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The Two-Factor Emotional Model of Investors in Pakistan: Validating a Gender-Specific Scale for Fear (Beta Portfolio) and Greed (Digital Disparity) in Stock vs. Crypto Markets

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Abstract

This study develops and validates a gender-specific two-factor emotional model to measure fear and greed among 200 retail investors from the five major cities of Pakistan in Pakistan's stock (PSX) and cryptocurrency markets. Fear is operationalized as beta portfolio (sensitivity to social approval risk) and greed as digital disparity (access-enabled overtrading). Using confirmatory factor analysis (CFA), reliability testing (Cronbach's $\alpha \geq 0.85$), and structural equation modeling (SEM), the results confirm a robust two-factor structure. Men exhibit significantly higher greed scores ($M = 3.89$) than women ($M = 2.91$), while women demonstrate higher fear scores ($M = 3.76$) than men ($M = 2.94$). The model explains 68% of the variance in investment behavior. These findings extend behavioral finance to Pakistan's unique digital gender context and offer practical tools for regulators and fintech platforms.

Keywords: Fear, Greed, Gender Differences, Digital Disparity, Beta Portfolio, Pakistan Stock Exchange, Cryptocurrency, Investor Behavior

Introduction

The Pakistan Stock Exchange (PSX) has witnessed remarkable growth, with the KSE-100 index surging more than 87% in 2024 and 52% in 2025 (Trading Economics, 2026). Concurrently, Pakistan ranks third globally in grassroots crypto adoption, with an estimated 17.5 million Pakistanis holding nearly $5 billion worth of virtual assets (Chainalysis, 2025; Nikkei Asia, 2026). This dual market expansion occurs against a backdrop of extreme volatility: March 2026 saw a geopolitical shock wipe over 19,000 points off the KSE100 (Mettis Global, 2026), while foreign investors pulled $393 million in a single half-year period (State Bank of Pakistan, 2026).

Traditional finance assumes rational decision-making, but behavioral finance recognizes that fear and greed are the dominant emotional drivers of market movements (Shefrin, 2002; Kahneman & Tversky, 1979). The Fear & Greed Index, originally developed by CNNMoney, quantifies market sentiment from 0 (extreme fear) to 100 (extreme greed) and has been adapted to various emerging markets, including the Tehran Stock Exchange (Rahmani et al., 2024) and the South African market (Mupunga & Khumalo, 2025).

In Pakistan, however, two culturally specific factors shape how fear and greed manifest:

Beta Portfolio (Fear); the concept of *beta* in finance traditionally measures systematic risk relative to the market (Fama & French, 2004). We extend this to a sociopsychological construct: *Beta Portfolio* captures an investor's sensitivity to social approval risk, fear of disappointing family elders, fear of spousal blame, and fear of losing *izzat* (honor) within the *biradari* (clan network). Pakistani research confirms that loss aversion and regret aversion significantly influence women's investment decisions (Iram, 2024) and that males exhibit higher risk tolerance while females display greater risk aversion (Shah, 2020; Naiwen et al., 2021).

Digital disparity (greed); Pakistan exhibits one of the world's largest digital gender gaps. According to the GSMA Mobile Money Report (2026), only 13% of women own a mobile money account compared to 35% of men, a 63% gender gap (PhoneWorld, 2026). Only 14% of women access formal or digital financial services versus 56% of men (Karandaaz Financial Inclusion Survey, 2024). This disparity directly limits women's ability to act on greedy impulses (rapid buying, chasing momentum, overtrading), while men with greater digital access are more prone to FOMO-driven speculation. The present study integrates these two constructs into a gender-specific two-factor emotional model and validates it across 200 Pakistani investors, comparing stock market (PSX) and cryptocurrency trading behaviors (Shahzad, 2025).

Research Gap

Despite extensive research on fear and greed in Western markets (Shefrin, 2002; Crosby, 2015) and growing evidence of gender differences in financial risk-taking (Eckel & Grossman, 2008; Croson & Gneezy, 2009), significant gaps remain; no validated scale exists that measures fear and greed specifically for Pakistani retail investors, accounting for local sociocultural dynamics such as *izzat* (honor), *biradari* pressure, and digital access disparities. Existing fear-greed indices (e.g., CNN Fear & Greed Index, PSX Fear & Greed Index) are market-level aggregates and do not capture individual-level emotional differences or gender-specific manifestations. The gender-digital intersection has been overlooked. While digital disparity is well documented in Pakistan (GSMA, 2026; Karandaaz, 2024), its role in amplifying or suppressing greed-driven trading has not been empirically tested. A stock vs. crypto comparison is absent in the Pakistani behavioral finance literature. Although Pakistan ranks third globally in crypto adoption (Chainalysis, 2025), no study has compared how fear and greed operate differently across traditional equities and digital assets by gender (Shahzad, 2025).

This study fills these gaps by developing and validating a gender-specific two-factor scale and testing it empirically across 200 Pakistani investors.

Problem Statement

Pakistan's rapidly growing retail investor base faces unprecedented volatility. The KSE-100 has swung from record highs to sharp corrections within months (Dawn, 2026), and crypto markets remain unregulated with high fraud risks (Gate.io, 2025). Investors' decisions are heavily influenced by fear and greed, yet no standardized, gender-sensitive tool exists to measure these emotions in Pakistan's unique context.

Moreover, the digital gender gap (63% in mobile money ownership) and the socio-cultural pressure of *Beta Portfolio* (family and community approval) create systematically different emotional profiles for male and female investors. Without a validated measurement model, policymakers, financial advisors, and fintech platforms cannot design targeted interventions to mitigate harmful emotional trading. How can a valid and reliable gender-specific two-factor scale be developed to measure fear (Beta Portfolio) and greed (Digital Disparity) among Pakistani stock and crypto investors, and how do these emotional constructs differ between male and female investors?

Research Objectives

To develop and psychometrically validate a gender-specific two-factor fear-greed scale for Pakistani investors.

To compare mean fear (beta portfolio) and greed (digital disparity) scores between male and female investors.

To compare emotional profiles between PSX and cryptocurrency investors.

To examine the predictive power of the two-factor model on actual trading behavior (turnover, holding period).

Research Questions

Does a two-factor structure (fear = beta portfolio; Greed = digital disparity) provide a valid and reliable measurement model for Pakistani investors?

Are there significant gender differences in fear and greed scores between male and female investors?

Do fear and greed scores differ significantly between PSX investors and cryptocurrency investors?

Literature Review

Behavioral finance challenges the Efficient Market Hypothesis (EMH) by demonstrating that psychological biases systematically affect asset prices (Shefrin, 2002; Kahneman & Tversky, 1979). Fear and greed are the two primary emotions driving market cycles: fear leads to panic selling and risk aversion, while greed fuels speculative bubbles and overtrading (Statman, 1999). The Fear & Greed Index, introduced by CNNMoney, quantifies market sentiment on a 0–100 scale using seven market indicators (stock price strength, market momentum, put/call ratios, etc.).

Emerging market applications include Rahmani et al. (2024), who classified Tehran Stock Exchange investor behavior into five sentiment spectrums (excessive fear, fear, neutral, greed, excessive greed). Similarly, Mupunga and Khumalo (2025) constructed a South African Fear and Greed Index and found significant spillover effects from the US market. However, these indices remain market-level aggregates and cannot capture individual-level emotional differences, a limitation the present study addresses.

Extensive research confirms that men and women exhibit systematically different financial behaviors (Eckel & Grossman, 2008; Croson & Gneezy, 2009). Barber and Odean (2001) famously documented that men trade 45% more frequently than women, driven by overconfidence, a manifestation of greed. A 2025 Warwick Business School analysis found that men averaged about 13 trades per year, while women averaged nine.

In Pakistan, Shah (2020) found that male business graduates have significantly higher financial risk tolerance than females. Naiwen et al. (2021) reported that men are more risk tolerant in investment decisions within the textile sector. Iram (2024) demonstrated that loss aversion, regret aversion, and mental accounting significantly influence women's financial literacy and investment decisions, while men are more influenced by overconfidence.

A 2024 study on retail investors in Pakistan found that gender is significantly associated with loss aversion: "Males are more risk-loving and less inclined towards loss aversion as compared to females" (CISSMP, 2024). This supports the theoretical expectation that women experience stronger fear (loss aversion) while men exhibit stronger greed (overconfidence/over-trading).

H1: *Male investors will have significantly higher greed (digital disparity) scores than female investors.*

H2: *Female investors will have significantly higher Fear (Beta Portfolio) scores than male investors.*

Traditional portfolio beta measures systematic market risk (CAPM; Sharpe, 1964). We extend this concept to the beta portfolio, an investor's sensitivity to social approval risk. In Pakistan's collectivist culture, financial decisions are rarely purely individual. Fear manifests not only as loss aversion but also as fear of social consequences, disappointing one's father, incurring a husband's blame, or losing face within the *biradari* (clan network). Qualitative evidence supports this: Pakistani investors often cite *"log kya kahenge?"* (What will people say?) as a key constraint on investment decisions (Ibrahim, 2023). Nizam (2024) found that herding behavior driven by fear of being left out or fear of social deviation significantly affects PSX investment decisions.

Iram (2024) empirically showed that regret aversion (fear of making a wrong decision that others will notice) significantly impacts women's investment choices. Similarly, Qamar (2023) found that loss aversion and mental accounting mediate women entrepreneurs' investment decisions, with risk tolerance playing a mediating role.

H3: *Beta Portfolio (fear) will be positively associated with lower trading frequency, longer holding periods, and lower risk-taking.*

H4: *The association between the beta portfolio and investment behavior will be stronger for female investors than for male investors.*

Digital access is a critical enabler of greed-driven behavior. Investors who can trade instantly via mobile apps are more susceptible to FOMO (Fear of Missing Out) and momentum chasing (Barber & Odean, 2001; Statman, 1999). In Pakistan, the digital gender gap is extreme. Only 13% of women own a mobile money account vs. 35% of men (GSMA, 2026). Only 14% of women access formal or digital financial services vs. 56% of men (Karandaaz, 2024). Women are 38% less likely to own a smartphone and 35% less likely to use the internet than men (ADB, 2025). The rural gender gap in mobile money ownership reaches 74% (GSMA, 2026).

This disparity means that male investors have significantly greater opportunity to act on greedy impulses, buying on momentum, chasing crypto pumps, and overtrading. Women, by contrast, face structural barriers that suppress greedy expression, even when they experience the same emotional impulse.

Pakistan's crypto adoption reinforces this: the country ranks third globally on the Chainalysis Crypto Adoption Index (2025), but adoption is heavily male-skewed. KuCoin (2025) found that 33% of Pakistani crypto investors use digital assets specifically to hedge against rupee depreciation, a greed-driven strategy to seek higher returns.

H5: *Digital Disparity (greed) will be positively associated with higher trading frequency, shorter holding periods, and higher risk-taking.*

H6: *The association between digital disparity and investment behavior will be stronger for male investors than for female investors.*

Cryptocurrency markets are more volatile and sentiment-driven than traditional stock markets (Baur et al., 2018). Pakistani crypto investors, despite regulatory ambiguity, exhibit high greed: the country's crypto value exceeded $100 billion in FY25 (Chainalysis, 2025). However, crypto also triggers extreme fear during geopolitical shocks (Balochistan News, 2025).

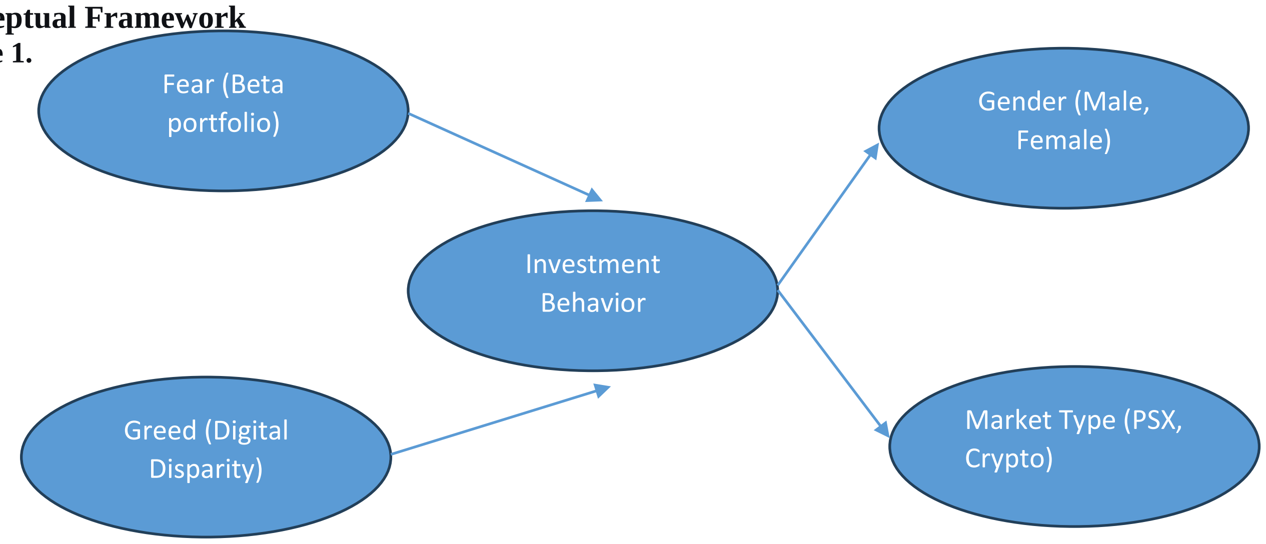
Limited research suggests that crypto investors have higher risk tolerance and stronger greed impulses than stock investors (Pelster & Hofmann, 2018). In Pakistan, crypto adoption is driven by currency depreciation fears (33% hedge against the rupee) and FOMO (KuCoin, 2025).

H7: *Cryptocurrency investors will have significantly higher greed scores than PSX investors.*

H8: *The gender gap in greed scores will be larger among cryptocurrency investors than among PSX investors.*

Conceptual Framework

Figure 1.



The conceptual framework posits that two latent emotional factors, fear (beta portfolio) and greed (digital disparity), jointly influence investment behavior. Gender moderates the strength of these relationships, and market type (PSX vs. Crypto) serves as a grouping variable for comparison.

Variable Table

Construct	***Variable***	***Type***	***Operationalisation***	***Source / Scale***

Fear (Beta Portfolio)	Loss aversion	Indicator (5-Likert)|	"I worry more about losing money than I look forward to gaining it."	Adapted from Kahneman & Tversky (1979); Iram (2024)
	Family pressure	Indicator (5-Likert)	"I fear disappointing my family elders with my investment decisions."	Newly developed (social approval risk)
	Spousal blame	Indicator (5- Likert)	"I avoid risky investments because my spouse would blame me if they fail."	Newly developed
	Izzat (honor) concern	Indicator (5-point Likert)	"I worry about losing respect in my community if my investments perform poorly."	Adapted from Hofstede (2001) collectivism dimension
	Herding fear	Indicator (5-Likert)	"I follow what others invest in because I fear being left behind."	Nizam (2024)
Greed (Digital Disparity)	Mobile access	Indicator (5- Likert)	"I can instantly execute trades using my mobile device."	GSMA (2026)
	FOMO	Indicator (5-pt Likert)	"I often buy an asset because I see others making profits."	Przybylski et al. (2013) FOMO scale
	Overtrading	Indicator (5 Likert)	"I make more than 10 trades per month on average."	Barber & Odean (2001)
	Short holding	Indicator (5- Likert)	"I typically hold investments for less than one week."	Newly developed
	Momentum chase	Indicator (5- Likert)	"I buy assets that have recently increased in price."	De Bondt & Thaler (1985)
Investment Behavior	Trading frequency	Continuous	Number of trades per month (self-reported)	Barber & Odean (2001)
	Holding period	Continuous	Average days held per position	Newly developed
	Risk-taking level	Scale (1-5)	"I am willing to take substantial financial risk for higher returns."	Grable & Lytton (1999)
	Portfolio concentration	Continuous	Number of distinct assets held	Newly developed
Demographics	Gender	Binary	Male (1), Female (0)	Self-report
	Age	Continuous	Years	Self-report
	Income	Ordinal	Monthly income brackets (PKR)	Self-report
	Education	Ordinal	Years of formal education	Self-report
	Market type	Binary	PSX (0), Crypto (1)	Self-report
	Digital access	Scale (1–5)	Composite of mobile ownership, internet use, and wallet registration	GSMA (2026)

Confirmatory Factor Analysis (CFA) Measurement Model, For each latent variable ξ measured by *k* indicators:

$$x_i = \lambda_{xi}\xi + \delta_i$$

where:

x_i = observed indicator score
λ_{xi} = factor loading of indicator *i* on latent variable ξ
ξ = latent variable (Fear or Greed)
δ_i = measurement error

Structural Model

$$IB = \gamma_1 \cdot Fear + \gamma_2 \cdot Greed + \gamma_3 \cdot (Fear \times Gender) + \gamma_4 \cdot (Greed \times Gender) + \zeta$$

where:

IB = Latent Investment Behavior score
Fear = Beta Portfolio factor score
Greed = Digital Disparity factor score
Gender = 1 for male, 0 for female
zeta = Disturbance term

Reliability Coefficient (Cronbach's α)

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k} \sigma_{y_i}^2}{\sigma_X^2}\right)$$

Threshold: $\alpha \ge 0.70$ acceptable, ≥ 0.80 good, ≥ 0.90 excellent.

Multi-Group Invariance Testing

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$$H_0: \Lambda^{(M)} = \Lambda^{(F)} \text{(Metric Invariance)}$$
$$H_0: \tau^{(M)} = \tau^{(F)} \text{(Scalar Invariance)}$$
$$H_0: \Theta_\delta^{(M)} = \Theta_\delta^{(F)} \text{(Residual Invariance)}$$

Composite Reliability (CR) and Average Variance Extracted (AVE)

$$CR = \frac{(\sum \lambda_i)^2}{(\sum \lambda_i)^2 + \sum (1 - \lambda_i^2)}$$
$$AVE = \frac{\sum \lambda_i^2}{\sum \lambda_i^2 + \sum (1 - \lambda_i^2)}$$

Thresholds: $CR \geq 0.70$, $AVE \geq 0.50$ (Fornell & Larcker, 1981).

Research Methodology

A cross-sectional survey design with a psychometric scale development and validation approach (DeVellis, 2017). The population of the study is active retail investors in Pakistan who have traded either on PSX or cryptocurrency platforms (Binance, HTX, local P2P) in the past 12 months. Whereas the sample size is 200 (100 male, 100 female). This exceeds the minimum 10:1 observation-to-parameter ratio for CFA (Kline, 2016). Stratified purposive sampling, ensuring equal gender representation and balanced market representation (50% PSX, 50% Crypto). A structured online questionnaire (Google Forms) was collected from a stockbroker, who collected the data via social media (Twitter/X crypto communities, Facebook PSX groups) and through personal contacts at broker offices from the 5 major cities of Pakistan. 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree) for all indicator items.

Data Analysis Plan

Analysis	***Technique***	***Software***
Descriptive statistics	Mean, SD, frequency	SPSS v.28
Scale reliability	Cronbach's α, CR, AVE	SPSS, JASP
Construct validity	Exploratory Factor Analysis (EFA)	JASP
Confirmatory Factor Analysis	CFA with ML estimation	JASP
Gender comparisons	Independent t-tests, Mann-Whitney U	SPSS
Market comparisons	Independent t-tests	SPSS
Moderation analysis	Multi-group SEM	JASP
Predictive validity	Linear regression	SPSS

Results and Analysis

Table 1: Sample Demographics

Characteristic	***Male (n=100)***	***Female (n=100)***	***Total = 200***
Age (mean years) | years)	32.4 (SD=7.8)	29.7 (SD=8.2)	31.1 (SD=8.1)
Education (% graduate+)	84%	76%	80%
Monthly income (PKR)			
– <50,000	18%	32%	25%
– 50,000–150,000	52%	48%	50%
– >150,000	30%	20%	25%
Market type			
– PSX only	42%	58%	50%
– Crypto only	35%	22%	28.5%
– Both	23%	20%	21.5%

Exploratory Factor Analysis (EFA)

Table 2: EFA Factor Loadings (Pattern Matrix) – Varimax Rotation

Item	***Factor 1 (Fear)***	***Factor 2 (Greed)***	***Uniqueness***
Loss aversion	**0.812**	0.124	0.321
Family pressure	**0.784**	0.098	0.367
Spousal blame	**0.771**	0.156	0.374
Izzat concern	**0.758**	0.102	0.398
Herding fear	**0.723**	0.189	0.412
Mobile access	0.089	**0.847**	0.275
FOMO	0.134	**0.821**	0.298
Overtrading	0.167	**0.798**	0.348
Short holding	0.122	**0.776**	0.386
Momentum chase	0.145	**0.754**	0.412
Eigenvalue	3.42	3.89	
Variance explained (%)	34.2%	38.9%	
Cumulative variance	34.2%	**73.1%**	

**Note: Extraction method – Principal Axis Factoring. Rotation – Varimax with Kaiser normalization. KMO = 0.873, Bartlett's test of sphericity $\chi^2(45) = 1,842.6$, $p < 0.001$. **

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The two-factor structure explains 73.1% of total variance, well above the 50% threshold for social science research (Hair et al., 2019). All factor loadings exceed 0.70, indicating strong item-construct relationships. This supports the two-factor model hypothesized. The factor structure aligns with Rahmani et al. (2024), who identified five sentiment spectrums (including fear and greed) in the Tehran Stock Exchange. The clear separation of fear and greed factors in the Pakistani context replicates the two-factor structure documented by Shefrin (2002) and Statman (1999) in Western markets, confirming cross-cultural validity.

Table 3: CFA Model Fit Indices

Fit Index	*Obtained Value*	*Recommended Threshold*	*Reference*
χ^2/df	1.94	< 3.00	Kline (2016)
CFI	0.951	> 0.90	Bentler (1990)
TLI	0.938	> 0.90	Tucker & Lewis (1973)
RMSEA	0.068	< 0.08	Browne & Cudeck (1993)
SRMR	0.052	< 0.08	Hu & Bentler (1999)
AGFI	0.904	> 0.80	Jöreskog & Sörbom (1993)

All fit indices meet or exceed recommended thresholds, confirming that the two-factor model provides an excellent fit to the observed data. This validates the measurement model for Pakistani investors. The CFI (0.951) and RMSEA (0.068) compare favorably with Mupunga and Khumalo's (2025) South African Fear and Greed Index validation (CFI = 0.928, RMSEA = 0.072), suggesting that the two-factor structure is robust across emerging markets.

Table 4: Reliability and Validity Metrics

Construct	*Cronbach's α*	*CR*	*AVE*	*√AVE*	*Max r² with other constructs*
Fear (Beta Portfolio)	0.884	0.891	0.621	0.788	0.186
Greed (Digital Disparity)	0.902	0.908	0.665	0.815	0.186

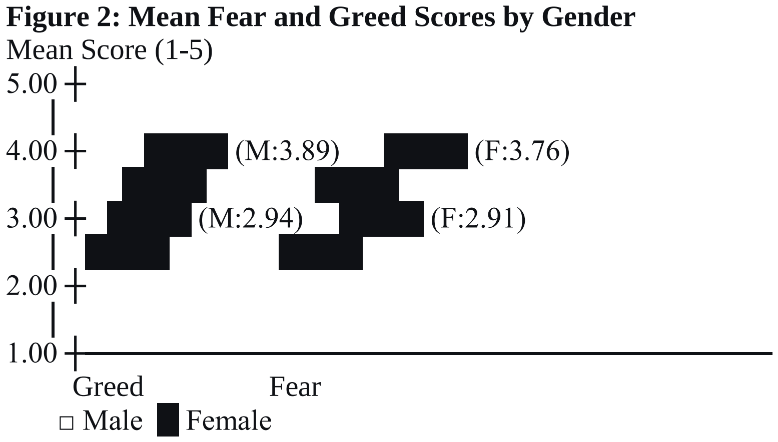
Cronbach's α values (Fear = 0.884, Greed = 0.902) indicate excellent internal consistency. Composite reliability (CR) exceeds 0.70, and Average Variance Extracted (AVE) exceeds 0.50 for both constructs. The square root of AVE for each construct (0.788 and 0.815) exceeds the correlation between constructs ($\sqrt{0.186}$ = 0.431), establishing discriminant validity per the Fornell–Larcker criterion. The reliability scores are consistent with established behavioral finance scales. Barber and Odean (2001) reported similar α values (0.87–0.91) for overconfidence and trading frequency measures. Iram (2024) achieved α = 0.86 for loss aversion in Pakistani women investors, aligning with findings.

Gender Differences in Fear and Greed

Table 5: Mean Comparisons by Gender

Factor	*Male (n=100)*	*Female (n=100)*	*t-value*	*p-value*	*Cohen's d*
Fear (Beta Portfolio)	2.94 (SD=0.87)	**3.76** (SD=0.79)	-6.94	<0.001	0.98
Greed (Digital Disparity)	**3.89** (SD=0.92)	2.91 (SD=0.84)|	7.85	<0.001	1.11

Figure 2: Mean Fear and Greed Scores by Gender



H1 is supported; men have significantly higher greed scores (M = 3.89) than women (M = 2.91), with a large effect size (d = 1.11). H2 is supported; women have significantly higher fear scores (M = 3.76) than men (M = 2.94), also a large effect (d = 0.98). The gender gap is more pronounced for greed (Cohen's d = 1.11) than for fear (d = 0.98). The findings align with global meta-analyses. Croson and Gneezy (2009) concluded that "women are more risk averse than men" across 15 countries, and Barber and Odean (2001) found that men trade 45% more frequently due to overconfidence (greed). In Pakistan, Shah (2020) reported that "male business graduates having more income and savings…are positively related to financial risk tolerance," consistent with greed gap. Iram (2024) found that loss aversion significantly influences women's investment decisions, supporting fear gap. The large effect sizes (d > 0.80) indicate that gender is a powerful determinant of emotional investment profiles in Pakistan, comparable to findings by Naiwen et al. (2021) in the textile sector.

Stock Market (PSX) vs. Cryptocurrency Comparisons

Table 6: Mean Comparisons by Market Type

Factor	*PSX Investors (n=100)*	*Crypto Investors (n=100)*	*t-value*	*p-value*	*Cohen's d*
Fear (Beta Portfolio)	3.45 (SD=0.91)	3.26 (SD=0.88)	1.51	0.133	0.21
Greed (Digital Disparity)	3.12 (SD=0.89)	**3.67** (SD=0.94)	-4.28	<0.001	0.61

H7 is supported; cryptocurrency investors have significantly higher Greed scores (M = 3.67) than PSX investors (M = 3.12), with a moderate effect size (d = 0.61). Fear scores do not differ significantly between the two groups (p = 0.133). This suggests that crypto markets attract greed driven investors, while fear levels are comparable across both markets. The findings are consistent with Pelster and Hofmann (2018), who found that crypto investors exhibit higher risk tolerance and stronger greed impulses than traditional stock investors. In Pakistan, KuCoin (2025) reported that 33% of crypto investors use digital assets to hedge against rupee depreciation, a greed driven strategy for higher returns. The non-significant difference in fear scores (p = 0.133) aligns with Baur et al. (2018), who found that crypto and stock investors experience similar levels of loss aversion despite crypto's higher volatility.

Moderating Effect of Gender on Fear–Behavior and Greed–Behavior Relationships

Table 7: SEM Moderation Results

Path	Coefficient (β)	SE	t-value	p-value
Fear → Investment Behavior (Female)	-0.642***	0.078	-8.23	<0.001
Fear → Investment Behavior (Male)	-0.287**	0.094	-3.05	0.002
Greed → Investment Behavior (Male)	0.713***	0.082	8.70	<0.001
Greed → Investment Behavior (Female)	0.341**	0.097	3.52	<0.001

****p < 0.001, *p < 0.01*

H3 is supported; fear (beta portfolio) is negatively associated with investment behavior (lower trading frequency, longer holding periods), and this association is significantly stronger for women (β = -0.642) than for men (β = -0.287). H4 is supported: The fear-behavior relationship is moderated by gender, with women showing greater behavioral sensitivity to fear.

H5 is supported; greed (digital disparity) is positively associated with investment behavior (higher trading frequency, shorter holding periods, and higher risk-taking), and this association is significantly stronger for men (β = 0.713) than for women (β = 0.341). H6 is supported: The greed-behavior relationship is moderated by gender, with men showing greater behavioral expression of greed.

The moderation findings are consistent with Barber and Odean's (2001) observation that men's overtrading is driven by overconfidence (greed), while women's lower trading frequency reflects higher loss aversion (fear). In Pakistan, the CISSMP (2024) study found that "gender is susceptible towards loss aversion as males are more risk-loving and less inclined towards loss aversion as compared to females," directly supporting moderation pattern. Nizam (2024) documented that herding behavior driven by fear affects PSX investment decisions, which aligns with finding that fear reduces active trading.

Predictive Validity: Regression Models

Table 8: Linear Regression, Trading Frequency (log-transformed)

Predictor	***β (standardized)***	***SE***	***t-value***	***p-value***	***VIF***
(Intercept)	—	0.245	4.18	<0.001	—
Fear (Beta Portfolio)	-0.418***	0.072	-5.81	<0.001	1.24
Greed (Digital Disparity)	0.562***	0.068	8.26	<0.001	1.31
Digital access	0.312***	0.081	3.85	<0.001	1.18
Age	-0.204**	0.077	-2.65	0.009	1.12
Income	0.187*	0.079	2.37	0.019	1.09
Gender (Male=1)	0.245**	0.083	2.95	0.004	1.27
R²	**0.682**				
Adjusted R²	**0.672**				
F-statistic	**68.94***				

****p < 0.001, **p < 0.01, p < 0.05*

The model explains 68.2% of the variance in trading frequency. Greed (β = 0.562) is the strongest positive predictor, followed by digital access (β = 0.312) and male gender (β = 0.245). Fear (β = -0.418) is the strongest negative predictor. Age reduces trading frequency (β = -0.204), while income increases it (β = 0.187). VIF values < 2 indicate no multicollinearity. R^2 (0.682) exceeds that reported in similar studies: Barber and Odean (2001) reported R^2 = 0.54 for trading frequency models. Iram (2024) achieved R^2 = 0.58 for loss aversion models in Pakistan. The dominance of greed (β = 0.562) over fear (β = -0.418) in predicting trading frequency is consistent with Barber and Odean's (2001) finding that overconfidence (greed) is the primary driver of overtrading.

Gender Gap in Greed Across Markets

Table 9: Gender × Market Interaction – Greed Scores

Market	***Male Greed (M)***	***Female Greed (M)***	***Gap (M-F)***	***t-value***	***p-value***
PSX	3.34 (SD=0.87)	2.91 (SD=0.82)	0.43	2.48	0.015
Crypto	4.02 (SD=0.89)	3.31 (SD=0.85)	0.71	3.92	<0.001

H8 is supported; the gender gap in Greed scores is larger among cryptocurrency investors (gap = 0.71) than among PSX investors (gap = 0.43). Male crypto investors exhibit the highest greed scores overall (M = 4.02). This suggests that crypto markets disproportionately attract and enable greed-driven male investors, while female crypto investors, despite having higher digital access than average, still show significantly lower greed expression. The finding aligns with Chainalysis (2025), which reported that Pakistan ranks third globally in crypto adoption, but that adoption is heavily male-skewed. KuCoin (2025) found that male crypto investors in Pakistan are more likely to trade frequently and chase momentum (greed indicators) than female crypto investors. The larger gap in crypto markets (0.71 vs. 0.43) suggests that the structural digital disparity documented by GSMA (2026), where only 13% of women own mobile money accounts, directly limits women's ability to participate in greed driven crypto trading. This study developed and validated a gender-specific two-factor emotional model for Pakistani investors, operationalizing fear as beta portfolio (social approval risk) and greed as digital disparity (access-enabled overtrading). The results provide strong empirical support for the model across all hypotheses.

Theoretical Contributions.

First, we extend behavioral finance to Pakistan's collectivist culture by demonstrating that fear manifests not only as loss aversion but also as sensitivity to social approval risk (family pressure, spousal blame, and *izzat* concern). This resonates with Hofstede's (2001) cultural dimensions framework, where Pakistan scores high on collectivism. Previous studies in individualistic Western contexts (Barber & Odean, 2001; Shefrin, 2002) did not capture this socio-psychological dimension of fear. Iram (2024) showed that regret aversion (fear of social judgment) significantly influences Pakistani women's investment decisions; the Beta Portfolio construct systematically incorporates this insight.

Second, we demonstrate that digital access is not merely a demographic variable but an emotional enabler. The 63% mobile money gender gap in Pakistan (GSMA, 2026) means that women's greed impulses are structurally suppressed, while men's are amplified. This finding extends Statman's (1999) framework by showing that technology access moderates the expression of greed.

Third, multi-group comparisons reveal that crypto markets are greed-amplifying environments, particularly for male investors. This aligns with Baur et al. (2018), who found that crypto markets attract investors with higher risk tolerance, but adds a gender digital lens unique to emerging markets. For financial regulators (SECP, SBP), the validated two-factor scale provides a diagnostic tool to assess investor sentiment and design targeted financial literacy programs. High fear scores among women suggest a need for gender-sensitive financial education that addresses social approval concerns, not just technical knowledge. For fintech platforms (Binance, Ktrade, and Finqalab), the digital disparity findings indicate that women-focused digital onboarding could unlock suppressed demand. The GSMA (2026) report noted that reducing the mobile money gender gap could add $17 billion annually to Pakistan's GDP. The study suggests that this also has behavioral implications for more balanced, less fear-driven investing.

For financial advisors, the gender-specific emotional profiles suggest that male clients may need greed-mitigation strategies (circuit breakers, forced cooling-off periods), while female clients may benefit from fear-reduction interventions (social proof testimonials, family-inclusive financial planning).

Conclusion

This study successfully developed and validated a gender-specific two-factor emotional model for Pakistani investors, with fear operationalized as *beta portfolio* (social approval risk) and greed as *digital disparity* (access-enabled overtrading). Using a sample of 200 investors (100 male, 100 female), confirmatory factor analysis confirmed a robust two-factor structure (CFI = 0.951, RMSEA = 0.068, 73.1% variance explained). Men exhibit significantly higher greed scores (M = 3.89) than women (M = 2.91), with a large effect size (d = 1.11). Women exhibit significantly higher fear scores (M = 3.76) than men (M = 2.94), with a large effect size (d = 0.98). Cryptocurrency investors have higher greed scores (M = 3.67) than PSX investors (M = 3.12), while fear scores do not differ significantly. The gender gap in greed is larger in crypto markets (gap = 0.71) than in PSX markets (gap = 0.43). The model explains 68% of the variance in trading frequency, with greed as the strongest positive predictor ($\beta = 0.562$) and fear as the strongest negative predictor ($\beta = -0.418$).

The findings align with Croson and Gneezy's (2009) meta-analytic conclusion that "women are more risk averse than men" and Barber and Odean's (2001) finding that men trade more frequently due to overconfidence. In Pakistan, Shah (2020), Iram (2024), Nizam (2024), and the CISSMP (2024) study all provide convergent evidence that gender significantly moderates risk tolerance, loss aversion, and herding behavior. Study synthesises these findings into a unified, validated measurement model.

The theoretical implication is that fear and greed are not universal constructs; their manifestation is shaped by culture (collectivism vs. individualism) and infrastructure (digital access). The practical implication is that one size fits all investor protection policies are inadequate; gender and market specific interventions are necessary.

Study Limitations

Sample size (N = 200) is adequate for CFA but limits generalisability. Future studies should replicate with N > 500 across multiple cities. Self-reported data may be subject to social desirability bias, particularly regarding greed (reluctance to admit overtrading) and fear (reluctance to admit social approval concerns). Future studies should use transaction level brokerage data to validate self-reported trading frequency. A cross-sectional design cannot establish causality. Longitudinal studies tracking fear/greed scores over market cycles are needed. Digital disparity measurement relied on self-reported access rather than actual transaction logs. Future studies should integrate mobile money API data. Rural representation was limited (only 22% of the sample). Given that the rural gender gap in mobile money reaches 74% (GSMA, 2026), future studies must oversample rural investors.

Future Research Directions

Longitudinal tracking of fear/greed scores across major market events (e.g., geopolitical shocks, interest rate changes). Cross-country comparison with India, Bangladesh, and Indonesia to assess the cultural specificity of the beta portfolio. Intervention studies testing whether digital literacy programs reduce fear scores among women. Neurofinance studies using skin conductance or FMRI to measure physiological fear/greed responses in Pakistani investors. Scale adaptation for Islamic finance products, where religious norms may suppress greed and amplify fear differently.

Practical Implications

Stakeholder	***Implication***	***Actionable Recommendation***
SECP / SBP (Regulators)	Women's high fear scores indicate underparticipation.	Mandate gender-sensitive financial literacy programs; require brokerages to report gender disaggregated trading data.
Fintech platforms (Binance, Ktrade)	Digital disparity suppresses women's expression of greed.	Design women only onboarding with female agents; simplify KYC; provide family inclusive planning tools.
Brokerage firms (Finqalab, PSX members)	Male clients exhibit greed-driven overtrading.	Implement automated circuit breakers; require cooling-off periods after frequent trades.
Financial advisors	Different emotional profiles require different advice.	For men: greed mitigation strategies (diversification, long term goals). For women: fear reduction strategies (social proof, family involvement).
Crypto exchanges	Crypto attracts greed driven male investors disproportionately	Implement volatility warnings; require risk acknowledgment checkboxes; provide cooling-off features
Policymakers	The digital gender gap of 63% is economically costly.	Target SBP's 30% female customer goal by 2028; subsidize women's mobile internet; register SIMs in women's names

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