and his/her decision turns out to be wrong, the blame will be distributed among all of them; however, in case the manager goes against the herd and his/her decision turns out to be wrong, he/she will get blamed.

Psychological and Social Influences

Thirdly, it involves psychological theories. Prospect Theory developed by Kahneman & Tversky (1979) forms a basic theory in determining how individuals assess risks and uncertainties while making decisions. At the core of Prospect Theory is the principle of loss aversion, which states that individuals feel losses much more intensely compared to gains. Due to this principle, investors become more concerned about the possibility of incurring a loss as opposed to gaining, which makes them risk averse in cases of uncertainties. Herding is the manifestation of loss aversion in financial markets since individuals will be afraid of being left out of the crowd; this means that following the crowd is less risky compared to making decisions alone, which could lead to a loss.

Social influence is also very strong. Investors take cues from their friends, family, media, or online platforms. If any particular share or stock sector gains momentum and everyone is talking about it, people might succumb to social influence and a fear of missing out (FOMO). They invest without doing a detailed analysis because of this fear of missing out. FOMO makes investors do things without considering everything. Many studies conducted on different markets have revealed this fact. For instance, Cu et al., (2025) showed that the fear of missing out (FOMO) and overconfidence makes investors follow the trend in society rather than fundamentals. Bajaj & Kaur (2025) have also proved that online platforms and social media increase emotional contagion and herding behavior among investors. Likewise, Gupta (2025); Soraya et al., (2023) revealed that psychological and social biases influence the reaction of the investors towards the news and peer influence. The Dar es Salaam Stock Exchange (DSE) is a small and closely knitted market where the emotions spread very quickly from one investor to other investors.

Taken together, these theories provide complementary explanations for investor herding. Theoretical explanations for herding behaviour include the Informational Cascade Theory which explains the tendency of investors to follow the herd when information is scarce or ambiguous; the Reputational Herding Theory which suggests that investors especially professionals tend to follow the herd to avoid reputational costs associated with taking a decision independently but unsuccessfully; and the Prospect Theory which explains how psychological biases especially loss aversion cause investors to seek safety in collective actions during periods of uncertainty. Collectively, these theoretical perspectives form the conceptual framework of this study and provide explanations on how information limitations, reputational considerations and psychological biases interact to influence herding behaviour in the Dar es Salaam Stock Exchange.

Empirical Review and Hypothesis Development

The Extent of Herding Behavior

Herding behavior is now seen as a common feature of financial markets, but it tends to appear more in emerging and frontier markets than in developed ones. Small markets usually have less information, few experts, and more retail investors who depend on what others do instead of their own analysis. Aawaar et al., (2020) examined 224 stocks in African markets and found strong evidence of herding in both frontier and emerging markets. Their study found that the global financial crisis of 2007–2009 did not increase herding, implying that this behaviour is already entrenched in the trading behaviour of investors in Africa.

In Tanzania, Komba (2020) found herding in the Dar es Salaam Stock Exchange (DSE), especially in banking and finance sectors. The pattern was stronger among large-cap stocks and during calm market periods. Studies from Asia also show that herding changes with the situation. Ah Mand & Sifat (2021) in Malaysia, using a dynamic Markov model, found that herding behavior comes and goes depending on the market state. It becomes stronger during turbulent or uncertain conditions. Memarista & Prasetio (2025) found the same in Indonesia that herding is stronger in bearish markets when fear dominates.

Other frontier and small markets show similar tendencies. El hami & Hefnaoui (2019) confirmed herding in Morocco in both rising and falling periods, which they linked to low transparency and poor information flow. Ivasiuc (2023) found weak but visible herding in Nordic frontier countries during crises, proving that even investors in structured economies are not immune when stress rises. Outside Africa and Asia, Luu & Luong (2020) found that herding grew during pandemic periods like COVID-19 in Vietnam and Taiwan. Fear, they argued, makes people move together. Likewise, Duygun et al., (2021) showed that herding in the U.S. and Eurozone became stronger in crisis times.

All these studies point to one thing that herding is universal, but it is worse in smaller markets with less transparency and weaker information systems. Tanzania's DSE fits this description, but very few studies have directly tested herding among its investors. This creates a gap that this research aims to fill:

H1: Investors at the Dar es Salaam Stock Exchange exhibit significant herding behavior in their investment decisions.

Demographic and Psychological Factors Influencing Herding

The study of demographic traits has become increasingly important within the context of the herding phenomenon although the results are still conflicting. For instance, recent research in Tanzania has shown that demographic characteristics such as age, gender, and income significantly influence financial behavior and adoption of digital financial services (Nathanael & Chami, 2026). For instance, Nofsinger & Sias (1999) found out that the herding practices of institutional investors are different from those of individual investors since the former tend to herd as a result of information asymmetries. Moreover, there is recent evidence that younger investors are more prone to herding because of their lack of experience (Komba, 2020; Sulhia et al., 2022). The same applies to investors having lower income and education since they tend to use social signals more often than others (Shah et al., 2024).

Nevertheless, the effect of demographic factors varies depending on the context. Specifically, it has been found out that demographic factors can explain less variance of herding phenomenon compared to psychological or institutional factors in developed markets (Abul, 2019). On the contrary, in frontier and emerging markets, the interaction of demographic traits and market conditions can enhance the tendency for herding (Zafar et al., 2024). Consequently, demographic factors affect herding behaviour differently depending on the market conditions.

Psychological aspects represent another major factor influencing stock herding behaviour. According to Barber & Odean (2013), most of the investors operate under the influence of limited attention, emotions, and overconfidence. Studies conducted recently within the Tanzanian setting also show how psychological biases such as present bias and overconfidence affect financial decision making, where behavioral aspects tend to prevail over financial literacy (Nathanael & Chami, 2026). They repeat behaviours that seemed to bring them some rewards in the past even if such behaviours are irrational. Şahin (2020) notes that from the standpoint of behavioural finance, the investors are emotional people influenced by such factors as fear, confidence, and need for belonging.

The results of studies conducted in different countries vary. Hence, Zafar et al., (2024) find a positive relationship between risk aversion and herding in Pakistan. In contrast, Nizam et al., (2024) find a negative correlation between these concepts. No evidence is found by Abul (2019); Gul & Khan (2019). This variability shows that the impact of the concept in question on stock herding may be situational. The situation is the same with overconfidence – Halim et al., (2024); Zafar et al., (2024) identify a positive correlation; Nizam et al., (2024) find the opposite result.

More recent studies introduce other aspects of stock herding. Shah et al., (2024) prove that stock herding, overconfidence, and investment decision-making are related, especially when small business investors are considered. Soraya et al., (2023) identify the direct impact of psychological biases and their indirect impact through the risk tolerance. Sulhia et al., (2022) note that even highly educated investors can be affected by psychological biases.

Contemporary herding is influenced by online fora and social media (Bajaj & Kaur, 2025) and is associated with the ease investors have to follow the posts or discussions of other investors. Cu et al., (2025) find that investors' herding behaviour is driven by the FOMO and

social media pressure. Nevertheless, the relationships between all these factors in the case of Tanzanian stock market are not fully disclosed. Therefore, the study puts forward the following hypotheses:

H2a: Demographic factors (younger age, lower education, and lower income) significantly increase investor herding at the DSE.

H2b: Psychological factors (higher risk aversion, higher overconfidence, and greater trust in peers) significantly increase investor herding at the DSE.

The Implications of Herding for Market Efficiency and Decision-Making

While initially it may appear to be neutral in its impact as it is simply an investment community acting in unison; in fact, the herding phenomenon may be a negative impact on market efficiency. This happens as once all the investors are buying/selling simultaneously, prices begin to deviate from the intrinsic value of the firms. Shiller (2015) referred to this situation as markets functioning on emotions rather than earnings and data.

In Africa, Auwal & Sanusi (2018) demonstrated the relationship between herding in petroleum shares and increased market volatility and liquidity disturbance. Rahaman (2024), in his turn, concluded that herding causes risk-taking and might lead to economic instability if it becomes common. The positive impact of herding on liquidity in small stock markets was proposed by Economou & Vassilios (2019) but only in small quantities.

Modern literature provides additional factors explaining the prevalence of herding as a negative phenomenon. Social conformity and media influence were revealed as the factors causing herding which contributes to increasing volatility and systemic risks by Gupta & Avasi (2025). In turn, Alamsyah et al., (2023) found the feedback effect between psychological biases and inefficient information flows. The present research tries to fill the gap by investigating the impact of herding on efficiency and performance of the DSE:

H3: Herding behaviour negatively affects market efficiency and leads to poor investment performance at the Dar es Salaam Stock Exchange.

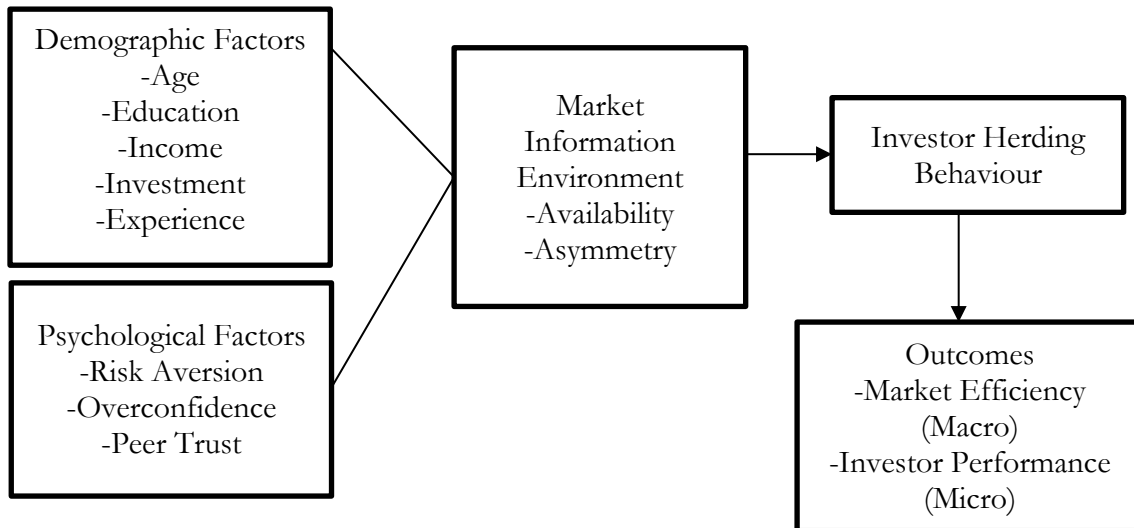
Conceptual Framework

In this study, a conceptual framework is developed that shows how the effects of demographic, psychological, and information-related factors lead to herding behaviour amongst investors in the Dar es Salaam Stock Exchange (DSE). This framework is informed by the Prospect Theory (Kahneman & Tversky, 1979) and the Reputational Herding Theory (Scharfstein & Stein, 1990), where the fear of loss and need for conformity is explained by the theory.

Demographic factors such as age, education, and income influence the decision-making style of an investor (Komba, 2020; Nofsinger & Sias, 1999). Risk-averse, overconfident, and peer-trusting behaviours make individuals more prone to imitation behaviour due to uncertainty (Barber & Odean, 2013; Cu et al., 2025). From the Informational Cascade Theory, it is clear that investors will be more likely to base their decisions on the actions that other people have taken in case of market situations whereby there is lack of information, delayed information or where the market information is seen as unreliable (Banerjee, 1992). In such situations,

the market information situation affects herding because investors become more reliant on social signals and overall market sentiments and not on fundamental analysis (Ah Mand & Sifat, 2021). Lack of information dissemination and asymmetric information makes the investors more likely to follow what others do thus increasing the possibility of herding. At the macro level, herding decreases the efficiency of the markets through making the price discovery process inefficient (Rahaman, 2024). At the micro level, herding results in emotional investments that may eventually harm the investments (Gupta & Avais, 2025).

Figure 1. **Conceptual Framework**



Based on the theoretical and empirical review, this research model illustrates the hypothesized relationships among demographic and psychological factors, the market information environment, investor herding behaviour, and market outcomes. It operationalizes the conceptual framework into measurable constructs tested using PLS-SEM.

Methods

This study used both descriptive and explanatory research designs to study herding behaviour among investors in the Dar es Salaam Stock Exchange (DSE). The descriptive design helped to show the general pattern of investor behaviour, while the explanatory part tried to understand the causes and effects why herding happens and what factors make it stronger or weaker.

The study followed a cross-sectional survey approach. Data was collected from both retail and institutional investors at one point in time. The idea was to get a snapshot of how different investors think and behave in the market. Because it was not easy to find all active investors directly, the study worked closely with licensed brokers and the Central Depository and Settlement Corporation (CDSC) to identify potential respondents.

The research population involved all the active investors at the DSE up to the year 2025. An active investor refers to an investor who has traded at least once in the last twelve months. These included the smaller individual investors who form the largest proportion of investors at the DSE, as well as institutional investors such as fund managers and pension schemes.

The population was selected because the investors actively trade shares and have direct contact with market information and influence from peers.

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Stratified random sampling technique was adopted. First, investors were grouped into two categories, retail and institutional. Respondents were then randomly selected from each category. This was done so as to ensure fair representation of both categories. The retail investors constituted the larger stratum since they form the larger proportion at the DSE.

The minimum number of respondents was calculated using (Yamane, 1967) formula at a 95% confidence level and a 5% margin of error:

$$n = \frac{N}{1 + N(e)^2}$$

n is the sample size, *N* is the total number of active investors (According to the Dar es Salaam Stock Exchange (2025), approximately 740,639 Central Depository System (CDS) accounts had been registered by 2025. Since not all registered accounts represent active investors, the target population comprised investors who had executed at least one securities transaction during the preceding twelve months, and e is the margin of error (0.05).

The stratified random sampling technique was employed. First, the investors were stratified into two categories; retail and institutional. Randomly from each stratum, respondents were chosen. Thus, there was a proportionate representation from both the strata. The retail investors formed the larger stratum as they are the majority on the DSE. This allocation reflected the approximate composition of active investors obtained from DSE and licensed brokerage records, where retail investors constitute the majority of market participants. Out of the total 370 investors that were to be surveyed, about 315 were retail investors while 55 were institutional investors, indicating the approximately 85:15 distribution between the two in the active investor population.

The main data collection tool was a structured questionnaire. The questions were simple and short, designed to capture the key ideas of the study investor demographics, psychological traits, perceptions about information, and herding behaviour.

The questionnaire was shared in online, using Google Forms for those who were ready to participate. Before the main survey, a pilot test was done with 30 investors. The purpose was to determine whether the questions were clear and easy to answer. Pilot feedback was used to improve the wording and order of the questions. The final version was clearer and more understandable for both retail and institutional respondents.

The questionnaire had four parts; (i) Demographic section: asking about age, gender, education, income, and years of investment experience, (ii) Psychological factors section: items measuring risk aversion, overconfidence, and peer trust, (iii) Market information environment section: questions about how investors perceive the availability and quality of market information, (iv) Herding and outcomes section: items assessing how investors follow others and how they view market efficiency and their own investment performance.

All responses were rated on a five-point Likert scale, from 1 = Strongly Disagree to 5 = Strongly Agree. This scale made it easier to measure differences in opinion and intensity.

The study included several variables demographic, psychological, informational, and behavioural each defined and measured carefully. Table 1 shows how these variables were operationalized.

Table 1. Operationalization of Variables

Variable	Definition	Indicators	Example Item	Scale
Demographic Factors	Investor characteristics that may influence decisions	Age, Gender, Education Level, Monthly Income, Investment Experience, Investor Type	Please indicate your age group	Categorical
Risk Aversion (RA)	Tendency to prefer safety over risk	RA1, RA2, RA3	I prefer guaranteed returns even if they are smaller.	Likert (1-5)
Overconfidence (OC)	Belief in one's own superior ability	OC1, OC2, OC3	I believe my knowledge of the stock market is above average.	Likert (1-5)
Peer Trust (PT)	Level of trust in friends or colleagues' advice	PT1, PT2, PT3	I often rely on friends or colleagues when making investment decisions.	Likert (1-5)
Market Information Environment (IE)	How investors perceive information flow and fairness	IE1, IE2, IE3, IE4	I have timely access to reliable information about companies listed on the DSE.	Likert (1-5)
Investor Herding Behaviour (HB)	Tendency to follow others' trading actions	HB1, HB2, HB3, HB4	I buy or sell stocks when I observe that many	Likert (1-5)

Variable	Definition	Indicators	Example Item	Scale
Market Efficiency Outcome (ME)	Investor perception of how well prices reflect information	ME1, ME2, ME3	other investors are doing so. Herding behaviour reduces the efficiency of price discovery in the DSE.	Likert (1-5)
Investor Performance Outcome (IP)	Self-reported results of following others	IP1, IP2, IP3	Following other investors has improved my returns. <i>(reverse-coded)</i>	Likert (1-5)

The demography of the sample is shown in Table 2 below. In this respect, the sample is very representative of the structure of the DSE. First, with regard to the type of investors, it can be stated that the respondents were mostly retail investors, representing 85.4% of the overall sample size, and institutional investors constituted 14.6%. This indicates the predominance of individual investors in the DSE (Komba, 2020; Nofsinger & Sias, 1999). Furthermore, in relation to the type of trading, 60.1% of the respondents consider themselves active traders buying and selling securities, and 39.9% represent buy-and-hold investors with a long-term approach to investing.

Table 2. Demographic Profile of Respondents

Variable	Category	Frequency (n)	Percentage (%)
Investor Type	Active Traders	214	60.1
	Passive Buy and Hold Investors	142	39.9
	Total	356	100.0
Age Group	20-29	68	19.1
	30-39	124	34.8

Variable	Category	Frequency (n)	Percentage (%)
Gender	40-49	102	28.7
	50+	62	17.4
	Total	356	100.0
	Male	241	67.7
	Female	115	32.3
	Total	356	100.0
Education Level	Primary	7	2.0
	Secondary	39	11.0
	Diploma/Certificate	89	25.0
	Undergraduate Degree	154	43.3
	Postgraduate Degree	67	18.8
	Total	356	100.0
Monthly Income (TZS)	Below 500,000	82	23.0
	500,000 - 1,000,000	168	47.2
	1,000,001 - 2,000,000	65	18.3
	2,000,001 - 5,000,000	30	8.4
	Above 5,000,000	11	3.1
	Total	356	100.0
Investment Experience	Less than 1 year	56	15.7
	1-3 years	92	25.8
	4-6 years	105	29.5

Variable	Category	Frequency (n)	Percentage (%)
	More than 6 years	103	28.9
	Total	356	100.0

From the point of view of age, the sample contained people aged from early twenties to people who are over fifty. The major age cohorts were respondents aged 30-39 (34.8%) and 40-49 (28.7%), who made up approximately two-thirds of the total number of respondents. Age groups represented in this way can be considered typical for the investors of the frontier markets because middle-aged people are more likely to have disposable income and experience in investing.

As far as gender is concerned, the majority of participants in the study were males (67.7%). This is a rather usual situation for financial market studies.

Concerning the educational level, the majority of respondents had undergraduate (43.3%) and postgraduate (18.8%) education. Moreover, 13% of the respondents had secondary education or below. Such results indicate that the majority of DSE investors are well-educated. That can be explained by the requirements which stock market participation has.

Income levels of respondents also varied a lot. However, the most numerous group was the one, which included middle-income people (TZS 500,000 - 1,000,000 per month, 47.2%). In addition, 23.0% of the respondents had incomes lower than TZS 500,000, while 29.8% had incomes higher than TZS 1,000,000. Therefore, it can be concluded that although the investors of the DSE represent a wide range of income levels, the market is mostly used by people of middle income.

Investment experience also varied a lot. Some of the participants were very new investors (15.7% of the respondents had less than a year of investment experience). However, some investors were already trading on the market for more than six years (28.9%). Moreover, the majority of respondents (25.8% and 29.5%) had 1-3 years and 4-6 years of investment experience correspondingly. Such variation was helpful because the study captured views from investors with different levels of experience.

To test the hypotheses, the conceptual framework was expressed as a simple regression-type model. This form shows how each factor affects herding and its outcomes. The general relationship can be written as:

$$HERDi = \beta_0 + \beta_1 DEMOi + \beta_2 PSYi + \beta_3 INFOi + \varepsilon_i$$

HERDi is the level of herding for investor i , DEMOi represents demographic factors (age, education, income, experience), PSYi represents psychological factors (risk aversion, overconfidence, peer trust), INFOi represents perceived quality of the market information environment, and ε_i is the random error term.

To examine how herding influences outcomes, two more equations were considered:

$$EFFi = \alpha_0 + \alpha_1 HERDi + \mu_i$$

$$PERFi = \gamma_0 + \gamma_1 HERDi + \eta_i$$

EFFi stands for perceived market efficiency and PERFi for self-reported investment performance.

In addition, to capture the indirect (mediating) role of the information environment, the following model was tested:

$$INFOi = \theta_0 + \theta_1 DEMOi + \theta_2 PSYi + v_i$$

$$HERDi = \delta_0 + \delta_1 INFOi + \delta_2 DEMOi + \delta_3 PSYi + \varepsilon_i$$

These models together reflect the logic of the conceptual framework and the research hypotheses (H1–H3).

The study used Partial Least Squares Structural Equation Modeling (PLS-SEM) to estimate the coefficients. PLS-SEM was chosen as the methodology of choice because the current study deals with more than one latent variable such as demographic variables, psychological variables, the information environment of the market, herding behaviour, and outcomes of the market, among others. This method is predictive, tolerant of non-normal multivariate distributions, and efficient in dealing with behavioural models using survey-based data. All these features make PLS-SEM ideal for studying behavioural finance (Nathanael & Chami, 2026; Hair et al., 2021).

Data were first checked for missing values and errors. Then, several steps were followed; descriptive analysis-to summarize demographic features and main response patterns, reliability and validity tests- using Cronbach's alpha and composite reliability to ensure the consistency of items, path analysis- to test the direct and indirect relationships between demographic, psychological, informational, and herding variables, bootstrapping - to obtain standard errors and confidence intervals for significance testing, the analysis was done using SmartPLS software, which fits well with the chosen model.

Ethical standards were observed throughout the study. Participation was voluntary, and respondents were informed about the purpose of the research before filling the questionnaire. No personal or identifying information was collected. All answers were kept confidential and used only for academic analysis. Participants had the right to skip questions or withdraw at any time. This approach helped maintain trust and honest participation.

Findings

This section presents the results and explains what they mean. The purpose was to understand how demographic and psychological factors, together with the market information environment, shape herding behaviour among investors in the Dar es Salaam Stock Exchange (DSE). The section also explores how this herding affects both the market and the investors themselves.

The data came from 356 valid questionnaires, collected from retail and institutional investors. The responses were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). This method was selected because it works well with complex relationships and allows the researcher to see both direct and indirect effects in one model.

The sample represented the structure of the DSE quite well. Most of the respondents were retail investors, but a good number of institutional investors also participated.

In terms of age, the respondents ranged from people in their early 20s to those above 50 years old. Many of them were in their 30s and 40s an age group often active in investing. Education levels were fairly high, with a large share of participants having college or university degrees. The income levels were mixed, but most respondents fell in the middle-income bracket.

The level of investment experience also differed. Some investors were new, with less than a year of experience, while others had traded for more than ten years. Most had between two and five years of experience. This variety was good because it allowed the study to capture views from both experienced and less experienced investors.

Before testing the hypotheses, the study first checked the quality of the measurement model as indicated on table 3. The goal here was to confirm that the questions and items used were reliable and valid. All the Cronbach's alpha and composite reliability values were above 0.70, meaning that the items were consistent with each other. The Average Variance Extracted (AVE) for all constructs was also above 0.50, showing that the indicators explained more than half of their underlying variable.

Table 3. **Measurement Model Assessment**

Construct	Cronbach's α	Composite Reliability (CR)	Average Variance Extracted (AVE)
Risk Aversion	0.782	0.813	0.548
Overconfidence	0.759	0.794	0.562
Peer Trust	0.771	0.806	0.578
Market Information Environment	0.798	0.835	0.601
Investor Herding Behaviour	0.813	0.849	0.632
Market Efficiency Outcome	0.745	0.788	0.514
Investor Performance Outcome	0.762	0.796	0.531

Discriminant validity was achieved as well. Each variable was more related to its own indicators than to other variables. These results on table 4 confirmed that the measurement tools were statistically sound and ready for structural testing.

Table 4. **Discriminant Validity (Fornell-Larcker Criterion)**

Construct	RA	OC	PT	MIE	IHB	MEO	IPO
Risk Aversion (RA)	0.740						
Overconfidence (OC)	0.312	0.750					
Peer Trust (PT)	0.283	0.364	0.760				
Market Info Env. (MIE)	0.415	0.398	0.442	0.775			
Investor Herding Behaviour (IHB)	0.382	0.376	0.451	0.612	0.795		
Market Efficiency Outcome (MEO)	0.295	0.321	0.338	0.478	0.528	0.717	
Investor Performance Outcome (IPO)	0.312	0.294	0.356	0.452	0.496	0.385	0.729

Note: Diagonal values (bold) represent the square root of AVE. Off-diagonal values represent correlations between constructs. All diagonal values exceed off-diagonal correlations, confirming discriminant validity.

Table 5. **HTMT Ratios for Discriminant Validity**

Relationship	HTMT Ratio	95% Confidence Interval	Discriminant Validity Established
RA ↔ MIE	0.678	(0.582, 0.768)	Yes
OC ↔ IHB	0.712	(0.624, 0.795)	Yes
PT ↔ IHB	0.745	(0.658, 0.826)	Yes
MIE ↔ IHB	0.834	(0.768, 0.892)	Yes
IHB ↔ MEO	0.788	(0.712, 0.856)	Yes
IHB ↔ IPO	0.752	(0.672, 0.824)	Yes

After testing the measurement model, the next step was to examine the relationships among the main variables. Bootstrapping with 5,000 subsamples was done to test the strength and direction of these paths. The resulting bootstrap distributions show how each factor relates to another in the DSE setting.

This figure 2 presents the structural relationships estimated using Partial Least Squares Structural Equation Modeling (PLS-SEM). The arrows show the direction and strength of the paths between the main constructs. The numbers on each path represent standardized coefficients. The blue circles represent latent constructs (unobserved variables), while the yellow boxes represent their indicators. The model confirms that psychological factors and the information environment have strong positive effects on investor herding behaviour, which in turn influences both market and individual out-comes.

Figure 2. Structural Model Outcomes

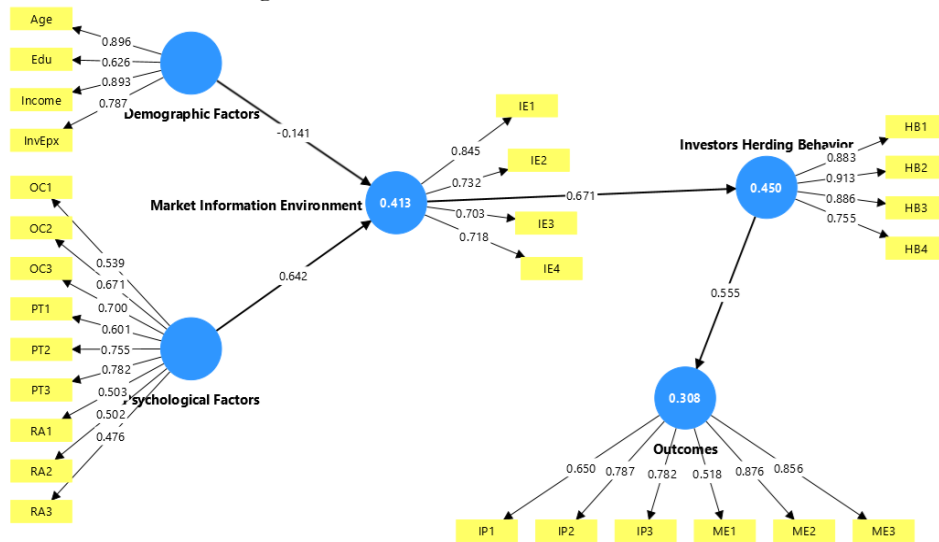
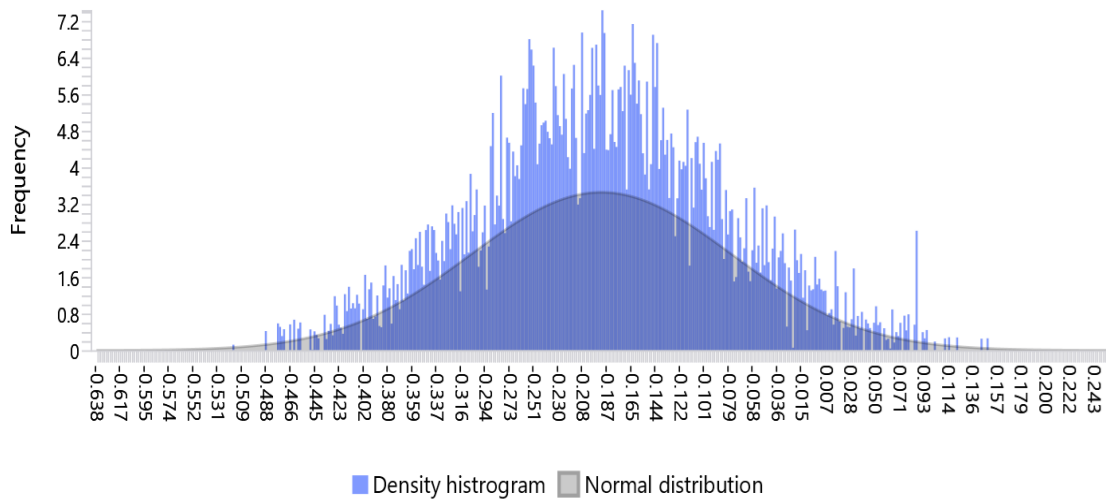


Figure 3. Bootstrapped Path Coefficient Distribution- Demographic Factors and Market Information Environment

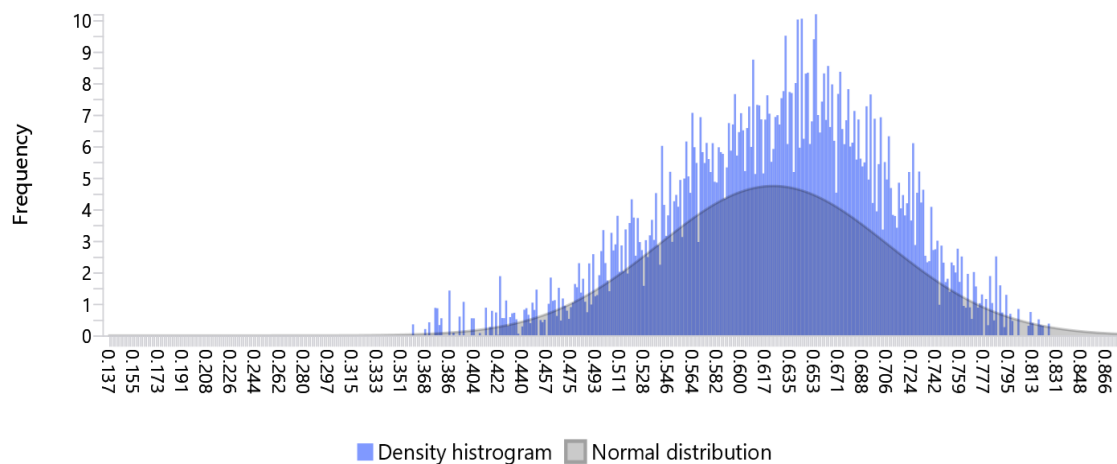


The bootstrapped path coefficients between demographic factors such as age, education, income, and investment experience and the market information environment showed a distribution that was almost normal, centered around zero (Figure 3). The mean coefficient was small, about 0.02 to 0.05, and the 95% confidence interval went from -0.12 to $+0.12$.

This indicates that the relationship was weak and statistically insignificant. Overall, these findings suggest that demographic characteristics, including age, education level, income, and investment experience, do not significantly influence investors' perceptions of the market information environment. Instead, investors appear to face similar information constraints regardless of their demographic characteristics. These findings suggest that information constraints are structural in nature and affect investors broadly, irrespective of their demographic characteristics.

This tells us that the main challenge is structural. It is not about investor differences, but about how the market provides and shares information. The same situation is seen in other frontier markets, where regulation and systems matter more than personal traits (Aawaar et al., 2020; Alamsyah et al., 2023; Komba, 2020).

Figure 4. **Bootstrapped Path Coefficient Distribution - Psychological Factors and Market Information Environment**

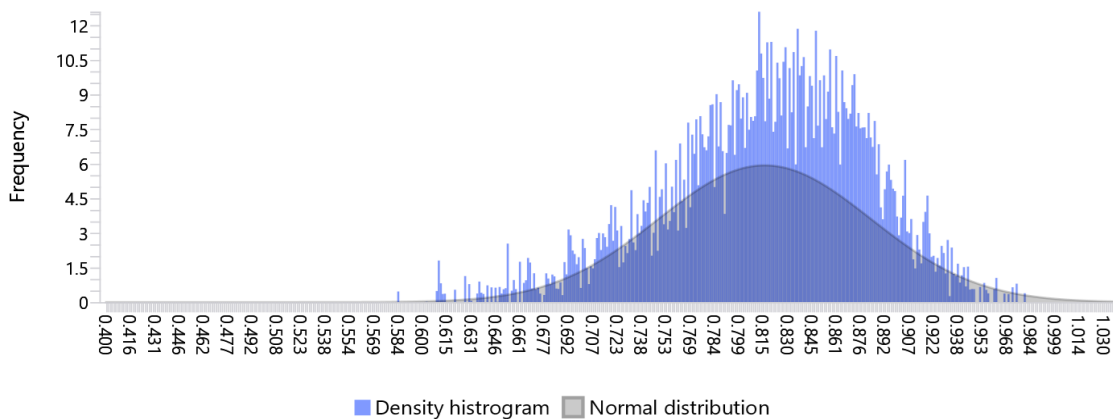


The second relationship, between psychological factors and the market information environment, was strong and clear. The histogram was right-skewed, with a mean coefficient of about 0.65 (Figure 4). The 95% confidence interval, between 0.50 and 0.85, was well above zero, showing the result was significant ($p < 0.01$).

This means that investors' psychological traits being risk-averse, overconfident, or trusting peers strongly shape how they see the market's information. Those who fear losses or depend too much on others often feel that information in the market is less transparent or fair. They sense more uncertainty even when the data is the same for everyone. These findings suggest that, psychological characteristics therefore influence how investors interpret identical market information: investors interpret identical market information differently because psychological biases influence information processing.

These findings agree with Prospect Theory (Kahneman & Tversky, 1979), which says that loss-averse people focus more on risk, and with Reputational Herding Theory (Scharfstein & Stein, 1990), which suggests that people follow others to avoid being wrong alone. They also match recent studies showing that emotions and confidence distort information processing. For instance, Zafar et al., (2024) found that risk-averse investors perceive higher uncertainty in volatile markets. Bajaj & Kaur (2025); Cu et al., (2025) showed that overconfidence, FOMO, and social influence make investors misjudge the clarity of market information.

Figure 5. **Bootstrapped Path Coefficient Distribution - Market Information Environment and Investor Herding Behaviour**



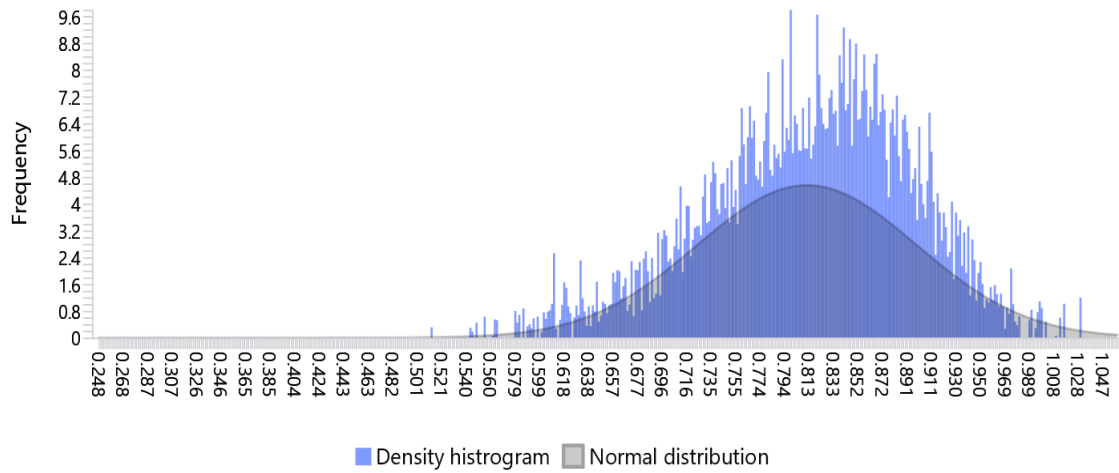
The association between the market information environment and investor herding behaviour was quite strong and positive. The path coefficients had high centers, with a mean of approximately 0.80 (see Figure 5). The 95% confidence interval was well above zero ranging from 0.65 to 1.03, signifying a strong and significant relationship ($p < 0.01$).

It implies that whenever there is poor information in the market, delayed information dissemination or unequal dissemination, there would be an increased likelihood of herding. In the case of the DSE, where the flow of data is slow and where dissemination is unequal, there is a tendency for the people to look at what other investors do and then base their investment decisions on those behaviours. It does not necessarily imply that people become irrational but rather that the system forces them to act like others.

This phenomenon is consistent with the Informational Cascade Theory (Banerjee, 1992; Bikhchandani et al., 1992), which argues that people herd in situations of uncertainty. There has been recent evidence supporting the above theory. For instance, Aawaar et al., (2020) demonstrated that poor information systems in the African context foster imitation. This was also evidenced in a study by Komba (2020) in Tanzania, whereas (Ah Mand & Sifat, 2021; Memarista & Prasetyo, 2025) have found herding behaviour where market signals are weak.

Overall, these findings indicate, when information is uncertain, investors are more likely to imitate one another's trading decisions. In the DSE, this often pushes prices away from company fundamentals and makes the market less efficient.

Figure 6. **Bootstrapped Path Coefficient Distribution–Investor Herding Behaviour and Outcomes**



The last key relationship connects herding behaviour with both market-level and individual-level outcomes. The distribution of coefficients was roughly normal but clearly positive, with a mean around 0.65 (Figure 6). The 95% confidence interval ranged from 0.44 to 0.88, and the result was significant ($p < 0.01$).

This means herding has a strong effect on how the market functions and how investors perform. At the macro level, strong herding reduces market efficiency prices move too fast, too far, and too often without clear fundamental reasons. At the micro level, investors who herd more often report poorer performance. They follow the crowd at the wrong times, buying high during market excitement and selling low during fear.

These findings match earlier studies like (Barber & Odean, 2013), who also found that herding behaviour hurts decision-making and leads to inefficient markets.

Table 6. **Total Effects of Structural Model Mean, STDEV, T-values, and P-values**

Relationship	Original Sample (O)	Sample Mean (M)	STDEV	T Statistics	P-value
Demographic → Herding	-0.163	-0.157	0.094	1.735	0.083
Demographic → Market Info Env.	-0.199	-0.193	0.115	1.723	0.085
Demographic → Outcomes	-0.103	-0.097	0.058	1.783	0.075
Herding → Outcomes	0.633	0.623	0.084	7.526	0.001
Market Info Env. → Herding	0.822	0.816	0.067	12.215	0.000
Market Info Env. → Outcomes	0.520	0.511	0.093	5.593	0.000
Psychological → Herding	0.680	0.664	0.103	6.610	0.000
Psychological → Market Info Env.	0.827	0.812	0.088	9.445	0.000
Psychological → Outcomes	0.430	0.418	0.099	4.350	0.000

The total effects from the PLS-SEM bootstrapping are presented in Table 6. These results show the overall strength and direction of relationships among the main variables demographic and psychological factors, market information environment, investor herding behaviour, and outcomes.

Table 6 shows both direct and indirect effects combined, making it easier to see which paths have the greatest overall influence in the model. The results show that psychological factors had the largest positive effects across multiple relationships. The path from psychological factors to the market information environment was very strong ($\beta = 0.827$, $t = 9.445$, $p < 0.000$), showing that investor psychology clearly shapes how people perceive information in the market. The same factor also had a strong total effect on investor herding behaviour ($\beta = 0.680$, $t = 6.610$, $p < 0.000$) and a moderate positive effect on outcomes ($\beta = 0.430$, $t = 4.350$, $p < 0.000$).

The market information environment itself had a strong positive effect on herding ($\beta = 0.822$, $t = 12.215$, $p < 0.000$) and a significant effect on outcomes ($\beta = 0.520$, $t = 5.593$, $p < 0.001$). This means that when information is poor or uneven, investors herd more, and market outcomes such as efficiency and stability are directly affected.

The link between herding behaviour and outcomes was also very strong ($\beta = 0.633$, $t = 7.526$, $p < 0.001$). This confirms that herd behaviour has a clear influence on how the market behaves overall and how investors perform individually.

In contrast, the effects of demographic factors on other constructs were small and statistically weak. For example, the paths from demographics to herding ($\beta = -0.163$, $p = 0.083$) and to the information environment ($\beta = -0.199$, $p = 0.085$) were both insignificant. This shows that personal background variables like age, income, or education do not play a major role in shaping investor behaviour in the DSE. Overall, the table confirms that the strongest relationships in the model are; psychological factors $\rightarrow$ market information environment; market information environment $\rightarrow$ investor herding behaviour; investor herding $\rightarrow$ outcomes. These three paths represent the behavioural chain that drives how investors act in the DSE.

The findings from the estimation of the structural model through the bootstrapping process are illustrated in Table 7. The analysis of the hypothesized relationships was carried out using the path coefficients (β), t-statistics, and the p-values. The significance of the hypothesized relationship was achieved at the p-value of 0.05 or below.

Table 7. Hypothesis Testing Summary

Hypothesis	Statement	Statistical Test	Test Statistic	β	p-value	Decision
H1	Investors at the Dar es Salaam Stock Exchange exhibit significant herding behaviour in their investment decisions.	One-sample t -test (Mean vs. 3.0)	18.42		0.000	Supported
H2a	Demographic factors (younger age, lower education, and lower income)	PLS-SEM Path Analysis	1.735	-0.163	0.083	Not Supported

Hypothesis	Statement	Statistical Test	Test Statistic	β	p-value	Decision
H2b	significantly increase investor herding at the DSE. Psychological factors (higher risk aversion, higher overconfidence, and greater trust in peers) significantly increase investor herding at the DSE.	PLS-SEM Path Analysis	6.610	0.680	0.000	Supported
H3	Herding behaviour negatively affects market efficiency and leads to poor investment performance at the Dar es Salaam Stock Exchange.	PLS-SEM Path Analysis	7.526	0.633	0.001	Supported

Note: H1 was evaluated using a one-sample t-test because it examines whether the mean investor herding behaviour score is significantly higher than the neutral midpoint of the five-point Likert scale rather than a structural relationship between latent constructs. Consequently, a standardized path coefficient (β) is not applicable. H2a–H3 were evaluated using PLS-SEM structural path analysis.

It can be seen from Table 7 that out of four, three hypotheses were found to be supported. The demographic factors had no significant impact on herding behaviour (H2a, $\beta = -0.163$, $p = 0.083$). But the psychological factors had a very strong impact on herding behaviour (H2b, $\beta = 0.680$, $p < 0.001$). In addition to that, the herding behaviour had a significant impact on market efficiency and performance of investments (H3, $\beta = 0.633$, $p < 0.001$). All of these results indicate that H1 is supported as there is a significant impact of psychological factors and market information environment on herding behaviour.

The results of this study show that investor herding is a strong and consistent behaviour in the Dar es Salaam Stock Exchange (DSE). Investors tend to follow what others are doing rather than act completely on their own. The findings also show that demographic characteristics such as age or income do not have much influence. What really drives investor behaviour are the psychological traits and the market information environment.

The relationship between psychological factors and how investors see market information was strong and positive. This means that how people think and feel changes how they read and understand information. Investors do not look at the market only through numbers or reports. Emotions, fear, and mental shortcuts also guide their judgment.

In this study, risk aversion, overconfidence, and trust in peers were the key psychological factors. Investors who fear losses or rely too much on others often see the market as unclear or unfair. They feel more uncertain. Overconfident investors may think they know more than they do, and in unclear situations, they end up following others instead of relying on their own analysis.

Recent work supports these patterns. Cu et al., (2025); Gupta (2025) found that overconfidence and fear of missing out (FOMO) distort how investors interpret market signals. Zafar et al., (2024) showed that risk-averse investors are more likely to herd during volatile periods. Halim et al., (2024); Soraya et al., (2023) observed that psychological biases directly affect how investors understand and react to financial information. Together, these

studies confirm that psychology acts as a filter. Investors see the market not as it is, but as their emotions allow them to.

This is consistent with Prospect Theory, where loss-averse people react more strongly to uncertainty (Kahneman & Tversky, 1979), and with Reputational Herding Theory (Scharfstein & Stein, 1990), which explains why many prefer to move with the group instead of standing out alone. Similar effects were seen in India (Ninan et al., 2025) and Indonesia (Memarista & Prasetyo, 2025), where investors showed stronger herding during unstable market periods.

The connection between the market information environment and herding behaviour was very strong ($\beta = 0.822$). This shows that the way information flows in the market plays a major role in shaping how investors act. When data is late, incomplete, or confusing, people tend to watch what others are doing and copy them.

This fits well with the Informational Cascade Theory (Banerjee, 1992; Bikhchandani et al., 1992), which says that when private information is weak, following others becomes rational. Recent studies also prove this point. Ah Mand & Sifat (2021) found that herding in Malaysia grows stronger when market information is unclear. Aawaar et al., (2020) observed similar results in African markets, where structural information gaps push investors to imitate others. Alamsyah et al., (2023); El hami & Hefnaoui (2019) also reported that in frontier markets, poor transparency and limited data make investors depend on the crowd.

In Tanzania, the same story appears. The Dar es Salaam Stock Exchange (DSE) operates with slow information flow and limited coverage. As a result, investors often look at others' behaviour as a signal. This shows that herding is both a psychological and a structural outcome emotion meets weak information, and together they lead to imitation.

The relationship between herding behaviour and market outcomes ($\beta = 0.633$) was strong and positive. This means that when investors move together, the whole market changes. Prices drift away from company fundamentals, and volatility increases. The market becomes less efficient and less stable.

For individual investors, herding often leads to poor performance. People buy when everyone else is buying, and sell when panic spreads usually at the wrong time. Barber & Odean (2013) earlier showed that herding hurts decision-making and distorts price discovery. Recent evidence agrees. Rahaman (2024) found that herding increases volatility and economic instability. Devi (2019) showed that Herding behaviour is negative in high liquid stock portfolios and present in less liquid ones, with significant herding during crisis periods and market upswings. Ijaz & Yahya (2025) found that herding crowd behaviour can reduce liquidity due to its dependence on market liquidity and information demand, as evidenced by the impact of illiquid markets on market failures during the COVID-19 pandemic. In small markets like the DSE, these effects are stronger because trading is thin and information is scarce.

When compared with other regions, the DSE's results follow a global trend. In Indonesia and India (Memarista & Prasetyo, 2025; Ninan et al., 2025), herding grew stronger during crises. In Malaysia (Ijaz & Yahya, 2025), herding was more intense under stress and weaker in calm periods. In African markets (Aawaar et al., 2020), poor information flow keeps

herding alive for a long time. Studies like Bajaj & Kaur (2025); Cu et al., (2025) also show that digital platforms and fast-moving online information can spread collective behaviour even faster.

These patterns show that herding is not only emotional it is also rational in uncertain environments. When information is limited and trust is fragile, following others feels safer than acting alone. The DSE reflects this same logic, where imitation becomes a form of protection in a market full of uncertainty.

For regulators, the results point to one main thing improve transparency. When information is clear and comes on time, investors rely less on others. Regular updates, strong disclosure rules, and wider analyst coverage can reduce the need for herding. Similarly, studies carried out regarding digital financial services in Tanzania have pointed out that consumer protection is essential in managing behavioral risks linked to financial decisions (Nathanael & Chami, 2026). For investors, the lesson is to know their own biases. Emotions like fear of loss, overconfidence, and too much trust in peers often shape decisions without them realizing it. Awareness can help them make choices based more on evidence than on emotion. For researchers, this study adds to the understanding that herding in frontier markets like Tanzania follows similar behavioural patterns seen elsewhere. What makes it stronger here is not culture or age but the weakness in information systems.

Conclusion

The current study aimed at establishing the impact of demographic characteristics, psychological aspects, and market information environment on investor herding behaviour at the Dar es Salaam Stock Exchange through PLS-SEM. According to the findings, psychological aspects have a significant effect on investor behaviour through the market information environment ($\beta = 0.642$, $p < 0.001$), while demographic characteristics have only a weak effect ($\beta = -0.141$, $p = 0.199$). The findings also indicate that poor market information environment has a significant effect on increasing investor herding behaviour ($\beta = 0.671$, $p < 0.001$), and that investor herding behaviour has a significant impact on market performance ($\beta = 0.555$, $p < 0.001$). Therefore, the current findings support the notion that behavioural and informational aspects are more important determinants of investor herding behaviour than demographic characteristics.

In essence, investors in Tanzania often follow the crowd because information is weak, emotions are strong, and uncertainty feels risky. This reaction makes sense in a market where data is limited and signals are mixed. But it also makes the market less efficient, as prices move more from imitation than from fundamentals. The results agree with what has been observed in other emerging and frontier markets. Studies in India, Indonesia, Ghana, and Malaysia show the same story: when markets are uncertain and information is uneven, herding becomes the easy and safe choice. Overall, the study confirms that herding in the DSE is both a psychological and structural issue. It comes from inside the investor and from the system itself.

Going beyond the current situation in Tanzania, the research results provide useful lessons in relation to the development of frontier markets in the East African region. Considering the initiatives taken by the East African Community (EAC) in financial market integration,

the standardization of disclosure and regulatory regimes may help reduce the problem of cross-border information asymmetries and the risk of herd behaviour in the region.

Moreover, there is an opportunity for regional regulators to cooperate in order to set up financial literacy standards and platforms for investment education. The fast development of financial technologies (fintech) in the region creates opportunities as well as poses threats. On one hand, fintech can provide equal access to market information, reducing dependence on peer channels of information transfer. On the other hand, it can intensify emotional contagion in case of its inappropriate usage.

Herding behaviour is equally relevant for market intermediaries such as brokers and portfolio managers, as they may benefit from using it to recognize when the price is deviating from the real value and take corresponding actions. Institutional investors that have an impact on small investors should also be more open in their trading activities not to lead people unintentionally.

Individual investors should take a step back and think twice before going along with the masses. Following others could be helpful sometimes; however, mimicking them unthinkingly is dangerous. Fundamental-based investors usually outperform trend-based ones.

Like any study, this one has its limitations. First, it used cross-sectional data, meaning responses were collected at one point in time. Because of this, the study could not fully capture how herding might change across different market periods, such as during crises or bull runs. Second, the analysis relied on self-reported data from investors. While this provides useful insights into attitudes and perceptions, it may also include some response bias. Future studies could combine survey data with actual trading records to cross-check behavioural patterns. Third, the study focused only on the Dar es Salaam Stock Exchange, which is relatively small and young. This limits how much we can generalize the results to other African markets. Future work could include comparisons with larger markets such as Nairobi or Johannesburg to provide a broader picture. Lastly, the study mainly focused on psychological and informational factors. Other possible influences like cultural norms, social networks, or digital trading platforms were not examined. These could offer more insights in future behavioural research.

Future studies could build on this work in several ways; use longitudinal or time-series data to observe how herding changes over different market conditions for example, before and after a financial shock. Include comparative regional studies, to see if similar behavioural patterns exist in neighboring frontier markets. Explore digital and social media influences, as online investment groups and fintech platforms are becoming new sources of crowd behaviour. Apply experimental or simulation methods to isolate specific psychological triggers behind imitation. Finally, consider the interaction of cultural values and behavioural finance, since social norms might affect how investors follow or resist the crowd.

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