Smartphone Addiction: A Disease in the Stock Market Driving Herding and Overconfidence – A PLS - SEM Analysis

Chandana Gunathilaka[1], Rasika S Wickramasinghe [2]

ARTICLE INFORMATION

Key words:
Overconfidence
Herd behavior
Social Media Addiction
Investment Decision

ABSTRACT

This article examines the smartphone-loved human behavior and the development of psychological biases leading to irrational investment decision-making. We use a survey among a sample of 95 equity investors in the Colombo Stock Exchange and analyze the results using the Partial Least Squares- Structural Equation Modelling approach. We confirm the existence of herd behavior and overconfidence bias which are triggered by smartphone addiction. Investment decisions are strongly influenced by overconfidence while overconfident investors show an ability to mediate the influence of herding. The findings indicate the risk of smartphone and social media addiction, a silent disease driving mispricing in equity markets.

1. Introduction

The literature explains investor behavior (Deene, 2013) through psychological principles of decision-making (Bondt et al., 2008) showing the impact of behavioral preferences over rationality. The existence of biases within investors, for instance, losses hurt more than gains (Kahneman and Tversky, 1979), self-attribution and overconfidence (Atmaningrum et al., 2021), opaque assets are more influenced by market sentiment (Gunathilaka et al., 2019) directs further research on market mispricing, especially in the current era of internet and smartphone addiction (Michela et al., 2022). The abuse of digital devices affects individuals' social life and well-being, and addiction is positively related to mood regulation. It triggers the practice of making mental shortcuts rather than being analytical. Addiction shows many consequences including stress, performance, satisfaction with life (Samaha & Hawi, 2016), and family and personal conflicts (Mahapatra, 2019). It exposes to the over-attachment risks like loss of concentration, and technostress thus the decision-making is affected as it helps develop biases in the individual. Accordingly, they tend to follow the crowd (Lakonishok et al., 1992; Scharfstein and Stein, 1990) and become overconfident attributing past success to their own skills and failure to bad luck, the self-attribution. Overconfidence is a cognitive bias which is related to the self-attribution where an individual attributes his success to own talent and ability blaming 'bad luck' for his past failure. One outcome of this self-deception is the tendency (Trivers, 1991) that one will utilize perceived superior ability and trade in equity markets (Odean, 1998) underestimating the

[1] Corresponding Author: Department of Finance, Faculty of Management Studies and Commerce, University of Sri Jayewardenepura, Sri Lanka. E-mail: chandana@sjp.ac.lk
[2] rasikawickramasinghe2@gmail.com

associated risks. However, rational decision theory emphasizes that individuals follow specific logical procedures to resolve problems (Lindblom, 2005) which is contradictory to the common evidence that displays irrational thinking (Atmaningrum et al., 2021), herding, and overconfidence.

Increasing tendency towards mobile phone use (Karadag et al., 2015a) and preferring virtual environments to real life has resulted in an addiction. The desire to access vast amounts of content via the internet (Hawi, 2012) shows an addiction to social media. Smartphones enable sharing of experiences, images, and information (Ariza et al., 2021) thus one might become overconfident in decision-making. Based thereon, we position our interest in exploring the impact of Smartphone addiction on investor decision making. In this context, Smartphone addiction is considered reflective of social media addiction because we examine respondents' social media practice through smartphones. Thus, our objective of this paper is to examine the relationship between social media and Smartphone addictions and investors' decision-making behavior. First, we examine empirically whether herding and overconfidence biases exist in the Colombo stock market. Then we investigate the interrelationship between smartphone addition, herding, overconfidence, and decision-making. Findings may help investors to minimize the negative impact of phone usage and behavioral biases and may help the investor to make judgments accordingly.

2. Related Literature

Internet users spend several of hours online each day (Young, 2017) and many use smartphones creating new troubles in real life (Karadag et al., 2015) including addictions to internet and gaming. Furthermore, social media life almost has become an addiction (Karaiskos et al., 2010; Turel & Serenko, 2012) the most used are Facebook (Karadag et al., 2015b) and Twitter (Andreassen et al., 2012) for social sharing. Nevertheless, the habit of surfing social media and smartphones affection has triggered a wide evolution in information structure and accessibility (Atmaningrum et al., 2021) with a remarkable role in the investment markets through social influences. Facebook is motivated by social interaction (Karadag et al., 2015b) but potentially damages interpersonal relationships because it interferes in them (Atmaningrum et al., 2021). Social interaction may develop herding as they tend to collect responses and sharing experiences of similar people. Herding is a behavioral pattern that is interconnected with individuals (Devenow & Welch, 1996) and usually results from day-today life habits to imitate the actions of others not because others' decisions are optimal but because people avoid extra efforts. Evidence suggest that the investors often follow the crowd (Lakonishok et al., 1992; Scharfstein and Stein, 1990; Campbell, 2004) and that investors are more inclined towards herding behavior during volatile market conditions. Moreover, institutional investors herd more than individual investors (Dennis and Strickland, 2002) and stock prices are more influenced by institutional investors (Nofsinger & Sias, 1999) than herding by individuals. Lee et al. (2004) find the contrary, where individual investors are more prone to herd behavior in comparison to institutional, consequently a positive impact on investors decision making (Kengatharan & Kengatharan, 2014) is expected. Findings of Lim (2012) however, is inconsistent with the previous studies where they find herding has no impact on investors' decision making. Studies that highlight the influence of smartphones in professionals (Atmaningrum et al., 2021) in promoting socialization also motivates the present study of exploring the social influence in the investment market.

The several of behavioral biases including overconfidence (Daniel et al., 1998) links investment decision-making (Rahman & Gan, 2020) to irrationality in markets despite the explanations of the utility theory. The expected utility theory proposes that investors behave rationally by judging all the alternatives on the basis of their utility and the associated risks. Self-attribution is a static and dynamic bias (Hirshleifer, 2001) and it makes the individual lean to be overconfident rather than converge on an accurate self-assessment. Ample evidence is available that suggests people are overconfident (Mushinada et al., 2019) in equity trading. Smartphone diffusion has significantly changed our lives (Mason et al., 2022), however, countries like Germany show less use of mobile phones (Olson et al., 2022) while a higher level of addiction is seen in Asian countries. Investors systematically misprocess publicly available information and overweight their private information (Daniel et al., 1998) which develops overconfidence, consequently they overreact (Odean, 1999) to the market information. Overconfidence may affect both positively (Lim, 2012; Javed *et al.,* 2017) and negatively (Kengatharan & Kengatharan, 2014) to investor decision-making. Investors' gender (Barber and Odean, 2001; Grinblatt and Keloharju, 2009; Statman *et al.,* 2006) and experience (Zaidi & Tauni, 2012) could affect overconfidence. The impact is more in the case of male investors, they get involved in excessive trading in periods of overconfidence.

Herding is decreasing with own experience (Menkhoff et al., 2006) and the herding degree and confidence degree are highly related when there is a clear market trend (Zhang et al., 2020). The evidence, in sum, could indicate a potential impact of smartphones addiction on investment decisions through herding among individuals. Hence, we formulate the following hypotheses testable.

H_1: Social Media Addiction (SMA) contributes to herding and overconfidence among investors.

H_2: Herding develops overconfidence and affects investor decision making.

H_3: Overconfidence affects investor decision making.

Hence, we hypothesize that SMA finally shows a significant impact to investor decision making. It may support the evidence that the subjective knowledge is more important than objective knowledge in formation of financial knowledge (Atmaningrum et al., 2021) and that financial knowledge affects the intention to invest.

3. Materials and Methods

3.1 Sample

We collected a sample of 119 responses through a google form, among the volunteered participants of those having equity investments in the Colombo Stock Exchange (CSE). Of them, 24 were eliminated owing to the passive investing cicriteria and missing answers. The survey was administered during June -October 2022 circulating among the investors using the networks and groups of the investor community. The respondents are mostly professionals and others include graduates, or postgraduate degree holders. The respondents included 21 self-business owners and, the rest (about 78%) are from the professional, public sector, and privet sector employers. Of all the respondents, approximately 62% were small-scale investors (Table 1).

Using a filter, the form was opened for respondents if he/she had investments and trading experience in CSE. The survey instrument includes items that reflect SMA, investor' overconfidence (OC), herd behavior (HB), and investment decision(ID). The questionnaire included 7-point scale (strongly agree [SA] to strongly disagree [SDA]) statements that reflected three (3) of the constructs: Over Confidance (OC), Herding behavior (HB) and Investment Decision (ID). Measurement of other construct, SMA, follows a 5-point scale. Figure 1 explains the Partial Least Squares – Structural Equation Modeling (PLS-SEM) with the four (4) constructs. Overconfidence is measured with four statements representing respondent's confidence about own ability than others, timing ability in the market, own skills to win, and predictability of future. Additionally, two items to reflect self-attribution, i.e., reference to the luck and past success, are included in measuring the overconfidence. Herd behavior is measured using six statements showing (1) respondents' belief about trading pattern of other investors, others stock selection decisions, (2) dependence on consultations and recommendations, family and friends' opinion, (3) decisions bias based on others response for market changes and trading volumes. These two constructs are well documented and the items have been adopted from the studies including Raut et al. (2020). Investment decision making style is measured through five statements that cover investment objectives, risk tolerance, experience, and time horizon.

It follows the approaches of Atmaningrum et al. (2021), Mushinada and Veluri (2019). SMA is measured using the scale adopted from Mason et al. (2022) that include six statements representing the level of smartphone usage. The items have been included in the appendix.

In view of the directional effects hypothesized and formed, we employ PLS-SEM in the current study. For instance, an overconfident investor is not expected to go with the herd, while herding may both increase or decrease overconfidence. It follows a two-step analytical procedure approach (Anderson & Gerbing, 1988). Structural Equation Modeling that constructs a path linking stages of social media and investers biases and investment decision are represented by a set of structural equations explained in Figure 1. The image was created through SmartPLS 4.08 version.

Table 1

Descriptive Profile

Gender		Civil Status		Age		Education		Employment		Scale	
Male	59	Single	29	Below 29	30	School	8	Self	21	Small	60
Female	36	Married	66	30-39	29	Degree	28	Private	48	Moderate	29
				40-49	22	Masters	25	Public	16	Mod – Large	5
				Above 50	14	Profesional	34	Profesional	10	Giant	1
Total	95		95		95		95		95		95

Table 1 reports descriptive profile of the sample of 95 respondents. Scale: the self descriptin by the investor as the size of the assets held: Small investor to a giant.

4. Results and Discussion

4.1 Measurement Model

The measurement model was examined in terms of construct reliability, convergent validity, and discriminant validity. Table 3 shows the statistics of convergent validity of the constructs observed by the measurement model. Each of these items is described in the Appendix. Factor loadings, Cronbach's Alpha (CrA), RhoA, Composite Reliability (CR), and Average Variance Extracted (AVE) are presented in Table 3. CrA

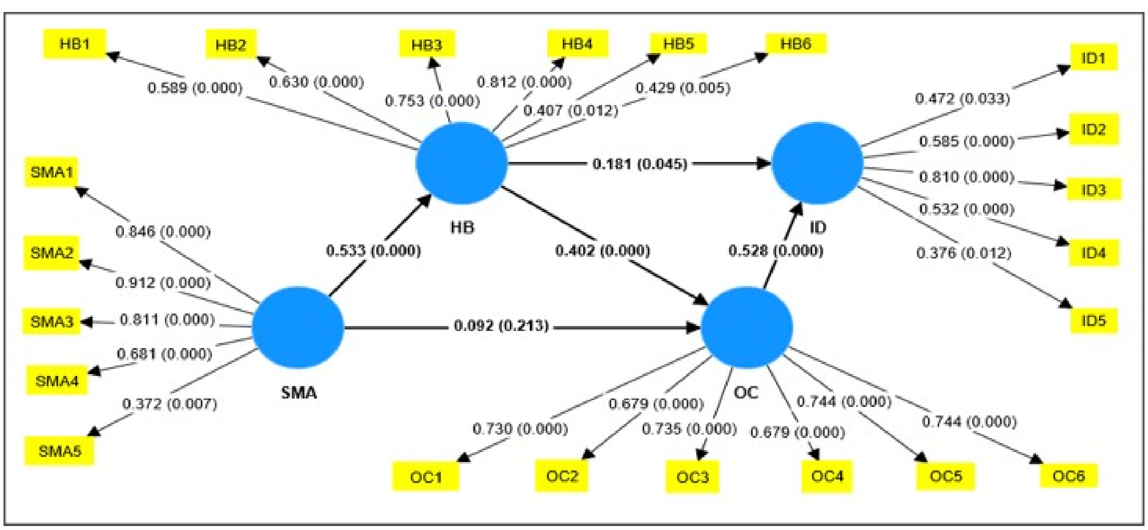

Figure 1. Structural model

Table 2
Mesurement Model Assesment : Validity of the Construct

	Item	Outer Lording	VIF	CrA	RhoA	CR	AVE	HTMT		
								HB	OC	SMA
ID	ID 4	0.772	1.046	0.711	0.734	0.796	0.629	0.419	0.714	0.536
	ID1	0.884	1.158							
	ID2	0.810	1.233							
	ID3	0.632	1.184							
	ID5	0.876	1.034							
HB	HB1	0.782	1.704	0.722	0.784	0.781	0.587		0.484	0.602
	HB2	0.721	1.805							
	HB3	0.758	1.252							
	HB4	0.813	1.376							
	HB5	0.705	1.282							
	HB6	0.730	1.231							
OC	OC1	0.730	2.237	0.815	0.817	0.865	0.517			0.345
	OC2	0.677	1.600							
	OC3	0.735	1.657							
	OC4	0.680	1.549							
	OC5	0.745	1.547							
	OC6	0.744	2.262							
SMA	SMA1	0.839	2.055	0.786	0.875	0.857	0.561			
	SMA2	0.883	2.172							
	SMA3	0.819	2.250							
	SMA4	0.696	1.582							
	SMA5	0.680	1.055							

Table 2 shows the mean score for the observed items, item loadings, and validity statistics. VIF=Variance Inflation. AVE=Average Variance Extracted; CrA=Cronbach's Alpha; RhoA; CR =Composite Reliability; . HB= Herding; OC=Overconfidence; ID= Investment Decision; SMA= Social Media Addiction; HTMT=Heterotrait-Monotrait ratio of correlations.

values for all constructs are above the standard value of 0.7 indicating internal consistency (Hair et al., 2020). The factor loadings of items are closer or greater than the 0.70 thresholds (Hair et al., 2020). Values reported for Variance Inflation Factor (VIF) are less than two for all HB and ID items. However, OC and SMA items with VIF less than 3 indicating moderate correlations. Additionally, we observe that the convergent validity of all variables had been established as the CR values fall above 0.7 (Hair et al., 2020; Liu & Wang, 2016). Moreover, AVE is greater than 0.50 for the same constructs indicating the convergent validity (Hair et al., 2020) of the model estimations. Heterotrait-Monotrait ratio of correlations (HTMT) method is more reliable in assessing the discriminant validity (Ghasemy et al., 2020). The values reported above show that these are independent constrcuts and the model shows an acceptable discriminant validity.

4.2 Structural Model

We examine the significance of our directional hypotheses using one-tailed bias-corrected and accelerated Bootstrap procedure based on a bootstrap subsample of 5,000 (Hair et al., 2017). Figure 1 depicts the structural model including coefficients and (p-values). Additionally, we report statistics in the Table 3, where the direct results are presented with the decision on each hypotheses. Accordingly, we find no influence of SMA on overconfidence (with the presence of a zero confidence interval as reported) but herding. All the VIF values are below 1.39 indicating that a muticolinearity issue does not persist. Supporting the hypothesis 1, the model confirms the influence of SMA on herd behavior. Similarly, herd behavior develops overconfidence bias while the overconfidence impacts investor possitive relationships between constructs. These results confirm our hypotheses that the smartphone has a significant influence over herd behavior. However, SMA does not lead to an overconfidence, it indicates that the investor's overconfidece level is not directly affected by the degree of social media addiction itself. Instead, it quietly explains that the smartphone and social media can create herding as they share similar information, news and the ideas among the similar

Table 3
Direct Results

Path	Coeff.	SD	P-value	S/N	Conf. Intervals 5%	Conf. Intervals 95%	VIF	R^2	F^2
HB -> ID	0.181	0.107	0.045	S	0.025	0.373	1.255	0.284	0.044
HB -> OC	0.402	0.109	0.000	S	0.244	0.585	1.396		0.146
OC -> ID	0.528	0.094	0.000	S	0.375	0.681	1.255	0.399	0.370
SMA -> HB	0.533	0.080	0.000	S	0.416	0.670	1.000		0.396
SMA -> OC	0.092	0.116	0.213	N	-0.103	0.277	1.396	0.209	0.008

Table 3 reports results for direct relationships. HB= Herding; OC=Overconfidence; ID= Investment Decision; SMA= Social Media Addiction; SD= standard deviation; S/N= supported or not; VIF =Variance Inflation Factor

Table 4
Mediation Analysis

Path	Coeff.	SD	T- stat	Conf.Intervals (Bias Corrected) 5%	Conf.Intervals (Bias Corrected) 95%	Total Effect	VAF	Results
HB -> ID	0.212	0.072	2.957	0.117	0.345	0.013	0.42	Partial
SMA-> OC	0.214	0.064	3.341	0.131	0.336	0.015	0.23	Partial

Table 4 reports indirect results, that is, Coeff; Standard deviation(SD); HB= Hearding behavior;OC=Over Confidents ; ID= Investment Decision; SMA= Social Media Addiction; VAF=Variance Accounted For

decision making. It suggests that herd behavior influences the investor decision with a direct impact, while overconfidence partially mediates the role of herding. We find partial relationships in the indirect analysis as reported in the Table 4.

Our analysis on the mediating roles of gender, education, size of the investment portfolio, or occupation did not produce meaningful results. Hence, we have reasonable evidence that the demographics do not make any difference in terms of social media addiction, its impact on herding, overconfidence, and decision making. We find all crowd. Moreover, herding strongly develops overconfidence, indicating that the investor has a strong attachment to the opinion of the herd to which they belong. However, the impact on herding on decision making is marginal, i.e., significant with a p-value of 0.045.

The results reveal that overconfidence impact the investor decisions significantly. Accordingly, they are self aligned and it develops an overconfidence within and among the herd. Investor might be overconfident when they feel that their thinking are aligned with society. The information comes through social media confirming that a group of people flies together may develop overconfidence in an investor who assume that he/she is belonging to the same herd.

4.3 Limitations and Future Research

The peresent study offers the conclusions with few of the limitations. Fisrt, it uses a limited sample, an extended sample may provide more strong evidence to the effects of SEM. Second, increased sub-samples and application of further constructs that reflect smartphone snubbing may produce better results.

5. Conclusion

This article examined the smartphones and social media usage and its impact on investor behavior decisions. Addictions are complex deceasses that disrupt the functions of the brain including the responsibility for learning, judgment and memory. We find that the SMA significantly influence herd behavior. Being in the herd, an overconfidence is developped in the investor. The disease may make the assets mispriced as the social influence is affecting psychological bias. Investor decision making is significantly affected by the overconfidence bias.

The study brings several insights for the discussion of investor behavior. It confirms the existance of herding and overconfidence in Colombo stock market. Additionally, in periods of herding become more pertinent, overconfidence develops as a consequence of smartphone addiction. Moreover, the impact of herding on investor decision making is partialy mediated by overconfidence. The evidence draws attention of investor community as the decisions may be bias due to smartphone glued life in the era we pass through.

References

Aspara, J., & Tikkanen, H. (2011a). Individuals' Affect-Based Motivations to Invest in Stocks: Beyond Expected Financial Returns and Risks. *Journal of Behavioral Finance*, *12*(2), 78–89. https://doi.org/10.1080/15427560.2011.575970

Atmaningrum, S., Kanto, D. S., & Kisman, Z. (2021b). Investment Decisions: The Results of Knowledge, Income, and Self-Control. *Journal of Economics and Business*, *4*(1). https://doi.org/10.31014/aior.1992.04.01.324

Barber, B. M., & Odean, T. (1999). The Courage of Misguided Convictions. *Financial Analysts Journal*.

Barber, B. M., & Odean, T. (2008). All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors. *Review of Financial Studies*, *21*(2), 785–818. https://doi.org/10.1093/rfs/hhm079

Bondt, W. D., Muradoglu, G., Shefrin, H., & Staikouras, S. K. (2008). Behavioral Finance: Quo Vadis? *BEHAVIORAL FINANCE*.

Chen, G., Kim, K. A., Nofsinger, J. R., & Rui, O. M. (2007). Trading performance, disposition effect, overconfidence, representativeness bias, and experience of emerging market investors. *Journal of Behavioral Decision Making*, *20*(4), 425–451. https://doi.org/10.1002/bdm.561

Din, S. M. U., Mehmood, S. K., Shahzad, A., Ahmad, I., Davidyants, A., & Abu-Rumman, A. (2021). The Impact of Behavioral Biases on Herding Behavior of Investors in Islamic Financial Products. *Frontiers in Psychology*, *11*, 600570. https://doi.org/10.3389/fpsyg.2020.600570

Dutta, A., Sinha, M., & Gahan, P. (2020). Perspective of the Behaviour of Retail Investors: An Analysis with Indian Stock Market Data. In H. S. Behera, J. Nayak, B. Naik, & D. Pelusi (Eds.), *Computational Intelligence in Data Mining* (Vol. 990, pp. 605–616). Springer Singapore. https://doi.org/10.1007/978-981-13-8676-3_51

Ebrahimi, P., Ahmadi, M., Gholampour, A., & Alipour, H. (2019). CRM performance and development of media entrepreneurship in digital, social media and mobile commerce. *International Journal of Emerging Markets*, *16*(1), 25–

50. https://doi.org/10.1108/IJOEM-11-2018-0588

Elizabeth, J., Murhadi, W. R., & Sutejo, B. S. (2020). Investor Behavioral Bias Based on Demographic Characteristics. *Proceedings of the 17 Th International Symposium on Management (INSYMA 2020)*. Proceedings of the 17 th International Symposium on Management (INSYMA 2020), Vung Tau City, Vietnam. https://doi.org/10.2991/aebmr.k.200127.002

Feng, L., & Seasholes, M. S. (n.d.). *Do Investor Sophistication and Trading Experience Eliminate Behavioral Biases in Financial Markets?*

Ferasso, M., & Bergamaschi, E. A. (2020). Bounded Rationality Effect on Firm's Choices on R&D Investments: A Model for Decision-Making Effectiveness Analysis. *Journal of Research in Emerging Markets*, *2*(1), 24–42. https://doi.org/10.30585/jrems.v2i1.449

Guazzini, A., Raimondi, T., Biagini, B., Bagnoli, F., & Duradoni, M. (2021). Phubber's Emotional Activations: The Association between PANAS and Phubbing Behavior. *Future Internet*, *13*(12), 311. https://doi.org/10.3390/fi13120311

Gunathilaka, C., Wickramasinghe, R. S., & Jais, M. (2022). COVID-19 and the Adaptive Role of Educators: The Impact of Digital Literacy and Psychological Well-Being on Education—A PLS-SEM Approach. *International Journal of Educational Reform*, *31*(4), 397–421. https://doi.org/10.1177/10567879221113546

Jain, J., Walia, N., & Gupta, S. (2019). Evaluation of behavioral biases affecting investment decision making of individual equity investors by fuzzy analytic hierarchy process. *Review of Behavioral Finance*, *12*(3), 297–314. https://doi.org/10.1108/RBF-03-2019-0044

Junsheng, H., Masud, M. M., Akhtar, R., & Rana, Md. S. (2020). The Mediating Role of Employees' Green Motivation between Exploratory Factors and Green Behaviour in the Malaysian Food Industry. *Sustainability*, *12*(2), 509. https://doi.org/10.3390/su12020509

Karadağ, E., Tosuntaş, Ş. B., Erzen, E., Duru, P., Bostan, N., Şahin, B. M., Çulha, İ., & Babadağ, B. (2015). Determinants of phubbing, which is the sum of many virtual addictions: A structural equation model. *Journal of Behavioral Addictions*, *4*(2), 60–74. https://doi.org/10.1556/2006.4.2015.005

Khan, S. U., Wang, M., Khan, I. U., & Liu, X. (2022). Evaluating stock trading behaviour: Information sources nexus through intrinsic and extrinsic motivation. *International Journal of Finance & Economics*, *27*(3), 2965–2976. https://doi.org/10.1002/ijfe.2307

Kumar, S., & Goyal, N. (2015). Behavioural biases in investment decision making – a systematic literature review. *Qualitative Research in Financial Markets*, *7*(1), 88–108. https://doi.org/10.1108/QRFM-07-2014-0022

Lukkarinen, A., Wallenius, J., & Seppälä, T. (2017). Investor Motivations and Decision Criteria in Equity Crowdfunding. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3263434

Mason, M. C., Zamparo, G., Marini, A., & Ameen, N. (2022). Glued to your phone? Generation Z's smartphone addiction and online compulsive buying. *Computers in Human Behavior*, *136*, 107404. https://doi.org/10.1016/j.chb.2022.107404

Mayall, M. (2010). A feeling for finance: Motivations for trading on the stock exchange. *Emotion, Space and Society*, *3*(2), 103–110. https://doi.org/10.1016/j.emospa.2009.10.005

Meira, J. V. de S., & Hancer, M. (2021). Using the social exchange theory to explore the employee-organization relationship in the hospitality industry. *International Journal of Contemporary Hospitality Management*, *33*(2), 670–692. https://doi.org/10.1108/IJCHM-06-2020-0538

Munerah, S., Koay, K. Y., & Thambiah, S. (2021). Factors influencing non-green consumers' purchase intention: A partial least squares structural equation modelling (PLS-SEM) approach. *Journal of Cleaner Production*, *280*, 124192. https://doi.org/10.1016/j.jclepro.2020.124192

Mushinada, V. N. C. (2020). Are individual investors irrational or adaptive to market dynamics? *Journal of Behavioral and Experimental Finance*, *25*, 100243. https://doi.org/10.1016/j.jbef.2019.100243

Mushinada, V. N. C., & Veluri, V. S. S. (2019). Elucidating investors rationality and behavioural biases in Indian stock market. *Review of Behavioral Finance*, *11*(2), 201–219. https://doi.org/10.1108/RBF-04-2018-0034

Noda, A. (2021). On the evolution of cryptocurrency market efficiency. *Applied Economics Letters*, *28*(6), 433–439. https://doi.org/10.1080/13504851.2020.1758617

Plastun, A., Sibande, X., Gupta, R., & Wohar, M. E. (2020). Evolution of Price Effects After One-Day of Abnormal Returns in the US Stock Market. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3751545

Rahman, M., Sa, C. L., & Masud, Md. A. K. (2021). Predicting Firms' Financial Distress: An Empirical Analysis Using the F-Score Model. *Journal of Risk and Financial Management*, *14*(5), 199. https://doi.org/10.3390/jrfm14050199

Rasool, S., Rehman, A., Cerchione, R., & Centobelli, P. (2021). Evaluating consumer environmental behavior for sustainable development: A confirmatory factor analysis. *Sustainable Development*, *29*(2), 318–326. https://doi.org/10.1002/sd.2147

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

Richards, D. (n.d.). *Do stop losses work? The disposition effect, stop losses and investor demographics.*

Ríos Ariza, J. M., Matas-Terron, A., Rumiche Chávarry, R. del P., & Chunga Chinguel, G. R. (2021a). Scale for Measuring Phubbing in Peruvian University Students: Adaptation, Validation and Results of Its Application. *Journal of New Approaches in Educational Research*, *10*(2), 175. https://doi.org/10.7821/naer.2021.7.606

Ríos Ariza, J. M., Matas-Terron, A., Rumiche Chávarry, R. del P., & Chunga Chinguel, G. R. (2021b). Scale for Measuring Phubbing in Peruvian University Students: Adaptation, Validation and Results of Its Application. *Journal of New Approaches in Educational Research*, *10*(2), 175. https://doi.org/10.7821/naer.2021.7.606

Sabir, S. A., Mohammad, H. B., & Shahar, H. B. K. (2019). The Role of Overconfidence and Past Investment Experience in Herding Behaviour with a Moderating Effect of Financial Literacy: Evidence from Pakistan Stock Exchange. *Asian Economic and Financial Review*, *9*(4), 480–490. https://doi.org/10.18488/journal.aefr.2019.94.480.490

Shafi, M. (2014). Determinants Influencing Individual Investor Behavior in Stock Market: A Cross Country Research Survey. *Nigerian Chapter of Arabian Journal of Business and Management Review*, *2*(1), 60–71. https://doi.org/10.12816/0003720

Shehata, S. M., Abdeljawad, A. M., Mazouz, L. A., Aldossary, L. Y. K., Alsaeed, M. Y., & Noureldin Sayed, M. (2021). The Moderating Role of Perceived Risks in the Relationship between Financial Knowledge and the Intention to Invest in the Saudi Arabian Stock Market. *International Journal of Financial Studies*, *9*(1), 9. https://doi.org/10.3390/ijfs9010009

Yousaf, S., Imran Rasheed, M., Kaur, P., Islam, N., & Dhir, A. (2022). The dark side of phubbing in the workplace: Investigating the role of intrinsic motivation and the use of enterprise social media (ESM) in a cross-cultural setting. *Journal of Business Research*, *143*, 81–93. https://doi.org/10.1016/j.jbusres.2022.01.043

Zahera, S. A., & Bansal, R. (2018). Do investors exhibit behavioral biases in investment decision making? A systematic review. *Qualitative Research in Financial*

Markets, *10*(2), 210–251. https://doi.org/10.1108/QRFM-04-2017-0028

Appendix

ID	1. In most cases my investment decisions support my investment OBJECTIVES
	2. My reactions towards losses are NORMAL.
	3. Usually, I get my expected RETURN on my investments
	4. I am ready to bear risks of my investment decisions
	5. My investment holding periods are spread over LONG time
SMA	1. I check my smartphone for social media [Twitter, Facebook] accounts even if I have some other work.
	2. I check my social media accounts whenever possible.
	3. I share what I did, what is going on with life, and similar things in social media.
	4. I follow activities, events, popular videos, and trend topics in social media.
	5. I check over the accounts of the people I know in social media.
	6. I check over anybody's account in social media