# 2025 Behavioural Science Study on Investor Behaviour in the Virtual Asset Markets: Heuristics in Virtual Assets Investment Decision-Making

## Research Report


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**June 2026**

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## Executive Summary

This report examines how Hong Kong retail investors make decisions in the virtual asset (VA) markets, focusing on heuristic-driven judgment and latent “investor archetypes.” Drawing on a 2025 survey of 1,000 active VA investors and a 2022 baseline (N = 501) that used the same 13-item heuristic measure, this study maps how behavioural patterns, market conditions, and regulatory structures have evolved over time. The 2025 data are treated as an up-to-date snapshot of investor behaviour, with the 2022 findings providing a contextual reference, rather than a formal longitudinal panel.

From 2022 to 2025, Hong Kong's VA regulatory landscape continued to evolve significantly, marked by the introduction of the Guidelines for Virtual Asset Trading Platform Operators taking effect on 1 June 2023, the expansion of licensing requirements under the Anti-Money Laundering and Counter-Terrorist Financing Ordinance (AMLO), and the rollout of VA-linked exchange-traded products. Underpinning these developments was a consistent "same business, same risks, same rules" policy stance, which progressively brought more activity onto licensed platforms and into listed products.

VA investment decisions are strongly shaped by heuristics. In 2025, investors report particularly high agreement with items capturing reliance on past experience, fear of missing out (FOMO) when prices are rising, the disposition effect, gambler’s fallacy-style expectations of price reversals, and recency bias. Social and authority-based cues also feature prominently, with many investors influenced by other investors’ buy/sell decisions, asset choices, and trading volumes, as well as perceived authority figures. Overconfidence and asymmetric risk-taking after gains and losses are evident but generally rank below experience and price path-driven shortcuts.

Exploratory factor analysis reveals that these heuristics cluster into four coherent archetypes in 2025: the Socially Influenced Risk Averter, the Stubborn Loss Holder, the Confident Risk-Seeking Optimist, and the FOMO-Driven Overreactor. Together, these segments cover the full sample, with

Socially Influenced Risk Averters forming the largest group (33.9%) and FOMO-Driven Overreactors forming the smallest (18.4%). Each archetype combines a distinctive mix of biases, such as social herding, loss aversion, the disposition effect, overconfidence, house money effects, FOMO, and recency bias, with characteristic demographic and investment profiles. Compared with the five more diffuse factors identified in 2022, the four-factor structure in 2025 suggests consolidation and clearer segmentation of behavioural risks in a more regulated mass retail market.

The report documents systematic variations in heuristic use across gender, age, education, income, liquid assets, experience, and trading frequency. Male, older, higher income, wealthier, and more experienced investors tend to show stronger overconfidence, greater reliance on experience and instinct, and lower post-loss risk aversion, whereas younger, lower income, and less experienced investors exhibit higher authority reliance and more pronounced herding in asset choices and trading volumes. These patterns underscore that behavioural vulnerabilities are not confined to inexperienced or low-income investors; rather, they manifest differently across socioeconomic groups and trading profiles of investors.

Factor and segment-level analyses are integrated with an interpretation of the broader market trajectory from 2022 to 2025. The consolidation of archetypes, the rise of FOMO-Driven Overreactors, and the emergence of Socially Influenced Risk Averters reflect a shift from a relatively fragmented, trader-dominated environment towards a domestic mass retail setting in which social proof, news cycles, and perceived safety within the regulatory perimeter play a larger role.

Simultaneously, the persistence of stubborn loss-holding and gambler's fallacy signals that greater institutionalisation does not automatically weaken deeply rooted biases; instead, these biases may now operate within ostensibly safer channels such as licensed platforms and VA-linked ETFs.

The findings are both promising and demanding for investor education bodies. On the positive side, the four-archetype framework offers a practical basis for segmentation, enabling tailored interventions that address specific bias clusters. On the challenging side, the study highlights heightened emotional reactivity, strong social influence, and the growing role of finfluencers and

social media, which can undermine traditional warnings and dilute the impact of formal regulatory communications.

The report recommends that education and policy strategies adopt an explicitly segmented and behaviourally informed approach to address the issue. For Socially Influenced Risk Averters, interventions should emphasise due diligence, platform licensing status, and simple rules for avoiding herd-driven overexposure. For Stubborn Loss Holders, portfolio review tools, precommitment mechanisms, and narratives that normalise cutting losses are critical. Confident Risk-Seeking Optimists may benefit from data-rich performance feedback, diversification prompts, and debiasing messages that challenge overconfidence without disengaging skilled investors. FOMO-Driven Overreactors require timely, emotionally attuned communication—often in short-form digital formats—that reframes “missing out”, highlights the risks of chasing rallies, and encourages cooling off before execution.

Finally, the report outlines several directions for future work: periodic repetition of the survey to track behavioural trends across market cycles and regulatory milestones; experimental testing of warnings and nudges embedded in real-world interfaces; and qualitative research with each archetype to deepen understanding of narratives, trust, and information sources. Taken together, these steps can help ensure that Hong Kong’s increasingly regulated and institutionally supported VA ecosystem is matched by more informed, resilient, and behaviourally aware investor decision-making process.

# 1. Introduction

## 1.1 Background: Virtual Asset Markets in Hong Kong

Over the past decade, Hong Kong has sought to position itself as a regional hub for virtual assets, with growing retail participation and the emergence of products such as cryptocurrencies, stablecoins, non-fungible tokens (NFTs), and tokenised securities. Within this evolving landscape, policymakers have progressively shifted from a largely observatory stance to a more proactive "responsible innovation" approach, introducing licensing regimes for virtual asset trading platforms and strengthening investor protection requirements. Against this backdrop, retail investors in Hong Kong now navigate a market that combines high price volatility and speculative narratives with increasing institutionalisation. Therefore, understanding how individual investors make decisions in this environment is critical for effective investor education and risk communication.

## 1.2 Behavioural Heuristics in Virtual Asset Investing

Virtual asset markets are characterised by information asymmetries, complex technology, and highly salient price swings, all of which encourage investors to rely on mental shortcuts. Behavioural finance research documents a range of heuristics and biases—such as anchoring on past prices or personal experience, herding based on other investors' actions, authority bias, recency bias, overconfidence, the disposition effect, the house money effect, and loss aversion—that are especially pronounced in speculative markets. In the context of virtual asset, these heuristics can shape how investors enter positions, respond to rallies and crashes, interpret news and social media signals, and decide when to realise gains or cut losses. Mapping these patterns systematically provides an evidence base for segmenting investors into distinct behavioural profiles and tailoring intervention strategies to specific vulnerabilities.

## 1.3 Research Objectives

This study examines how Hong Kong virtual asset investors make decisions, with a particular focus on the role of behavioural economic factors. The 2025 survey profiles investors' use of heuristics and their latent decision styles and explores how these patterns relate to market and regulatory developments in the recent years. An earlier 2022 survey using a similar instrument provides a useful point of reference, but the present report primarily treats the 2025 data as an up-to-date snapshot of investor behaviour. The overarching objective is to generate behavioural science evidence that can inform IFEC's investor education strategy by clarifying key heuristics, persistent vulnerabilities, emerging trends, and priority segments for targeted communication and support, thereby helping investors make better-informed and more prudent virtual asset investment decisions.

## 1.4 Scope and Key Research Questions

This study focuses on individual investors aged 18–69 in Hong Kong who have traded or held virtual assets in the past 12 months and examines their self-reported reliance on a set of theoretically derived behavioural heuristics in investment decision-making. Building on a baseline instrument first used in 2022, the 2025 survey applies the same core measurement and broadly similar sampling logic, allowing for cautious comparison of item-level endorsement and underlying latent structures over time. Within this scope, this report addresses four core questions:

1. To what extent do Hong Kong virtual asset investors rely on specific heuristics (e.g. anchoring, herding, authority bias, overconfidence, recency, disposition effect, and loss aversion) in their decision-making?

2. How do these heuristics cluster into latent behavioural factors or "investor archetypes," and how many distinct decision styles can be empirically identified in the 2025 data?

3. Where relevant, how do these patterns compare with those observed in the earlier 2022 baseline, considering shifts in sample composition and the evolving market and regulatory context?

4. What are the implications of the observed behavioural patterns for the design, targeting, and messaging of investor education and risk warning initiatives in Hong Kong's virtual asset markets?

# 2. Research Design and Methodology

## 2.1 Study Design

This 2025 study is a cross-sectional quantitative survey of virtual asset investors in Hong Kong. A total of 1,000 respondents were recruited through stratified sampling via street intercepts at high-traffic locations across the territory. Prior to the main survey, an establishment survey was conducted among the general population to establish the demographic profile of virtual asset investors and to set the quota parameters for recruitment. The establishment survey was fielded in April 2025 among 1,000 individuals aged 18-69 using street interviews. While the questionnaire design and sampling logic drew on an earlier 2022 baseline study (N = 501), the present survey is conceived primarily as a standalone, updated assessment of heuristic-driven decision-making in Hong Kong′ s virtual asset markets, with the 2022 data serving only as a contextual reference point for tentative comparisons over time.

## 2.2 Target Population and Sampling

The target population comprised Hong Kong residents aged 18–69 years who had traded or held virtual assets or related products (including cryptocurrencies, stablecoins, NFTs, tokenised securities, and virtual asset ETFs) in the preceding 12 months. Sampling in both waves focused on active retail investors rather than the general population, ensuring that all respondents had recent and concrete experience with virtual asset investment decisions. A professional market research agency was commissioned to recruit respondents through street interviews conducted from 15 November to 30 December 2025 with quotas set on key demographic variables (e.g. age, gender, employment status, personal income level, and residential district) to reflect the profile of virtual asset investors established in the establishment survey.

## 2.3 Data Collection Procedures

Data were collected through interviewer-administered surveys, with trained interviewers using tablet devices to record the responses in real time. The interviewers first screened potential participants for demographic eligibility and recent virtual asset activity before proceeding to the full questionnaire. The instrument, available in Chinese, was carefully worded to capture behavioural tendencies in an accessible, non-technical manner, and respondents were assured of anonymity and confidentiality to mitigate social desirability bias. Standard quality control procedures were implemented, including the exclusion of cases with excessive non-response.

## 2.4 Measurement of Heuristics and Key Constructs (13-item scale)

Heuristic use in virtual asset decision-making was measured using a 13-item scale, with each statement reflecting a specific heuristic or decision shortcut drawn from the behavioural finance literature. The items covered anchoring on past experience, fear of missing out (FOMO), the disposition effect, gambler's fallacy, authority bias, recency bias, overconfidence (instinct and perceived skill), herding (others' buying/selling, asset type, and volume), the house money effect (greater risk-seeking after gains), and increased risk aversion after losses. Respondents indicated their agreement with each statement on a 5-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). This scale was originally developed in the 2022 baseline study and was retained here to ensure continuity, with a small number of additional items on awareness and understanding of the evolving regulatory environment considered where they add clear value without unduly lengthening the questionnaire. Higher scores on each item indicate a stronger reliance on heuristic-driven decision-making.

**Table 1**

*Behavioural Statements and Primary Heuristics*

| Behavioural Statements | Primary Heuristics |
|---|---|
| a) I rely on my previous experiences in the market for my next investment.<br>我依靠我在市場上的過往經驗來進行下一次投資。 | Anchoring |
| l) When I see virtual asset prices keep rising, I am afraid of missing out on opportunities for profit.<br>當我看到虛擬資產價格不斷上升時，我會害怕錯過獲利機會。 | Availability/ FOMO |
| d) I avoid selling virtual assets that have decreased in value and readily sell virtual assets that have increased in value.<br>我避免出售價值下降的虛擬資產，並傾向出售已升值的虛擬資產。 | Disposition effect |
| m) When prices continue to fall, I think that there will be a price reversal, so I hold on to virtual assets.<br>當價格持續下跌時，我會認為價格會回升，因此我會繼續持有虛擬資產。 | Gambler's fallacy |
| k) When it comes to investing in/trading virtual assets, I rely on authority figures telling me what to do.<br>在投資/買賣虛擬資產上，我會依靠權威人士來告訴我該怎麼做。 | Authority bias |
| j) I give more weight to recent experiences over long-term averages when analysing prospects and their probabilities.<br>在分析市場前景及其機遇時，我會優先考慮近期的經驗而不是資產長遠的平均價值。 | Recency bias |
| f) My instinct has often helped me make good investments.<br>我的直覺經常幫助我做出好的投資。 | Overconfidence |
| i) Other investors' decisions on buying and selling virtual assets have an impact on my investment decisions.<br>其他投資者買入或賣出虛擬資產的選擇會影響我的投資決定。 | Herding (social proof) |

| Behavioural Statements | Primary Heuristics |
|---|---|
| b) I believe that my skills and knowledge of the virtual assets market can help me to outperform the market.<br>我相信我對虛擬資產市場的技能和知識可以幫助我跑贏大市。 | Overconfidence |
| g) Other investors' decisions on choosing virtual asset **types** have an impact on my investment decisions.<br>其他投資者選擇虛擬資產的**類型**會影響我的投資決定。 | Herding (social proof) |
| h) Other investors' decisions on virtual assets **volume** have an impact on my investment decisions.<br>其他投資者投資虛擬資產的**交易量**會影響我的投資決定。 | Herding (social proof) |
| c) After a prior gain, I am more risk-seeking than usual.<br>在先前的投資獲利之後，我會比平時追求更高風險的投資。 | Mental accounting/ House money effect |
| e) After a prior loss, I become more risk-averse.<br>在先前的投資虧損之後，我變得更不願承擔風險。 | Loss aversion |

## 2.5 Data Analysis Strategy

The analysis was conducted in several stages. First, descriptive statistics were computed for all demographic variables and heuristic items, including frequency distributions, means, and standard deviations, to profile the sample and identify the most and least endorsed heuristics. Second, exploratory factor analysis (EFA) was conducted for the data using principal axis factoring (PAF) extraction with oblique rotation to uncover latent dimensions of decision-making and to determine how the 13 items clustered into broader behavioural styles. Third, factor scores or composite indices derived from the factor solutions were used as inputs in segmentation analyses, which classified investors into distinct archetypes characterised by different combinations of social-herding, loss anchoring, overconfidence, and FOMO/recency tendencies. Finally, cross-wave comparisons were used to examine changes in item means, factor structures, and archetype distributions to assess temporal shifts in behavioural patterns.

# 3. Sample Profile and Market Context

## 3.1 Demographic Profile of Respondents

The two survey waves broadly capture similar populations of active virtual asset investors in Hong Kong, but with notable shifts in age, education, and income composition. The 2022 baseline comprised 501 respondents, while the 2025 follow-up expanded to 1,000 respondents, substantially increasing the coverage of the investor community. Across both waves, men constitute the majority of participants, although the proportion of women rises modestly over time, indicating a gradual broadening of participation beyond early male adopters. In both years, most respondents report at least some tertiary education, with the 2025 sample particularly concentrated among degree holders and working-age adults in their 20s and 30s. See Table 2 below.

**Table 2**

*Sample Characteristics in 2022 and 2025*

| Demographics | 2022 Study (*N*=501) | 2025 Study (*N*=1,000) |
|---|---|---|
| **Age** | | |
| 18–29 | 169 (34%) | 520 (52%) |
| 30–39 | 215 (43%) | 330 (33%) |
| 40–69 | 117 (23%) | 150 (15%) |
| **Gender** | | |
| Male | 359 (72%) | 680 (68%) |
| Female | 142 (28%) | 320 (32%) |
| **Education Level** | | |
| Secondary or below | 107 (21%) | 130 (13%) |

| Demographics | 2022 Study (*N*=501) | 2025 Study (*N*=1,000) |
|---|---|---|
| Tertiary or above | 394 (79%) | 870 (87%) |
| **Monthly Personal Income** | | |
| < HK$30K | 286 (59%) | 414 (45%) |
| HK$30K–< 50K | 135 (28%) | 395 (43%) |
| ≥ HK$50K | 61 (13%) | 111 (12%) |

## 3.2 Investor Composition by Survey Wave

The demographic profiles of the 2022 and 2025 study samples reflect the quota structures applied in each wave, which were derived from establishment surveys of the general population aged 18–69 conducted in the respective years. As VA remains a niche market in Hong Kong — with investor incidence below 10% in both establishment surveys — the resulting demographic benchmarks are based on relatively small subsamples and should be interpreted with caution, as they are subject to variation across waves rather than representing confirmed shifts in the broader VA investor population.

With this caveat in mind, the two samples differ in several respects. The share of respondents aged 18–29 is higher in 2025 (52%) than in 2022 (34%), while the 30–39 and 40–69 brackets both show lower representation. Gender composition is slightly more balanced in 2025, with women comprising 32% compared to 28% in 2022. Educational attainment is also higher in the 2025 sample, with tertiary-educated respondents accounting for 87% versus 79% in 2022. In terms of income, the lower-income group (< HK$30,000/month) accounts for a smaller share in 2025 (45% vs. 59%), while the middle-income group (HK$30,000–< HK$50,000) is more prominent (43% vs. 28%); the highest income group remains comparatively stable (12% vs. 13%). The 2025 study also doubles the sample size from 501 to 1,000, improving statistical precision within the wave. These between-wave differences in composition are noted for transparency and are accounted for in subsequent analyses where relevant.

## 3.3 Regulatory and Market Developments in Virtual Assets

From 2022 to 2025, Hong Kong's virtual asset regulatory landscape continued to evolve significantly, marked by the introduction of the Guidelines for Virtual Asset Trading Platform Operators taking effect on 1 June 2023, and the progressive development of a more regulated ecosystem (Financial Services & the Treasury Bureau [FSTB], 2022, 2025; Securities and Futures Commission [SFC], 2023). Authorities introduced a dedicated licensing regime for virtual asset trading platforms under the Anti-Money Laundering and Counter Terrorist Financing Ordinance (AMLO), extended existing anti-money laundering and investor protection standards to virtual asset intermediaries, and articulated a clearer policy stance that balances innovation with risk management (SFC, 2023; FSTB, 2024, 2025). In parallel, the market sees the launch and scaling up of regulated virtual assets trading platforms, broader retail access through availability of more service channels, and growing institutional interest supported by an explicit government commitment to building a “trusted, sustainable and deeply integrated” digital asset ecosystem (FSTB, 2022, 2025). These developments are likely to shape who participates in the market and how they behave, as clearer rules and safer access points make virtual assets more accessible to retail investors (FSTB, 2025).

# 4. Heuristic Use in Virtual Asset Decisions

## 4.1 Overall Agreement with Heuristic Statements

### Experience- and price-path-driven decision making

As shown in Table 3, the highest-ranked behavioural items indicate that investment decisions in virtual assets are predominantly guided by past experience and recent price trends, reflecting a reliance on experiential and momentum-based cues over deliberate, reflective evaluation. Endorsement is particularly strong for relying on past experiences (mean = 3.86) and FOMO when prices are rising (mean = 3.77), followed by the disposition effect (mean = 3.68), price-reversal expectations when prices continue to fall (mean = 3.66), and the recency bias (mean = 3.55). This configuration suggests that retail investors systematically extrapolate from salient recent outcomes and personal histories when forming expectations, with short-term price dynamics and memorable gains or losses exerting a significant influence on judgment.

### Social and authority-based influences

The ranking also highlights the notable role of social and authority-related cues. Authority bias has a relatively elevated mean of 3.63, indicating that guidance from perceived experts and authority figures constitutes an important decision heuristic. Herding-related statements show moderate endorsement, with means of 3.49 for being influenced by others' buying and selling decisions, 3.30 for being influenced by others' choices of asset types, and 3.19 for being influenced by others' trading volume. Overall, the pattern reflects an information environment in which investors regularly use the observed behaviour and opinions of others as heuristic substitutes for independent analysis, but with authority cues weighted somewhat more strongly than general crowd behaviour.

**Overconfidence and asymmetric risk-taking**

Overconfidence-related statements occupy a middle position in the ranking, with a mean of 3.49 for reliance on instinct and 3.31 for the belief in being able to outperform the market, suggesting that confidence in one's skills, knowledge, and intuition is present but not the most prominent bias in the sample. Items capturing asymmetric risk-taking are located toward the lower end, with a mean of 2.89 for increased risk-seeking after gains (the house money effect) and 2.71 for greater risk aversion after losses. In combination, these results suggest that, in the context of virtual asset investing, classic prospect-theoretic gain-loss asymmetries are evident but are comparatively less salient than heuristics linked to recent price patterns, emotionally charged reactions to rallies and downturns, and guidance derived from authorities and the broader investor crowd.

**Table 3**

*Response Distribution and Mean Scores for Behavioural Heuristic Statements*

| Behavioural Statements | Primary Heuristics | Strongly disagree (%) | Disagree (%) | Neither (%) | Agree (%) | Strongly Agree (%) | *M* | *SD* |
|---|---|---|---|---|---|---|---|---|
| a) Rely on past experiences | Anchoring | 0.8 | 5.4 | 17.8 | 59.2 | 16.8 | 3.86 | 0.78 |
| l) FOMO when prices rising | Availability/ FOMO | 3.0 | 8.9 | 17.2 | 50.0 | 20.9 | 3.77 | 0.98 |
| d) Disposition effect | Disposition effect | 3.2 | 10.8 | 19.6 | 47.9 | 18.5 | 3.68 | 1.00 |
| m) Price reversal hope | Gambler's fallacy | 4.0 | 11.0 | 20.4 | 44.1 | 20.5 | 3.66 | 1.05 |
| k) Authority reliance | Authority bias | 0.4 | 8.0 | 35.2 | 41.2 | 15.2 | 3.63 | 0.85 |
| j) Recency bias | Recency bias | 2.9 | 9.8 | 25.4 | 53.7 | 8.2 | 3.55 | 0.88 |
| f) Instinct reliance | Overconfidence | 1.6 | 11.0 | 32.9 | 46.1 | 8.4 | 3.49 | 0.86 |
| i) Herding (buy/sell) | Herding (social proof) | 3.2 | 15.7 | 20.2 | 51.1 | 9.8 | 3.49 | 0.98 |
| b) Belief in beating market | Overconfidence | 2.1 | 13.9 | 40.4 | 37.9 | 5.7 | 3.31 | 0.86 |
| g) Herding (asset types) | Herding (social proof) | 2.8 | 21.9 | 24.1 | 45.2 | 6.0 | 3.30 | 0.97 |
| h) Herding (volume) | Herding (social proof) | 4.8 | 26.8 | 19.5 | 42.2 | 6.7 | 3.19 | 1.06 |
| c) Risk-seeking after gains | Mental accounting/ House money effect | 13.7 | 27.4 | 20.1 | 33.4 | 5.4 | 2.89 | 1.17 |
| e) Risk-averse after losses | Loss aversion | 13.7 | 37.9 | 20.1 | 20.5 | 7.8 | 2.71 | 1.17 |

## 4.2 Significant Changes from 2022 to 2025

Table 4 describes the behavioural heuristic patterns observed in 2025 and the statistically significant changes compared to 2022. The arrows in the data highlight several significant shifts in how investors approach the VA markets:

**Increasing Reliance on Internal and External Guidance**

- **Instinct Reliance**: There has been a significant increase in investors relying on their gut instinct for decision-making, rising from a mean of 3.28 in 2022 to 3.49 in 2025.
- **Authority Reliance**: Dependence on market experts or authority figures has also grown notably, increasing from 3.44 to 3.63.

**Decreasing Trend-Following and Experience-Based Bias**

- **Relying on Past Experiences**: While still the top-ranked factor, the intensity of anchoring on past experiences has significantly declined from 4.03 to 3.86.
- **Social Herding (Volume & Asset Types)**: Investors are significantly less likely to follow market volume signals (dropping from 3.63 to 3.19) or mimic the specific asset types that others are buying (dropping from 3.49 to 3.30).
- **House Money Effect**: The tendency to become risk-seeking after achieving gains has seen a significant decrease, falling from 3.11 to 2.89.

**Stable Behavioural Heuristics**: Several core psychological drivers showed no significant change between the two periods, including FOMO, the disposition effect, price reversal hope (Gambler's Fallacy), recency bias, and the belief in one’s ability to beat the market. This suggests that these biases remain deeply embedded in the Hong Kong investor profile, regardless of changing market conditions.

**Table 4**

*Mean Scores for Behavioural Heuristic Statements in 2025 and 2022*

| Behavioural Statements | 2025 vs 2022 | 2025 M (SD) | 2022 M (SD) | *p* | 2025 vs 2022 *(controlling for demographics)* |
|---|---|---|---|---|---|
| a) Rely on past experiences | ↓ | 3.86 (0.78) | 4.03 (0.67) | < .001 | ↓ |
| l) FOMO when prices rising | - | 3.77 (0.98) | 3.68 (0.81) | .06 | - |
| d) Disposition effect | - | 3.68 (1.00) | 3.68 (0.83) | .94 | - |
| m) Price reversal hope | - | 3.66 (1.05) | 3.58 (0.76) | .09 | - |
| k) Authority reliance | ↑ | 3.63 (0.85) | 3.44 (0.88) | < .001 | ↑ |
| j) Recency bias | - | 3.55 (0.88) | 3.53 (0.92) | .84 | - |
| i) Herding (buy/sell) | - | 3.49 (0.98) | 3.52 (0.81) | .49 | - |
| f) Instinct reliance | ↑ | 3.49 (0.86) | 3.28 (0.79) | < .001 | ↑ |
| b) Belief in beating market | - | 3.31 (0.86) | 3.30 (0.81) | .71 | - |
| g) Herding (asset types) | ↓ | 3.30 (0.97) | 3.49 (0.79) | < .001 | ↓ |
| h) Herding (volume) | ↓ | 3.19 (1.06) | 3.63 (0.81) | < .001 | ↓ |
| c) Risk-seeking after gains | ↓ | 2.89 (1.17) | 3.11 (0.94) | < .001 | ↓ |
| e) Risk-averse after losses | ↓ | 2.71 (1.17) | 2.82 (0.82) | .03 | - |

## 4.3 Demographic Variations: Gender, Age, Education, Income

In the following item-level analyses, we concentrate on overall linear trends rather than detailed post hoc comparisons between individual cells, as the large number of cells would render such comparisons unwieldy and of limited interpretive value.[1]

### 4.3.1 Gender Variations

As shown in Table 5, male respondents reported significantly higher agreement than female respondents on several heuristics. Specifically, males scored higher on reliance on past experiences ($M = 3.95$ vs. 3.66, $p < .001$), belief in beating the market (3.49 vs. 2.94, $p < .001$), risk-seeking after gains (3.03 vs. 2.61, $p < .001$), and instinct reliance (3.62 vs. 3.21, $p < .001$) than females. Males also reported lower risk aversion after losses than females (2.59 vs. 2.96, $p < .001$), indicating a greater tendency to maintain or increase risk exposure after negative outcomes.

In contrast, females showed significantly higher endorsement of authority reliance than males (3.84 vs. 3.53, $p < .001$), suggesting a stronger tendency to look to formal or expert guidance when making virtual asset investment decisions. Females also reported slightly lower agreement with price-reversal hope than males (3.52 vs. 3.73, $p < .01$), indicating a lower inclination to expect a rebound after price declines.

Overall, the pattern suggests that male investors are more likely to endorse self-driven and risk-tolerant heuristics, whereas female investors show greater reliance on authority cues, with broadly similar levels of social and price-path-related heuristics across genders.

[1] The item-level analyses in this section cover all 13 heuristic statements, including items (a) and (k), which — as discussed in Section 5 — did not form part of the final factor solution but nevertheless show meaningful variation across demographic groups and are therefore reported here for completeness.

**Table 5**

*Gender Differences in Behavioural Investment Bias*

| Behavioural Statements | Male (*n*=680) *M (SD)* | Female (*n*=320) *M (SD)* | *t* (998) | *p* |
|---|---|---|---|---|
| a) Rely on past experiences | 3.95 (0.73) | 3.66 (0.85) | 5.58*** | < .001 |
| b) Belief in beating market | 3.49 (0.80) | 2.94 (0.85) | 9.76*** | < .001 |
| c) Risk-seeking after gains | 3.03 (1.15) | 2.61 (1.14) | 5.30*** | < .001 |
| d) Disposition effect | 3.69 (1.00) | 3.65 (1.00) | 0.65 | .51 |
| e) Risk-averse after losses | 2.59 (1.12) | 2.96 (1.23) | -4.79*** | < .001 |
| f) Instinct reliance | 3.62 (0.80) | 3.21 (0.90) | 7.12*** | < .001 |
| g) Herding (asset types) | 3.30 (0.98) | 3.29 (0.94) | 0.07 | .94 |
| h) Herding (volume) | 3.20 (1.05) | 3.18 (1.07) | 0.16 | .88 |
| i) Herding (buy/sell) | 3.46 (0.97) | 3.55 (0.98) | -1.42 | .16 |
| j) Recency bias | 3.56 (0.87) | 3.51 (0.91) | 0.95 | .34 |
| k) Authority reliance | 3.53 (0.85) | 3.84 (0.80) | -5.42*** | < .001 |
| l) FOMO when prices rising | 3.78 (0.96) | 3.74 (1.01) | 0.63 | .53 |
| m) Price reversal hope | 3.73 (1.01) | 3.52 (1.10) | 2.89** | .004 |

*$p < .05$. **$p < .01$. ***$p < .001$.

Upward trend  Downward trend

### 4.3.2 Age Variations

As shown in Table 6, the most pronounced age differences are observed in belief in beating the market, herding by asset type, and risk aversion after losses. Belief in beating the market increases steadily with age ($F(2,997) = 11.18$, $p < .001$), and the disposition effect shows a similar upward trend ($F(2,997) = 3.00$, $p = .05$). In contrast, herding in asset type choice displays the opposite

pattern, with markedly higher endorsement among younger respondents ($F(2,997) = 11.17$, $p < .001$). Risk aversion after losses likewise declines with age ($F(2,997) = 11.09$, $p < .001$), indicating that younger investors are more likely to report becoming risk-averse following losses, while older investors report both stronger market-beating confidence and lower post-loss risk aversion. Authority reliance also declines with age ($F(2,997) = 3.09$, $p = .05$).

Several other heuristics show more modest but still statistically significant age effects. Reliance on past experiences displays a slight upward trend with age ($F(2,997) = 2.99$, $p = .05$), suggesting that older investors place greater weight on accumulated experience. Herding based on trading volume is slightly higher among younger respondents ($F(2,997) = 2.95$, $p = .05$), and herding based on buy/sell decisions follows a similar pattern, with higher endorsement in the youngest cohort and lower endorsement in older groups ($F(2,997) = 6.60$, $p < .001$).

Overall, the pattern suggests a crossover in heuristics: younger investors exhibit stronger herding (especially in asset type choices, trading volume, and buy/sell decisions), higher post-loss risk aversion, and greater reliance on authority, whereas older investors display stronger confidence in their ability to beat the market and somewhat greater reliance on accumulated past experience and the disposition effect.

**Table 6**

*Age Differences in Behavioural Investment Bias*

| Behavioural Statements | 18–29 (*n*=520) *M (SD)* | 30–39 (*n*=330) *M (SD)* | 40–69 (*n*=150) *M (SD)* | *F* (2,997) | *p* |
|---|---|---|---|---|---|
| a) Rely on past experiences | 3.80 (0.79) | 3.92 (0.77) | 3.91 (0.79) | 2.99 | .051 |
| b) Belief in beating market | 3.20 (0.82) | 3.38 (0.88) | 3.54 (0.85) | 11.18*** | < .001 |
| c) Risk-seeking after gains | 2.96 (1.15) | 2.83 (1.20) | 2.81 (1.15) | 1.83 | .16 |
| d) Disposition effect | 3.64 (1.00) | 3.65 (1.03) | 3.86 (0.91) | 3.00* | .05 |
| e) Risk-averse after losses | 2.87 (1.18) | 2.57 (1.11) | 2.45 (1.16) | 11.09*** | < .001 |
| f) Instinct reliance | 3.46 (0.88) | 3.48 (0.87) | 3.61 (0.74) | 1.97 | .14 |
| g) Herding (asset types) | 3.43 (0.92) | 3.17 (0.99) | 3.10 (1.01) | 11.17*** | < .001 |
| h) Herding (volume) | 3.27 (1.04) | 3.09 (1.10) | 3.15 (0.99) | 2.95 | .053 |
| i) Herding (buy/sell) | 3.59 (0.94) | 3.35 (1.02) | 3.43 (0.95) | 6.60** | .001 |
| j) Recency bias | 3.55 (0.88) | 3.56 (0.88) | 3.49 (0.92) | 0.38 | .68 |
| k) Authority reliance | 3.69 (0.84) | 3.59 (0.84) | 3.51 (0.90) | 3.09* | .046 |
| l) FOMO when prices rising | 3.82 (0.96) | 3.68 (1.01) | 3.81 (0.97) | 2.26 | .11 |
| m) Price reversal hope | 3.67 (0.97) | 3.62 (1.13) | 3.71 (1.11) | 0.41 | .67 |

*$p < .05$. **$p < .01$. ***$p < .001$.

Upward trend

Downward trend

### 4.3.3 Education Level

Education is associated with systematic differences in several key heuristics. As shown in Table 7, belief in beating the market is firmer among respondents with bachelor's and postgraduate qualifications (means = 3.45 and 3.65) than among those with senior secondary or below (3.22) or college/diploma/associate education (3.19; $F = 8.42$, $p < .001$). Risk-seeking after gains shows a clear monotonic increase from 2.53 (senior secondary or below) and 2.79 (college/diploma) to 3.08 (bachelor's) and 3.50 (master's or above) ($F = 11.44$, $p < .001$), indicating greater willingness to take on risk following gains at higher education levels. In contrast, authority reliance is highest in the two lower education groups (3.73 and 3.75) and declines among those with bachelor's (3.49) and master's or above (3.31) degrees ($F = 9.05$, $p < .001$), suggesting that more highly educated investors are less dependent on formal or expert guidance in their virtual asset decisions.

**Table 7**

*Education Differences in Behavioural Investment Bias*

| **Behavioural Statements** | **Sec. or below (*n*=130) *M (SD)*** | **College/ diploma (*n*=427) *M (SD)*** | **Bachelor's (*n*=417) *M (SD)*** | **Master's or above (*n*=26) *M (SD)*** | ***F* (3.996)** | ***p*** |
|---|---|---|---|---|---|---|
| a) Rely on past experiences | 3.77 (0.93) | 3.83 (0.84) | 3.91 (0.68) | 3.96 (0.45) | 1.40 | .24 |
| b) Belief in beating market | 3.22 (0.98) | 3.19 (0.86) | 3.45 (0.80) | 3.65 (0.69) | 8.42*** | < .001 |
| c) Risk-seeking after gains | 2.53 (1.16) | 2.79 (1.22) | 3.08 (1.08) | 3.50 (0.91) | 11.44*** | < .001 |
| d) Disposition effect | 3.64 (1.18) | 3.71 (1.07) | 3.66 (0.85) | 3.58 (1.03) | 0.33 | .80 |
| e) Risk-averse after losses | 2.59 (1.14) | 2.82 (1.22) | 2.66 (1.12) | 2.19 (0.90) | 3.75* | .011 |
| f) Instinct reliance | 3.42 (0.91) | 3.48 (0.86) | 3.52 (0.85) | 3.46 (0.65) | 0.47 | .71 |

| Behavioural Statements | Sec. or below (*n*=130) *M (SD)* | College/ diploma (*n*=427) *M (SD)* | Bachelor's (*n*=417) *M (SD)* | Master's or above (*n*=26) *M (SD)* | *F* (3.996) | *p* |
|---|---|---|---|---|---|---|
| g) Herding (asset types) | 3.25 (1.06) | 3.26 (1.01) | 3.36 (0.89) | 3.15 (0.88) | 1.03 | .38 |
| h) Herding (volume) | 3.32 (1.06) | 3.16 (1.07) | 3.17 (1.05) | 3.35 (0.94) | 1.01 | .39 |
| i) Herding (buy/sell) | 3.33 (1.12) | 3.47 (1.01) | 3.56 (0.89) | 3.38 (0.90) | 1.95 | .12 |
| j) Recency bias | 3.46 (1.01) | 3.53 (0.93) | 3.58 (0.80) | 3.58 (0.76) | 0.68 | .56 |
| k) Authority reliance | 3.73 (0.82) | 3.75 (0.85) | 3.49 (0.83) | 3.31 (0.79) | 9.05*** | < .001 |
| l) FOMO when prices rising | 3.71 (1.09) | 3.85 (0.99) | 3.70 (0.92) | 3.85 (0.97) | 1.90 | .13 |
| m) Price reversal hope | 3.61 (1.29) | 3.68 (1.11) | 3.67 (0.89) | 3.54 (1.03) | 0.27 | .85 |

*$p$ < .05. **$p$ < .01. ***$p$ < .001.

Upward trend

Downward trend

### 4.3.4 Income Level

As shown in Table 8, the most pronounced income-related differences are observed for belief in beating the market, risk-seeking after gains, risk aversion after losses, instinct reliance, and authority reliance. Belief in beating the market increases with income, with mean scores rising from 3.11 (under HKD30k) to 3.46 (HKD30k-under40k) and 3.62 (HKD40k and above) ($F(2,917) = 34.49$, $p < .001$). A similar upward trend is found for risk-seeking after gains (2.74, 2.90, 3.14; $F(2,917) = 9.62$, $p < .001$) and for instinct reliance (3.35, 3.50, 3.72; $F(2,917) = 15.62$, $p < .001$), indicating that higher-income investors are more confident, more willing to take risks after gains, and more likely to trust their intuition. In contrast, risk aversion after losses declines with income (2.91, 2.71, 2.39; F(2,917)

= 16.20, p < .001), suggesting that lower-income investors are more prone to becoming cautious following losses.

Authority reliance shows the opposite pattern to overconfidence-related items. It is highest in the lowest income group and decreases as income rises, with means of 3.82, 3.56, and 3.41 for the three income bands (F(2,917) = 20.31, p < .001), implying that lower-income investors depend more on formal guidance or expert opinion, whereas higher-income investors are more self-directed.

Smaller but significant differences emerge for reliance on past experiences and herding based on trading volume: both show modest increases with income (relying on past experiences: 3.79, 3.90, 3.97; F(2,917) = 4.51, p = .01; herding volume: 3.09, 3.14, 3.34; F(2,917) = 4.48, p = .01). Price reversal hope also differs by income (3.78, 3.60, 3.59; F(2,917) = 3.56, p = .03), with slightly higher endorsement in the lowest income group than in the two higher income groups.

**Table 8**

*Income Differences in Behavioural Investment Bias*

| **Behavioural Statements** | **<HKD30k (*n*=414) *M (SD)*** | **HKD30k to <40k (*n*=248) *M (SD)*** | **≥HKD40k (*n*=258) *M (SD)*** | ***F*(2,917)** | ***p*** |
|---|---|---|---|---|---|
| a) Rely on past experiences | 3.79 (0.87) | 3.90 (0.75) | 3.97 (0.63) | 4.51** | .011 |
| b) Belief in beating market | 3.11 (0.84) | 3.46 (0.83) | 3.62 (0.75) | 34.49*** | < .001 |
| c) Risk-seeking after gains | 2.74 (1.20) | 2.90 (1.09) | 3.14 (1.13) | 9.62*** | < .001 |
| d) Disposition effect | 3.73 (1.00) | 3.71 (0.98) | 3.55 (1.00) | 2.87 | .057 |
| e) Risk-averse after losses | 2.91 (1.21) | 2.71 (1.13) | 2.39 (1.05) | 16.20*** | < .001 |
| f) Instinct reliance | 3.35 (0.87) | 3.50 (0.85) | 3.72 (0.75) | 15.62*** | < .001 |
| g) Herding (asset types) | 3.38 (0.98) | 3.20 (0.96) | 3.26 (0.95) | 2.96 | .052 |
| h) Herding (volume) | 3.09 (1.06) | 3.14 (1.08) | 3.34 (1.01) | 4.48** | .012 |
| i) Herding (buy/sell) | 3.51 (1.04) | 3.51 (0.92) | 3.45 (0.90) | 0.42 | .66 |

| Behavioural Statements | <HKD30k (*n*=414) *M (SD)* | HKD30k to <40k (*n*=248) *M (SD)* | ≥HKD40k (*n*=258) *M (SD)* | *F*(2,917) | *p* |
|---|---|---|---|---|---|
| j) Recency bias | 3.51 (0.89) | 3.58 (0.80) | 3.58 (0.90) | 0.67 | .51 |
| k) Authority reliance | 3.82 (0.84) | 3.56 (0.82) | 3.41 (0.85) | 20.31*** | < .001 |
| l) FOMO when prices rising | 3.81 (0.95) | 3.71 (0.95) | 3.74 (0.99) | 0.90 | .41 |
| m) Price reversal hope | 3.78 (0.99) | 3.60 (1.03) | 3.59 (1.07) | 3.56* | .03 |

*$p < .05$. **$p < .01$. ***$p < .001$.

Upward trend

Downward trend

## 4.4 Wealth and Investment-Related Variables

### 4.4.1 Liquid Assets

Focusing on broadly linear tendencies, higher levels of liquid assets are associated with greater confidence, stronger reliance on personal experience and intuition, and lower reliance on authority, with notably lower post-loss caution at the top end. As shown in Table 9, belief in beating the market increases from 3.08 in the below HKD200k group to 3.23 in the HKD200k–under500k group, 3.38 in the HKD500k–under1m group, and 3.60 among those with HKD1m or more ($F(3,996) = 15.17$, $p < .001$). Reliance on past experience and instinct show similar upward tendencies (experience: 3.81, 3.76, 3.91, 3.99; $F = 4.14$, $p = .01$; instinct: 3.42, 3.39, 3.53, 3.64; $F = 4.23$, $p = .01$). Risk aversion after losses is highest in the lower asset bands (2.80–2.87) and drops markedly to 2.19 in the HKD1m or more group ($F = 18.01$, $p < .001$), indicating substantially lower post-loss caution among investors with the largest liquid reserves. Simultaneously, authority reliance is strongest in the two lower asset groups (3.71 and 3.74) and declines to 3.57 and 3.44 in the HKD500k–under1m and HKD1m or more groups ($F = 6.16$, $p < .001$), while herding in asset type choices is somewhat lower in the highest asset group (3.09 vs. 3.30–3.40 in lower bands; F(3,996)

= 4.42, p = .004), suggesting a broader shift towards more self-directed and independent decision-making among the highest asset investors.

**Table 9**

*Liquid Assets Differences in Behavioural Investment Bias*

| **Behavioural Statements** | **<HKD200k (*n*=225) *M (SD)*** | **HKD200k–<500k (*n*=295) *M (SD)*** | **HKD500k–<1m (*n*=275) *M (SD)*** | **≥HKD1m (*n*=205) *M (SD)*** | ***F*(3,996)** | ***p*** |
|---|---|---|---|---|---|---|
| a) Rely on past experiences | 3.81 (0.80) | 3.76 (0.82) | 3.91 (0.75) | 3.99 (0.74) | 4.14** | .006 |
| b) Belief in beating market | 3.08 (0.78) | 3.23 (0.86) | 3.38 (0.83) | 3.60 (0.88) | 15.17*** | < .001 |
| c) Risk-seeking after gains | 2.77 (1.15) | 2.90 (1.19) | 2.96 (1.14) | 2.93 (1.19) | 1.14 | .33 |
| d) Disposition effect | 3.68 (1.02) | 3.64 (1.02) | 3.67 (0.95) | 3.74 (1.02) | 0.43 | .73 |
| e) Risk-averse after losses | 2.80 (1.11) | 2.87 (1.25) | 2.84 (1.13) | 2.19 (0.99) | 18.01*** | < .001 |
| f) Instinct reliance | 3.42 (0.82) | 3.39 (0.93) | 3.53 (0.86) | 3.64 (0.76) | 4.23** | .006 |
| g) Herding (asset types) | 3.34 (0.94) | 3.40 (0.94) | 3.30 (0.97) | 3.09 (1.00) | 4.42** | .004 |
| h) Herding (volume) | 3.25 (1.02) | 3.24 (1.04) | 3.14 (1.09) | 3.13 (1.07) | 0.89 | .45 |
| i) Herding (buy/sell) | 3.53 (0.93) | 3.50 (1.00) | 3.53 (0.99) | 3.35 (0.96) | 1.83 | .14 |
| j) Recency bias | 3.62 (0.82) | 3.56 (0.92) | 3.48 (0.89) | 3.53 (0.89) | 1.11 | .34 |
| k) Authority reliance | 3.71 (0.75) | 3.74 (0.89) | 3.57 (0.87) | 3.44 (0.84) | 6.16*** | < .001 |
| l) FOMO when prices rising | 3.90 (0.82) | 3.74 (1.05) | 3.70 (0.99) | 3.77 (1.00) | 2.00 | .11 |

| Behavioural Statements | <HKD200k (*n*=225) *M (SD)* | HKD200k–<500k (*n*=295) *M (SD)* | HKD500k–<1m (*n*=275) *M (SD)* | ≥HKD1m (*n*=205) *M (SD)* | *F*(3,996) | *p* |
|---|---|---|---|---|---|---|
| m) Price reversal hope | 3.76 (0.97) | 3.64 (1.09) | 3.65 (0.99) | 3.60 (1.14) | 1.06 | .37 |

*$p < .05$. **$p < .01$. ***$p < .001$.

Upward trend

Downward trend

### 4.4.2 Investment Experience in VA

Investment experience is strongly related to most behavioural tendencies. Several tendencies increase linearly with experience, while others follow a more complex, non-linear pattern. As shown in Table 10, the largest effect is for belief in beating the market, which rises from a mean of 2.74 for investors with less than one year of experience to 3.40 for those with 1–5 years and 3.76 for those with at least six years, $F(2, 997) = 62.77$, $p < .001$. Risk-seeking after gains also varies substantially by experience, though in a non-linear fashion: investors in the 1–5 year group show the highest risk-seeking ($M = 3.07$) compared with both beginners ($M = 2.55$) and the most experienced group ($M = 2.09$), $F(2, 997) = 39.66$, $p < .001$. Reliance on instinct increases steadily from 3.04 to 3.56 and 3.78 across the three groups, $F(2, 997) = 33.47$, $p < .001$, and reliance on past experiences similarly rises from 3.46 to 3.92 and 4.11, $F(2, 997) = 32.00$, $p < .001$. FOMO when prices are rising and the disposition effect also intensify with experience, with means increasing from 3.69 to 3.73 and 4.23 for FOMO, $F(2, 997) = 11.00$, $p < .001$, and from 3.41 to 3.71 and 3.97 for the disposition effect, $F(2, 997) = 10.52$, $p < .001$. Recency bias and price reversal hope show smaller but still significant increases with experience (recency bias: 3.40, 3.54, 3.87, $F(2, 997) = 8.38$, $p < .001$; price reversal hope: 3.40, 3.71, 3.78, $F(2, 997) = 6.77$, $p = .001$).

In contrast, several tendencies decrease with greater experience levels. The most pronounced decline is found for risk aversion after losses, which falls from 3.19 among investors with less than

one year of experience to 2.73 among those with 1–5 years and 1.56 among those with at least six years ($F(2, 997) = 64.13$, $p < .001$), indicating that more experienced investors are much less loss averse. Herding in asset type choices also declines with experience, with means of 3.35, 3.38, and 2.48, $F(2, 997) = 36.19$, $p < .001$. Herding in buy/sell decisions drops from 3.66 to 3.54 and 2.70, respectively ($F(2, 997) = 33.99$, $p < .001$). Authority reliance shows a smaller but significant downward trend (3.81, 3.61, 3.44), $F(2, 997) = 6.83$, $p = .001$.

**Table 10**

*Virtual Assets Experience in Behavioural Investment Bias*

| **Behavioural Statements** | **< 1 year (*n*=178) *M (SD)*** | **1–5 years (*n*=735) *M (SD)*** | **≥ 6 years (*n*=87) *M (SD)*** | ***F*(2, 997)** | ***p*** |
|---|---|---|---|---|---|
| a) Rely on past experiences | 3.46 (0.94) | 3.92 (0.74) | 4.11 (0.52) | 32.00*** | < .001 |
| b) Belief in beating market | 2.74 (0.86) | 3.40 (0.82) | 3.76 (0.61) | 62.77*** | < .001 |
| c) Risk-seeking after gains | 2.55 (1.16) | 3.07 (1.14) | 2.09 (0.94) | 39.66*** | < .001 |
| d) Disposition effect | 3.41 (1.00) | 3.71 (0.97) | 3.97 (1.17) | 10.52*** | < .001 |
| e) Risk-averse after losses | 3.19 (1.23) | 2.73 (1.11) | 1.56 (0.68) | 64.13*** | < .001 |
| f) Instinct reliance | 3.04 (1.06) | 3.56 (0.79) | 3.78 (0.54) | 33.47*** | < .001 |
| g) Herding (asset types) | 3.35 (0.94) | 3.38 (0.94) | 2.48 (0.90) | 36.19*** | < .001 |
| h) Herding (volume) | 3.04 (1.19) | 3.24 (1.03) | 3.13 (1.01) | 2.70 | .07 |
| i) Herding (buy/sell) | 3.66 (1.04) | 3.54 (0.92) | 2.70 (0.93) | 33.99*** | < .001 |
| j) Recency bias | 3.40 (0.99) | 3.54 (0.88) | 3.87 (0.63) | 8.38*** | < .001 |

| Behavioural Statements | < 1 year (*n*=178) *M (SD)* | 1–5 years (*n*=735) *M (SD)* | ≥ 6 years (*n*=87) *M (SD)* | *F*(2, 997) | *p* |
|---|---|---|---|---|---|
| k) Authority reliance | 3.81 (0.94) | 3.61 (0.84) | 3.44 (0.71) | 6.83** | .001 |
| l) FOMO when prices rising | 3.69 (1.08) | 3.73 (0.96) | 4.23 (0.73) | 11.00*** | < .001 |
| m) Price reversal hope | 3.40 (1.09) | 3.71 (0.98) | 3.78 (1.39) | 6.77** | .001 |

*$p$ < .05. **$p$ < .01. ***$p$ < .001.

Upward trend

Downward trend

### 4.4.3 Trading Frequency

Among active traders (1–5, 6–10, and ≥ 11 transactions), several behavioural tendencies show clear linear trends with trading frequency. As shown in Table 11, the strongest increasing trend is for belief in beating the market, which rises from 3.17 in the 1–5 group to 3.26 in the 6–10 group and 3.78 among those trading at least 11 times per year, F(3, 996) = 24.84, p < .001. Relying on past experiences also increases steadily with trading frequency (3.72, 4.00, 4.02), F(3, 996) = 12.98, p < .001. Instinct reliance follows a similar rising pattern (3.39, 3.48, 3.75), F(3, 996) = 8.19, p < .001.

The most pronounced declining pattern is for risk aversion after losses, which decreases from 2.98 in the 1–5 group to 2.62 in the 6–10 group and 2.14 among those trading at least 11 times, F(3, 996) = 25.47, p < .001. Herding in asset type choices also declines with trading frequency (3.48, 3.18, 2.99), F(3, 996) = 14.36, p < .001, as does herding based on trading volume (3.32, 3.06, 3.05), F(3, 996) = 5.63, p < .001.

Non-traders (no transactions in the past 12 months, n = 27) differ from traders on several key tendencies. Compared with low-frequency traders (1–5 trades), non-traders report slightly higher belief in beating the market (3.26 vs. 3.17) and somewhat higher risk-seeking after gains (3.15 vs. 3.10), even though they are not actively trading. They also show a similar reliance on past experiences (3.56 vs. 3.72) and instincts (3.37 vs. 3.39), suggesting that their confidence and intuition are not markedly weaker than those of occasional traders. Simultaneously, non-traders tend to be more influenced by others and authorities than most trader groups. Their authority reliance (3.78) is higher than that of all trader categories (3.69, 3.73, 3.27), and their herding based on trading volume (3.48) exceeds that of traders (3.32, 3.06, 3.05). Non-traders also show the highest price reversal hope (3.93 vs. 3.70–3.38 among traders), consistent with a "holding and hoping" stance rather than the active adjustment of positions.

**Table 11**

*Trading Frequency in Behavioural Investment Bias*

| **Behavioural Statements** | **Not traded in P12M (*n*=27) *M (SD)*** | **1–5 txns (*n*=474) *M (SD)*** | **6–10 txns (*n*=316) *M (SD)*** | **≥ 11 txns (*n*=170) *M (SD)*** | ***F*(3,996)** | ***p*** |
|---|---|---|---|---|---|---|
| a) Rely on past experiences | 3.56 (1.09) | 3.72 (0.85) | 4.00 (0.69) | 4.02 (0.62) | 12.98*** | < .001 |
| b) Belief in beating market | 3.26 (1.43) | 3.17 (0.92) | 3.26 (0.68) | 3.78 (0.66) | 24.84*** | < .001 |
| c) Risk-seeking after gains | 3.15 (1.26) | 3.10 (1.13) | 2.60 (1.19) | 2.83 (1.09) | 12.94*** | < .001 |
| d) Disposition effect | 3.26 (1.13) | 3.64 (0.96) | 3.82 (1.01) | 3.60 (1.03) | 4.42** | .004 |
| e) Risk-averse after losses | 2.85 (1.06) | 2.98 (1.14) | 2.62 (1.20) | 2.14 (0.96) | 25.47*** | < .001 |
| f) Instinct reliance | 3.37 (1.11) | 3.39 (0.98) | 3.48 (0.71) | 3.75 (0.60) | 8.19*** | < .001 |

| Behavioural Statements | Not traded in P12M (*n*=27) *M (SD)* | 1–5 txns (*n*=474) *M (SD)* | 6–10 txns (*n*=316) *M (SD)* | ≥ 11 txns (*n*=170) *M (SD)* | *F*(3,996) | *p* |
|---|---|---|---|---|---|---|
| g) Herding (asset types) | 3.56 (1.19) | 3.48 (0.91) | 3.18 (1.00) | 2.99 (0.93) | 14.36*** | < .001 |
| h) Herding (volume) | 3.48 (1.16) | 3.32 (1.02) | 3.06 (1.09) | 3.05 (1.03) | 5.63*** | < .001 |
| i) Herding (buy/sell) | 3.44 (1.19) | 3.55 (0.97) | 3.43 (1.02) | 3.43 (0.87) | 1.24 | .30 |
| j) Recency bias | 2.78 (1.31) | 3.43 (0.94) | 3.74 (0.75) | 3.60 (0.76) | 15.43*** | < .001 |
| k) Authority reliance | 3.78 (1.05) | 3.69 (0.87) | 3.73 (0.78) | 3.27 (0.78) | 14.16*** | < .001 |
| l) FOMO when prices rising | 3.04 (1.65) | 3.65 (0.96) | 3.94 (0.87) | 3.90 (0.98) | 12.36*** | < .001 |
| m) Price reversal hope | 3.93 (1.04) | 3.70 (0.96) | 3.73 (1.12) | 3.38 (1.08) | 5.77*** | < .001 |

*$p < .05$. **$p < .01$. ***$p < .001$.

Upward trend

Downward trend

# 5. Latent Decision Styles: Factor Analytic Findings

## 2025 Factor Structure: Four Behavioural Archetypes

We derived four investor archetypes using exploratory factor analysis (EFA) on the full set of behavioural items related to virtual asset investment decisions. The EFA was conducted on standardised item scores using principal axis factoring with oblique rotation, so that correlated latent dimensions could emerge, and items were allowed to load on more than one factor before we applied a loading cutoff. Items with salient loadings (|loading| ≥ .30) were retained on the factor where they showed the strongest conceptual and statistical fit, and each factor was interpreted as a distinct behavioural archetype based on its highest loading statements. Two items, item (a) Rely on past experiences and item (k) Authority reliance, were excluded from the final solution because they did not load strongly on any factor (all absolute loadings < .30) and showed cross-loadings that did not support a clear conceptual assignment.[2] The resulting four-factor structure provided a parsimonious and interpretable basis for defining the four investor archetypes used in subsequent analyses.

We assigned each participant to one of the four virtual asset investor archetypes by identifying the archetype for which they had the highest factor score and then applied labels that capture the core characteristics of that dominant profile:

- **Socially Influenced Risk Averter「跟風錫身型」**: This investor is heavily influenced by the behaviour of others, focusing on the types of assets that other investors choose. They also track when others buy or sell to inform their decisions and tend to become more risk-averse after experiencing a loss.

[2] The two items "reliance on past experiences" (item a) and "authority reliance" (item k) - featured prominently in the demographic analyses in Section 4 due to their significant variation across groups - were excluded from the archetype classification as neither item loaded strongly on any factor in the EFA.

- **Stubborn Loss Holder「套住唔走型」**: This archetype is characterised by a belief in price reversals; they hold onto assets during price drops, expecting a recovery. They exhibit the "disposition effect", avoiding the sale of assets that have lost value while being quick to sell those that have increased in value.
- **Confident Risk-Seeking Optimist「自信搏殺型」**: These investors rely on their instincts and perceived market knowledge to outperform the market. They often become more risk-seeking following a financial gain (the "house money" effect) and monitor the trading volumes of other investors.
- **FOMO-Driven Overreactor「唯恐執輸型」**: This investor is motivated to buy when prices rise rapidly. They prioritise recent market experiences and short-term trends when analysing potential investments.

Among the 1,000 respondents, the largest group is the Socially Influenced Risk Averters (跟風錫身型), who account for 33.9% of the sample size. Stubborn Loss-Holders (套住唔走型) make up 25.5%, while Confident Risk-Seeking Optimists (自信搏殺型) represent 22.2%. The smallest group is the FOMO-Driven Overreactors (唯恐執輸型), who comprise 18.4% of the participants. See Table 12 below.

**Table 12**

*4 Behavioural Archetypes in 2025*

| Behavioural Statement | Key Heuristic | Socially Influenced Risk Averter 跟風錫身型 (33.9%) | Stubborn Loss Holder 套住唔走型 (25.5%) | Confident Risk-Seeking Optimist 自信搏殺型 (22.2%) | FOMO-Driven Overreactor 唯恐執輸型 (18.4%) |
|---|---|---|---|---|---|
| **g) Herding (asset types)** | Herding (social proof) | 0.719 | 0.006 | 0.160 | -0.075 |
| **i) Herding (buy/sell)** | Herding (social proof) | 0.597 | -0.109 | -0.040 | 0.137 |
| **e) Risk-averse after losses** | Loss aversion | 0.505 | 0.073 | -0.336 | -0.099 |
| **m) Price reversal hope** | Gambler's fallacy | 0.059 | 0.752 | 0.133 | -0.019 |
| **d) Disposition effect** | Disposition effect | -0.103 | 0.592 | -0.033 | 0.072 |
| **f) Instinct reliance** | Overconfidence | -0.181 | -0.066 | 0.520 | -0.131 |
| **b) Belief in beating market** | Overconfidence | -0.053 | 0.107 | 0.454 | 0.089 |
| **c) Risk-seeking after gains** | Mental accounting/ House money effect | 0.213 | 0.146 | 0.403 | -0.005 |
| **h) Herding (volume)** | Herding (social proof) | 0.201 | -0.248 | 0.354 | 0.065 |
| **l) FOMO when prices rising** | Availability/ FOMO | 0.000 | 0.010 | -0.023 | 0.656 |
| **j) Recency bias** | Recency bias | 0.014 | 0.043 | 0.015 | 0.470 |

# 6. Investor Segmentation and Profiling

## 6.1 Demographic of Each Archetype

The demographic profiles of the four archetypes are as follows (see Table 13):

- **Socially Influenced Risk Averter (跟風錫身型)**

  This archetype is characterised as the **youngest and most female-dominant** group. They are predominantly aged **18–29** years (65.8%) and are significantly more likely to be female (42.8%) than the overall population. This profile typically consists of individuals with lower earning power, as over half earn **less than $30,000 a month**.

- **Stubborn Loss Holder (套住唔走型)**

  This group represents a **settled mid-career** demographic. Their defining feature is a unique concentration in the **30–39 age range** (38.0%), making them the most prominent archetype in this life stage. This suggests a portrait of an investor who is more established but potentially less flexible in their financial decision-making.

- **Confident Risk-Seeking Optimist (自信搏殺型)**

  The portrait of this archetype is that of a **high-earning, highly educated male**. They are overwhelmingly male (78.8%) and most likely to hold an **undergraduate degree** (56.3%). Financially, they are the most affluent, with nearly **45% earning $40,000 or more** per month. This represents the profile of professional, high-capacity individuals who feel confident in pursuing market gains.

- **FOMO-Driven Overreactor (唯恐執輸型)**

  This archetype presents a unique social profile, being the only group with a significant overrepresentation of **homemakers** (8.7%) and individuals with **secondary education or less** (16.8%). Their portraits suggest a demographic that may be less connected to formal

academic or professional networks. This group appears more susceptible to market "noise", likely driven by a fear of missing out rather than a structured strategy.

**Table 13**

*Demographic Profiles of 4 Behavioural Archetypes*

| | Socially Influenced Risk Averter 跟風錫身型 (33.9%) | Stubborn Loss Holder 套住唔走型 (25.5%) | Confident Risk-Seeking Optimist 自信搏殺型 (22.2%) | FOMO-Driven Overreactor 唯恐執輸型 (18.4%) | Total |
|---|---|---|---|---|---|
| **Gender** | | | | | |
| Male | 57.2% | 72.5% | 78.8% | 68.5% | 68.0% |
| Female | 42.8% | 27.5% | 21.2% | 31.5% | 32.0% |
| | | | | | |
| **Age** | | | | | |
| 18–29 | 65.8% | 43.5% | 44.6% | 47.3% | 52.0% |
| 30–39 | 24.5% | 38.0% | 39.2% | 34.2% | 33.0% |
| 40–59 | 9.7% | 18.4% | 16.2% | 18.5% | 15.0% |
| | | | | | |
| **Education** | | | | | |
| Secondary & below | 10.3% | 14.9% | 11.7% | 16.8% | 13.0% |
| College | 47.5% | 47.8% | 27.9% | 44.6% | 42.7% |
| Undergraduate | 40.4% | 35.3% | 56.3% | 35.3% | 41.7% |
| Postgraduate | 1.8% | 2.0% | 4.1% | 3.3% | 2.6% |
| | | | | | |
| **Work Status** | | | | | |
| Working | 92.0% | 91.4% | 95.0% | 89.1% | 92.0% |
| Homemaker | 2.7% | 4.3% | 0.5% | 8.7% | 3.7% |
| Student | 5.0% | 4.3% | 4.5% | 1.6% | 4.1% |
| Unemployed | 0.3% | 0.0% | 0.0% | 0.5% | 0.2% |
| | | | | | |
| **Monthly Personal Income** | | | | | |
| <30k | 57.1% | 49.8% | 27.0% | 38.4% | 45.0% |
| 30k–<40k | 25.3% | 27.9% | 28.4% | 26.8% | 27.0% |
| ≥40k | 17.6% | 22.3% | 44.5% | 34.8% | 28.0% |

Overrepresented  Underrepresented

## 6.2 Investment and VA-related Behavioural Correlates of Each Archetype

The following integrated portraits describe each archetype's distinctive profile of investment and virtual asset–related behaviours within the VA markets (see Table 14 below):

- **Socially Influenced Risk Averter (跟風錫身型)**

  Economically, they are entry-level and overrepresented in the lowest income (<$30k) and asset brackets (<$500k). Their investment behaviour is characterised by simplicity and hesitation: they typically hold only one other financial product and are primarily newcomers with less than three years of VA experience. They trade the least frequently (1–5 times per year) and possess only a surface-level ("somewhat") understanding of VAs and regulations.

- **Stubborn Loss Holder (套住唔走型)**

  While they are not the most frequent traders (favouring 6–10 transactions annually), they have the longest market tenure, with the highest proportion of veterans holding VAs for over 10 years. They distinguish themselves through technical and regulatory depth, boasting the highest confidence in digital wallet protection (41.3% "very well") and superior understanding of VA regulations.

- **Confident Risk-Seeking Optimist (自信搏殺型)**

  This group is the "Sophisticated Power-Trader." They manage the most diversified portfolios (holding three to four other products) and have a solid four to five years of experience. They are the most aggressive participants, uniquely overrepresented in high-frequency trading (>30 transactions) and possessing the highest loss tolerance (≥30%). Their self-confidence is backed by the highest "quite well" self-rating for VA understanding (72.5%).

- **FOMO-Driven Overreactor (唯恐執輸型)**

  The "Reactive High-Net-Worth Participant" presents a unique social profile; they are surprisingly wealthy, with a high proportion of members holding liquid assets of $1m or more

(28.3%). They are characterised by intense market reactivity; they are the most active group in the 6–30 transaction range and have the highest self-rated "quite well" awareness of VA regulations (60.3%), likely to ensure they can move quickly on market news.

**Table 14**

*VA Investment Profile of 4 Behavioural Archetypes*

| | Socially Influenced Risk Averter 跟風錫身型 (33.9%) | Stubborn Loss Holder 套住唔走型 (25.5%) | Confident Risk-Seeking Optimist 自信搏殺型 (22.2%) | FOMO-Driven Overreactor 唯恐執輸型 (18.4%) | TOTAL |
|---|---|---|---|---|---|
| **Liquid Assets** | | | | | |
| <200k | 26.8% | 23.9% | 16.2% | 20.1% | 22.5% |
| 200k–<500k | 32.7% | 28.6% | 24.8% | 30.4% | 29.5% |
| 500k–<1m | 31.9% | 23.9% | 30.2% | 21.2% | 27.5% |
| ≥1m | 8.6% | 23.5% | 28.8% | 28.3% | 20.5% |
| | | | | | |
| **Other Financial Product Holdings** | | | | | |
| 0 | 17.1% | 15.3% | 15.8% | 18.5% | 16.6% |
| 1 | 43.4% | 33.3% | 31.1% | 33.7% | 36.3% |
| 2 | 26.8% | 32.2% | 27.9% | 29.9% | 29.0% |
| 3 | 10.9% | 15.7% | 19.4% | 15.2% | 14.8% |
| 4 | 1.5% | 2.7% | 5.0% | 2.7% | 2.8% |
| 5 | 0.3% | 0.8% | 0.9% | 0.0% | 0.5% |
| | | | | | |
| **VA Experience** | | | | | |
| <1 year | 27.4% | 12.2% | 7.2% | 20.7% | 17.8% |
| 1–3 years | 56.3% | 40.4% | 36.0% | 41.3% | 45.0% |
| 4–5 years | 15.9% | 30.6% | 50.5% | 22.3% | 28.5% |
| 6–10 years | 0.3% | 13.7% | 5.4% | 14.7% | 7.5% |
| >10 years | 0.0% | 3.1% | 0.9% | 1.1% | 1.2% |
| | | | | | |
| **Frequency of Trading** | | | | | |
| Not in P12M | 3.2% | 2.4% | 3.2% | 1.6% | 2.7% |
| 1–5 transactions | 61.1% | 39.6% | 51.4% | 28.3% | 47.4% |
| 6–10 transactions | 30.1% | 39.6% | 18.0% | 39.7% | 31.6% |
| 11–30 transactions | 5.3% | 17.6% | 23.4% | 29.9% | 17.0% |
| >30 transactions | 0.3% | 0.8% | 4.1% | 0.5% | 1.3% |

| | |
|---|---|
| Overrepresented | Cells where observed counts exceed expected counts. |
| Underrepresented | Cells where observed counts fall below expected counts. |

| | Socially Influenced Risk Averter 跟風錫身型 (33.9%) | Stubborn Loss Holder 套住唔走型 (25.5%) | Confident Risk-Seeking Optimist 自信搏殺型 (22.2%) | FOMO-Driven Overreactor 唯恐執輸型 (18.4%) | TOTAL |
|---|---|---|---|---|---|
| **Loss tolerance** | | | | | |
| <10% | 7.1% | 5.9% | 4.1% | 8.2% | 6.3% |
| 10–<30% | 78.8% | 72.2% | 64.9% | 75.5% | 73.4% |
| ≥30% | 14.2% | 22.0% | 31.1% | 16.3% | 20.3% |
| | | | | | |
| **Understanding of VA** | | | | | |
| Not at all | 0.9% | 2.7% | 1.4% | 1.6% | 1.6% |
| Not very well | 17.1% | 5.9% | 2.7% | 5.4% | 8.9% |
| Somewhat | 52.5% | 32.5% | 22.1% | 45.7% | 39.4% |
| Quite well | 27.7% | 57.3% | 72.5% | 46.7% | 48.7% |
| Very well | 1.8% | 1.6% | 1.4% | 0.5% | 1.4% |
| | | | | | |
| **Understanding of VA Regulations** | | | | | |
| Not at all | 6.8% | 5.9% | 2.3% | 4.9% | 5.2% |
| Not very well | 19.5% | 11.4% | 11.3% | 7.1% | 13.3% |
| Somewhat | 49.3% | 23.1% | 30.6% | 14.1% | 32.0% |
| Quite well | 23.6% | 34.1% | 52.7% | 60.3% | 39.5% |
| Very well | 0.9% | 25.5% | 3.2% | 13.6% | 10.0% |
| | | | | | |
| **Awareness of Digital Wallet Protection** | | | | | |
| Not at all | 0.0% | 0.4% | 0.0% | 0.0% | 0.1% |
| Not very well | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| Somewhat | 7.5% | 3.6% | 2.0% | 0.0% | 3.8% |
| Quite well | 81.2% | 54.7% | 72.8% | 78.3% | 71.4% |
| Very well | 11.4% | 41.3% | 25.2% | 21.7% | 24.7% |

| | |
|---|---|
| Overrepresented | Cells where observed counts exceed expected counts. |
| Underrepresented | Cells where observed counts fall below expected counts. |

For an overall summary of the demographic and VA-related profiles for the four archetypes, see Table 15 below:

**Table 15**

*A Summary of the 4 VA Investor Archetypes*

| **Archetype Profile** | **Socially Influenced Risk Averter (跟風錫身型)** | **Stubborn Loss Holder (套住唔走型)** | **Confident Risk-Seeking Optimist (自信搏殺型)** | **FOMO-Driven Overreactor (唯恐執輸型)** |
|---|---|---|---|---|
| **Segment Size** | 33.9% | 25.5% | 22.2% | 18.4% |
| **Unique Demographics** | **Youngest & Female-Leaning**: 65.8% aged 18–29; highest female proportion (42.8%); primarily income <$30k (57.1%). | **Mid-Career Focus**: Highest concentration in the 30–39 age bracket (38.0%). | **Affluent Professionals**: 78.8% male; 56.3% undergraduate; nearly 45% earn ≥$40k monthly. | **Diverse & High-Income**: Significant overrepresentation of homemakers (8.7%); 34.8% earn ≥$40k monthly. |
| **VA Investment Behaviours** | **The Cautious Novice**: 83.7% have <3 years of experience; low liquid assets (<$500k); 61.1% make 1–5 trades. | **The Secure Veteran**: Longest tenure (6–10+ years); highest confidence in digital wallet protection (41.3% "very well"). | **The Power-Trader**: High assets (28.8% ≥$1m); aggressive high-loss tolerance (31.1% at ≥30%); most experienced in the 4–5 yr range. | **The Active Participant**: High assets (28.3% ≥$1m); highly active (29.9% make 11–30 trades); best understanding of regulations. |
| **Factor Makeup (Heuristics)** | **Socially-Guided Defence**: High loadings for Herding asset types (0.719), Herding buy/sell (0.597), and Loss Aversion (0.505). | **Irrational Persistence**: Driven by the Gambler's Fallacy (Price reversal hope: 0.752) and the Disposition Effect (0.592). | **Self-Assured Aggression**: Anchored in Overconfidence (Instinct: 0.520; Beating market: 0.454) and the House Money Effect (0.403). | **Sentiment Reactivity**: Lead by intense FOMO when prices are rising (0.656) and Recency Bias (0.470). |

# 7. Cross Wave Comparison of Factor Structures

## 7.1 2022 Factor Structure: Five Behavioural Archetypes

We re-ran the same exploratory factor analysis on the 2022 dataset, but with items l (FOMO when prices rise) and d (Disposition effect) removed, and then derived five investor archetypes by assigning each participant to the factor on which they showed the highest loading. See Table 16 below.

**Table 16**

*5 Behavioural Archetypes in 2022*

| Behavioural Statements | Key Heuristics | Social Herder 跟風從眾型 | Instinct-Driven Optimist 自信直覺型 | Authority-Reliant Defensive Investor 倚權避險型 | Momentum-Based Trend Follower 乘勝追擊型 | Reversal Hopeful Gambler 博價反彈型 |
|---|---|---|---|---|---|---|
| i) Herding (buy/sell) | Herding (social proof) | 0.842 | -0.060 | -0.123 | -0.039 | 0.026 |
| h) Herding (volume) | Herding (social proof) | 0.753 | 0.029 | 0.094 | 0.067 | -0.023 |
| g) Herding (asset types) | Herding (social proof) | 0.741 | 0.035 | 0.080 | -0.023 | 0.020 |
| f) Instinct reliance | Overconfidence | -0.005 | 0.870 | 0.058 | -0.032 | -0.017 |
| e) Risk-averse after losses | Loss aversion | -0.001 | 0.016 | 0.532 | 0.110 | -0.199 |
| k) Authority reliance | Authority bias | 0.098 | 0.191 | 0.480 | -0.047 | 0.105 |
| b) Belief in beating market | Overconfidence | 0.061 | 0.311 | -0.474 | 0.088 | -0.130 |

| Behavioural Statements | Key Heuristics | Social Herder 跟風從眾型 | Instinct-Driven Optimist 自信直覺型 | Authority-Reliant Defensive Investor 倚權避險型 | Momentum-Based Trend Follower 乘勝追擊型 | Reversal Hopeful Gambler 博價反彈型 |
|---|---|---|---|---|---|---|
| j) Recency bias | Recency bias | 0.066 | -0.155 | 0.086 | 0.605 | -0.074 |
| c) Risk-seeking after gains | Mental accounting/ House money effect | 0.014 | 0.039 | -0.166 | 0.431 | 0.098 |
| a) Rely on past experiences | Anchoring | -0.122 | 0.154 | 0.086 | 0.404 | 0.135 |
| m) Price reversal hope | Gambler's fallacy | 0.026 | -0.038 | -0.048 | 0.057 | 0.694 |

## 7.2 Comparison of Archetypes and Behavioural Items

The transition from the 2022 to the 2025 study shows a substantial consolidation in VA investor profiles, with the number of archetypes shrinking from five to four. This evolution suggests that what was previously a more diffuse, trader-leaning set of factors in 2022 coalesced into a more consolidated, mass retail structure by 2025, indicating a clearer and more integrated understanding of how specific behavioural biases cluster in the increasingly regulated VA markets.

Table 17 maps the behavioural economic items within each factor across both studies to illustrate their evolution. The changing trends in both years represent resemblance and convergence, as well as the divergence and consolidation of behavioural items.

**Table 17**

*Comparison of Archetypes and Behavioural Items*

| 2022 Archetype (5 Factors) | Key Behavioural Items (2022) | 2025 Archetype (4 Factors) | Key Behavioural Items (2025) |
|---|---|---|---|
| **Archetype 1: Social Herder** | Herding: Buy/Sell, Volume, & Asset Types | **Archetype 1: Socially Influenced Risk Averter** | Herding: Asset Types & Buy/Sell; **Loss Aversion** |
| **Archetype 2: Instinct-Driven Optimist** | Instinct Reliance; Belief in Beating Market | **Archetype 3: Confident Risk-Seeking Optimist** | Instinct Reliance; Belief in Beating Market; **House Money Effect; Herding (Volume)** |
| **Archetype 3: Authority-Reliant Defensive Investor** | **Loss Aversion**; Authority Bias; Negative Belief in Beating Market | (Consolidated into 2025 Archetype 1) | Loss Aversion |
| **Archetype 4: Momentum-Based Trend Follower** | Recency Bias; **House Money Effect**; Anchoring | **Archetype 4: FOMO-Driven Overreactor** | **Recency Bias**; FOMO/Availability Bias |
| **Archetype 5: Reversal Hopeful Gambler** | **Gambler's Fallacy (Price Reversal Hope)** | **Archetype 2: Stubborn Loss Holder** | **Gambler's Fallacy**; Disposition Effect |

**Resemblances and Convergences**

- **Persistence of Social Proof**: Reliance on others remains a dominant factor. In 2022, "Social Herders" (Arch 1) were defined by mimicking buying/selling and asset types. This core behaviour converged with loss aversion in 2025 to form the Socially Influenced Risk Averter.
- **The "Market-Beater" Identity**: The 2022 "Instinct-Driven Optimist" (Arch 2) and the 2025 "Confident Risk-Seeking Optimist" (Arch 3) both share a foundational overconfidence, specifically the belief that they can beat the market and a heavy reliance on gut instinct.
- **The Gambler's Core**: The singular focus on price reversal hope (Gambler's Fallacy) found in 2022's Archetype 5 is preserved and expanded in 2025's "Stubborn Loss Holder".

**Divergences and Consolidation**

- **Integration of Risk Attitudes with Social Behaviour**: A major divergence is the consolidation of 2022's "Social Herder" and the "Authority-Reliant Defensive Investor." While the 2022 model kept social mimicking and loss aversion separate, the 2025 model integrates them, suggesting that socially influenced investors are also those most likely to become risk-averse after a loss.
- **Expansion of the Optimist Profile**: In 2025, the "Confident Risk-Seeking Optimist" profile became more complex. It absorbed the House Money Effect (becoming risk-seeking after gains) from 2022's Archetype 4 and added Herding (Volume), suggesting that modern optimists do not just trust their gut; they also use market volume as confirmation of their aggressive strategy.
- **Emergence of FOMO**: While 2022 focused on Recency Bias and Anchoring (Arch 4), the 2025 study highlights FOMO (Availability Bias) as a primary driver for the "Overreactor" profile, marking a shift from simply following recent trends to being driven by the psychological fear of missing rising prices.
- **Technical Refinement**: The 2022 model deleted items related to the Disposition Effect and FOMO during the cross-wave comparison to maintain structure, but these items were successfully reintegrated as defining characteristics in the 2025 archetypes.

Table 18 shows that the core decision shortcuts used by Hong Kong VA investors have not disappeared but have been reorganised and intensified in new ways. Social herding, overconfidence, and loss aversion remain foundational forces in both 2022 and 2025, indicating that following the crowd, believing in one's own skill, and being sensitive to losses continue to shape decisions across market cycles. Simultaneously, biases that were previously peripheral or dropped from the 2022 factor structure have moved to centre stage: FOMO and the disposition effect now act as major leading factors in 2025, reflecting investors' heightened tendency to chase rallies and to hold on to losing positions rather than realise losses. Authority bias, which formed a distinct defensive style in 2022, is absorbed into broader patterns by 2025, suggesting that investors' reliance on experts is now woven into other styles instead of defining a separate group. Finally, the gambler's fallacy shifted from a stand-alone "reversal hopeful" profile in 2022 to being tightly integrated with the disposition effect in 2025, capturing a stubborn belief that prices will bounce back and reinforcing the emergence of the Stubborn Loss Holder archetype in the new factor solution.

**Table 18**

*Summary of Behavioural Heuristic Shifts*

| Heuristic Driver | 2022 Status | 2025 Status |
|---|---|---|
| **Social Herding** | Primary Factor | Primary Factor |
| **Overconfidence** | Primary Factor | Primary Factor |
| **Loss Aversion** | Primary Factor | Primary Factor |
| **FOMO** | Deleted from structure | **Major Leading Factor** |
| **Disposition Effect** | Deleted from structure | **Major Leading Factor** |
| **Authority Bias** | Distinct Driver | Consolidated/Reduced |
| **Gambler's Fallacy** | Single-Factor Driver | Integrated with Disposition |

# 8. Implications for Investor Education

The evolution of VA investor archetypes from 2022 to 2025 presents both challenges and opportunities for financial educators and policymakers, because it creates new complexities but also offers clearer, evidence-based behavioural targets within a more regulated market. The shift from diffuse 2022 biases to four distinct 2025 archetypes – Socially Influenced Risk Averter, Stubborn Loss Holder, Confident Risk Seeking Optimist and FOMO Driven Overreactor – enables targeted, bias-specific VA education, for example, explicitly addressing FOMO, herding, overconfidence and loss anchoring using concrete virtual asset examples rather than generic financial literacy.

The SFC 2025 ASPIRe roadmap, which is a five-pillar framework covering access, safeguards, products, infrastructure and relationships, incorporates investor education and stakeholder engagement within its Relationships pillar and complements the conduct safeguards and supervisory measures set out across the broader framework. Within this architecture, behaviourally informed and VA-specific investor education programmes can be delivered using experiential or simulation-based learning tools, emotional regulation and mindfulness components, and personalised or personality-aware approaches that are aligned with each archetype's risk tendencies.

However, this new landscape is more demanding. Emotional and impulse-driven trading is prevalent, with a mass retail investor base increasingly influenced by social proof, news cycles, finfluencer content and FOMO-driven narratives, which often carry more salience than official communications. The Stubborn Loss Holder archetype in particular combines the disposition effect with gambler's fallacy style expectations of reversals, which makes it especially resistant to efforts to reduce risk and less responsive to traditional warnings and disclosures. A widening knowledge and attention gap compounds this pattern, as younger and more digitally native investors rely heavily on platform native, short-form content, which underscores the need to

embed social media and influencer literacy into investor education and to prioritise Gen Z and millennial cohorts through digital-first delivery.

For financial educators, the priority is to deploy segmented strategies that directly tackle clustered patterns of FOMO, social influence and stubborn loss holding and to replace one-size-fits-all campaigns with tailored interventions for each archetype. In practice, this implies bias-specific, VA contextual education for all investor segments, experiential and simulation-based tools and emotional regulation techniques for FOMO Driven Overreactors, social media and finfluencer literacy modules focused on herding and narrative risks for Socially Influenced Risk Averters and younger investors, and data-rich feedback and diversification prompts for Confident Risk Seeking Optimists who may underestimate downside risk.

# 9. Conclusions and Future Directions

Between 2022 and 2025, Hong Kong's virtual asset (VA) markets have continued to develop within an increasingly regulated environment, anchored by licensed VATPs, VA-linked ETFs, and the Regulatory Regime for Stablecoin Issuers that commenced on 1 August 2025. As VA products have become more accessible to the general public, retail participation has broadened, bringing in a wider, less-experienced investor base that is more susceptible to behavioural biases. Across this period, investors continue to rely heavily on heuristic shortcuts — anchoring on past experience, FOMO in rising markets, the disposition effect, gambler's fallacy, social herding, and overconfidence — rather than deliberate, rules-based decision-making.

The 2025 factor solution identifies four distinct archetypes—Socially Influenced Risk Averter, Stubborn Loss Holder, Confident Risk-Seeking Optimist, and FOMO-Driven Overreactor—that together account for the full sample of active VA investors. Each archetype combines a characteristic mix of biases with specific demographic and investment profiles, from younger, lower-income “cautious novices” to affluent, high-frequency “power traders” and reactive high-net-worth participants. Compared with the five more diffuse factors identified in 2022, this consolidation appears to reflect the structural shift towards a more regulated, mass retail market, in which a broader but more consistently structured investor base gives rise to more clearly delineated behavioural patterns. This sharper segmentation shows that one size does not fit all: behavioural vulnerabilities are not uniform, and different investor groups exhibit different combinations of biases, risk appetites, and decision patterns. However, the prominence of FOMO, loss anchoring, and overconfidence in 2025 also indicates that emotionally charged trading is prevalent among active retail VA investors.

For investor education, these findings are both encouraging and demanding. The four-archetype framework offers a sharper behavioural map for financial educators and policymakers, supporting tailored interventions that target specific bias clusters and communication channels. At the same time, the persistence of stubborn loss-holding, recency-driven FOMO, and overconfidence—

especially among more experienced and higher-income investors—shows that formal regulation alone cannot neutralise behavioural vulnerabilities, which are further amplified by finfluencers and social media reinforcing social proof and availability biases.

These results point to a clear implication: education must go beyond generic risk warnings or product facts and directly address how investors actually think, feel, and behave when making VA investment decisions. Investor education in Hong Kong should therefore become more segmented, behaviourally informed, and archetype-specific. Less-experienced investors may need foundational support on volatility, risk perception, and scam awareness; stubborn loss holders may need tools for exit discipline and pre-commitment rules; overconfident and FOMO-driven investors may require interventions that slow impulsive trading, challenge excessive self-belief, and counter social and recency effects. Ultimately, improving investor outcomes will depend less on broad-brush messaging and more on whether education and communication strategies succeed in changing how different archetypes perceive risk, process information, and respond to market cycles.

**Future Directions**

Several avenues for future research follow directly from the limitations and contributions of this study. First, repeating the survey at regular intervals would allow closer monitoring of behavioural shifts across market cycles and regulatory milestones and would test the stability of the four-archetype solution over time. Panel designs would enable stronger inferences about how specific heuristics translate into realised trading patterns, loss profiles, and resilience during stress events.

Second, experimental and quasi-experimental studies are needed to evaluate educational and regulatory interventions tailored to each archetype. Examples include testing alternative warning framings, dashboards, and “portfolio clinic” tools for Stubborn Loss Holders; real-time prompts or “cool off” mechanisms for FOMO-Driven Overreactors; data-rich performance feedback and debiasing nudges for Confident Risk-Seeking Optimists; and socially framed, safety-first messages for Socially Influenced Risk Averters. Embedding such experiments within licensed platforms and

widely used social media channels would provide ecologically valid evidence of what works at scale.

Third, qualitative research, such as focus groups and in-depth interviews with members of each archetype, could deepen the understanding of the narratives, social contexts, and trust relationships that sustain heuristic use. Particular attention should be paid to the roles of finfluencers, online communities, and informal learning channels in shaping perceived expertise, social norms, and reactions to official guidance.

Fourth, future studies should more systematically integrate financial capability and digital literacy measures, as well as psychological constructs such as risk preferences, time discounting, and numeracy, to clarify how structural characteristics (income, education, and assets) interact with behavioural traits in producing high-risk patterns. This would support more precise targeting of both protective regulation and empowerment-oriented education, consistent with Hong Kong's "same business, same risks, same rules" approach.

Finally, as tokenisation, stablecoins, and cross-border VA activity continue to develop, comparative research across jurisdictions would help situate Hong Kong's experience within the broader regional and global trends. Cross-market comparisons of archetype structures and heuristic profiles could reveal which behavioural patterns are context-specific and which are generic to VA markets, informing both local policy and international standard-setting.

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# Appendix

**Reasons for Trading Virtual Assets by Age Group**

| Reason for trading virtual assets | Total (N=1,000) | Aged 18-29 (n=520) | Aged 30-39 (n=330) | Aged 40-69 (n=150) |
|---|---|---|---|---|
| Believe virtual assets will play a major role in the financial market's development | 68% | 65% | 72% | 72% |
| For short-term gain | 65% | 64% | 67% | 64% |
| It is popular / do not want to miss out | 60% | 64% | 57% | 49% |
| Curiosity or participation in new technology | 49% | 51% | 49% | 45% |
| Support / believe in the notion of decentralised finance | 37% | 34% | 42% | 35% |
| For risk diversification | 33% | 24% | 40% | 48% |
| For long-term investment | 31% | 26% | 32% | 47% |
| For taking part in DeFi to earn return | 25% | 23% | 26% | 31% |
| Hedging against fiat currency depreciation/inflation | 24% | 18% | 32% | 27% |
| For personal collection/games | 11% | 13% | 8% | 9% |
| For payment | 8% | 5% | 8% | 17% |
| Disappointment with the traditional financial system | 5% | 5% | 5% | 6% |

*Note*. Multiple responses were allowed for this question.