

Smartphone Trading Apps and Retail Investor Behaviour: A PLS-SEM Analysis of Investors in the National Capital Region (NCR)

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ABSTRACT

Smartphone trading applications have widened retail participation in Indian financial markets, but evidence on how app features, investor attributes and the wider environment jointly shape investment behaviour is still limited. This study examines the effect of three sets of determinants (financial trading mobile application characteristics, investors' characteristics and external factors) on the investment behaviour of retail investors. A cross-sectional survey was conducted among 350 investors in the National Capital Region (NCR) of India. Respondents were recruited through snowball sampling and completed a closed-ended questionnaire on a five-point scale, with four indicators per construct. The data were analysed with partial least squares structural equation modelling (PLS-SEM) in SmartPLS 4.0. Composite reliability exceeded 0.79 for all constructs, and indicator loadings ranged from 0.651 to 0.767. All three determinants had positive and statistically significant effects on investment behaviour ($p < 0.001$): investors' characteristics ($\beta = 0.370$), application characteristics ($\beta = 0.300$) and external factors ($\beta = 0.203$). Together they explained 61.1% of the variance in investment behaviour ($R^2 = 0.611$), a moderate level of explanatory power. The findings suggest that the investor matters at least as much as the app being used, and that app design, investor education and the market environment should be considered together. The study complements transaction-data research on developed markets with survey-based evidence from an emerging market.

Keywords: Fintech; mobile trading applications; investment behaviour; retail investors; PLS-SEM

1. INTRODUCTION

Financial technology (Fintech) has changed how people invest, borrow and manage money (Arner et al., 2015; Gomber et al., 2018; Maldonado, 2019). Digital platforms deliver financial services faster, more conveniently and at lower cost than traditional channels (Thakor, 2020; Vives, 2019), and they have widened access for groups that were previously underserved (Demirgüç-Kunt et al., 2022; Philippon, 2019).

In India, many households save first and plan spending later, find it hard to organise their expenses and judge their financial position, and have had limited access to good investment advice, which has often been confined to wealthy individuals. Mobile investment applications address part of this gap through simple interfaces, goal-based suggestions and low-cost access to stocks, mutual funds and other products (Choudhary, 2021; Gomber et al., 2018). Algorithm-based advisory services go further by automating investment advice and portfolio management (D'Acunto et al., 2019).

This convenience has a downside. Evidence from app-based brokerages shows that gamified, attention-grabbing interfaces can push inexperienced investors towards excessive and riskier trading (Barber et al., 2022; Welch, 2022), and smartphone adoption has been linked to more intensive trading and a shift in the assets investors buy (Cen, 2021; Kalda et al., 2021). Whether such patterns apply to Indian retail investors, and how app features interact with investor characteristics and the market environment, remains an open question.

This study therefore examines how financial trading mobile application characteristics, investors' characteristics and external factors influence the investment behaviour of retail investors in the National Capital Region (NCR). It makes three contributions: (i) it offers survey-based evidence from an emerging market, where most existing evidence comes from developed-market transaction data; (ii) it considers app, investor and environment factors in a single model; and (iii) it reports measurement and structural results that can be replicated. The rest of the paper is organised as follows. Section 2 states the objectives, Section 3 reviews the literature, Section 4 presents the conceptual framework and hypotheses, Section 5 describes the methodology, Section 6 reports the results, Section 7 discusses them, Section 8 draws implications, Section 9 notes limitations and directions for future research, and Section 10 concludes.

2. OBJECTIVES OF THE STUDY

The purpose of this research is to analyse the impact of technology on the decisions of investors. The specific objectives are:

- O1:** To investigate the role of financial trading mobile application characteristics in influencing investors' investment decisions and behaviour.
- O2:** To investigate the impact of investors' characteristics on their investment decisions and behaviour.
- O3:** To analyse the impact of external (macro) factors and the availability of investment applications on investors' investment behaviour and patterns.

3. REVIEW OF LITERATURE

3.1 Fintech and mobile investment applications

Fintech, a combination of “financial” and “technology”, refers to the use of innovative technology in the delivery of financial services (Arner et al., 2015). Fintech firms use software and digital platforms to offer online banking, mobile payments, peer-to-peer lending and blockchain-based transactions (Gomber et al., 2018; Varma et al., 2022). Miah (2019) identifies several major applications: digital banking and mobile payments, which let individuals monitor and move money through internet platforms and apps (Gomber et al., 2018); peer-to-peer lending and crowdfunding, which connect borrowers directly with a network of investors (Bollaert et al., 2021); algorithm-based advisory services (D'Acunto et al., 2019); and cryptocurrency and blockchain transactions (Nakamoto, 2008).

Fintech can lower costs, improve processes, expand access and increase transparency (Gomber et al., 2018; Sahay et al., 2020; Thakor, 2020). It also raises concerns about regulation, cybersecurity and data privacy (Anagnostopoulos, 2018), and it continues to evolve as new technologies emerge (Arner et al., 2015).

Mobile investment applications are Fintech services delivered through smartphones and tablets. Through them, investors can manage portfolios, buy and sell securities, follow market movements and obtain guidance at any time and place (Frost, 2020; Gomber et al., 2018). India has a diverse set of such platforms (Choudhary, 2021). Zerodha Kite and Upstox are low-cost brokerage platforms for equities, commodities and derivatives; Groww offers stocks, mutual funds and exchange-traded funds; and Paytm Money, ETMoney and Scripbox focus mainly on mutual funds, pension products and goal-based investing, including systematic investment plans (SIPs). These platforms have made investing more convenient and cheaper, and they have given ordinary retail investors access to products once limited to affluent individuals and institutions (Choudhary, 2021; Sahay et al., 2020).

3.2 Behavioural foundations

Research in behavioural finance explains why technology may change how investors act. Overconfident investors tend to trade too much (Barber & Odean, 2001b; Benos, 1998; Caballé & Sákovics, 1998; Daniel et al., 1998); investors may overreact to past information (De Bondt & Thaler, 1985); and their return expectations tend to follow recent experience (Greenwood & Shleifer, 2014). The degree of overconfidence can also differ with national culture (Antonczyk & Salzmann, 2014). Kahneman and Tversky (1982) laid early groundwork on how people judge uncertainty, and Ritter (2003) reviews advances in the field. Mobile apps can strengthen these tendencies by making market information and trading constantly available.

3.3 Empirical studies on technology and investor behaviour

Table 1 summarises the main studies that inform this research.

Table 1: Summary of selected studies

Author(s) and year	Study	Key insight
Barber & Odean (2001a)	The Internet and the Investor	Examines how online investors decide in an environment with more data and no personal intermediary, and how this affects their decision-making.
Zoglami & Matoussi (2009)	A Survey of the Tunisian Investors' Behaviours	Analyses psychological biases that influence investor behaviour, including confidence, conservatism and an informational inferiority complex.
Shashidhar & Shiva Shankar (2017)	A study on technology and its impact on investment behaviour	Explores the conceptual framework of technology and the investment avenues open to investors; stresses that up-to-date technological knowledge helps maximise returns and limit risk, giving rise to the “digital investor”.
Mak & Ip (2017)	An exploratory study of investment behaviour of investors	Finds significant differences in investment behaviour between Mainland Chinese and Hong Kong investors and highlights the role of demographic, psychological and sociological determinants.
Kulkarni & Chaudhry (2021)	Design Patterns of Investing Apps and Their Effects on Investing Behaviors	Draws on finance, psychology and design research to propose eight design guidelines for retail investing applications.
Kalda et al. (2021)	Smart(Phone) Investing? A within investor-time analysis of new technologies and trading behavior	Studies how smartphone use changes individual investors' trading and suggests that it can shift demand towards certain assets.
Cen (2021)	Smartphone Trading Technology, Investor Behavior, and Financial Fragility	Finds that app adoption leads investors to pay more attention and trade more intensively, possibly by amplifying self-control problems and overconfidence, and changes how they respond to short-term signals.

Taken together, these studies show that technology changes how much attention investors pay, how often they trade and which assets they choose, and that investor traits and app design both matter. However, they rarely examine app characteristics, investor characteristics and external factors in the same model, and few use data from India.

3.4 Research gaps

Five gaps emerge from the review.

- 1. Cultural influences.** Studies of specific regions (for example, Mainland China and Hong Kong) exist, but little research examines cultural influences on investment decisions across a wider range of countries.
- 2. Long-term strategies.** Most work concerns short-term, app-based trading; the effect of technology on long-term wealth building and financial planning is less studied.
- 3. Vulnerable investor groups.** Novice and elderly investors, and those with limited financial literacy, receive little separate attention.
- 4. Ethical and social implications.** Questions of financial inclusion, market transparency, data privacy and algorithmic bias in technology-driven investing need further study.
- 5. App design.** The psychological effects of app design patterns on decision-making are only beginning to be examined.

The present study addresses the app-design and investor-characteristic gaps at the level of overall effects, using Indian data. The remaining gaps are taken up in Section 9 as directions for future research.

4. CONCEPTUAL FRAMEWORK AND HYPOTHESES

The conceptual model (Figure 1) treats investment behaviour as the outcome and three sets of determinants as predictors. Table 2 defines the constructs.

Table 2: Constructs and their dimensions

Construct (label)	Role	Dimensions
Financial trading mobile application characteristics (FTMAC)	Predictor	App features and functionality (real-time data, technical analysis tools, portfolio tracking); user experience design; accessibility and availability across devices and operating systems; trading fees and costs.
Investors' characteristics (InvestChar)	Predictor	Financial literacy; experience in trading; risk tolerance; age and generation; educational background.
External factors (ExtFactor)	Predictor	Macro-level factors in the investment environment.
Investment behaviour (InvestBehav)	Outcome	Trading frequency; risk appetite; investment strategy; investment performance.

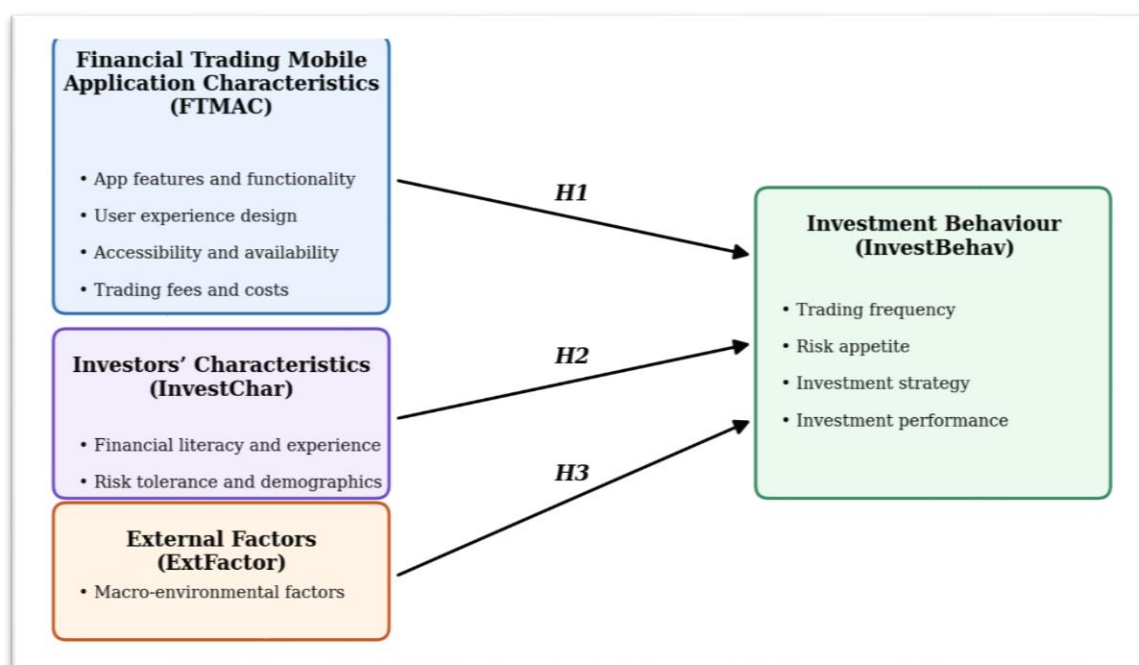


Figure 1: Conceptual model

Source: Authors' conceptualisation

Features such as real-time data, analysis tools and low fees reduce the cost and effort of trading, and interface design shapes attention and impulsiveness (Barber et al., 2022; Kulkarni & Chaudhry, 2021). Smartphone trading has been linked to more frequent trading and changes in asset choice (Cen, 2021; Kalda et al., 2021). This leads to the first hypothesis.

H1: Financial trading mobile application characteristics have a significant positive effect on investment behaviour.

Financial literacy, experience, risk tolerance and demographic attributes influence how investors use information and take risk (Mak & Ip, 2017; Zoglami & Matoussi, 2009).

H2: Investors' characteristics have a significant positive effect on investment behaviour.

Market conditions and the availability of investment channels form the environment in which investors act (Frost, 2020).

H3: External factors have a significant positive effect on investment behaviour.

Investors' characteristics are modelled here as a direct determinant of behaviour. A moderating role for these characteristics is possible and is noted as a direction for future research.

5. RESEARCH METHODOLOGY

5.1 Research design and sample

The study used a cross-sectional survey design. Data were collected from 350 retail investors in the National Capital Region (NCR) through snowball sampling, in which initial respondents referred other eligible investors. The sample is well above the minimum needed for a PLS-SEM model in which no construct receives more than three structural paths (Hair et al., 2019).

5.2 Instrument and measures

Data were gathered with a closed-ended questionnaire using a five-point rating scale, which gives a standardised response format. Four constructs were measured: financial trading mobile application characteristics (FTMAC), investors' characteristics (InvestChar), external factors (ExtFactor) and the outcome, investment behaviour (InvestBehav). Each construct was measured with four indicators (for example, FTMAC1 to FTMAC4).

5.3 Analytical approach

The data were analysed with partial least squares structural equation modelling (PLS-SEM) in SmartPLS 4.0. PLS-SEM suits prediction-oriented models with several constructs and does not require normally distributed data (Hair et al., 2019). Analysis followed two steps. First, the measurement model was assessed through indicator loadings, composite reliability (CR) and average variance extracted (AVE). Loadings of 0.70 or more are preferred, although indicators with loadings between 0.40 and 0.70 can be kept when CR and AVE are adequate; CR should be at least 0.70 and AVE at least 0.50 (Fornell & Larcker, 1981; Hair et al., 2019). Second, the structural model was assessed through bootstrapping, which gives path coefficients and their p-values, and through the coefficient of determination (R^2). Following Hair et al. (2019), R^2 values of about 0.25, 0.50 and 0.75 are read as weak, moderate and substantial.

6. RESULTS

6.1 Measurement model

Figure 2 and Table 4 show the measurement results. All 16 indicator loadings lie between 0.651 and 0.767. Eleven of them are at or above 0.70; the other five (FTMAC2, FTMAC4, InvestChar2, InvestChar3 and InvestBehav3) lie between 0.651 and 0.683. These were retained because CR is above the 0.70 threshold for every construct (0.791 to 0.805). AVE is just above 0.50 for FTMAC, InvestChar and ExtFactor. For InvestBehav it is 0.486, marginally below 0.50. Where AVE is slightly under 0.50 but CR is above 0.60, convergent validity can still be considered adequate (Fornell & Larcker, 1981).

Table 4: Measurement model results

Construct	Indicator loadings	Composite reliability	AVE
FTMAC	FTMAC1 = 0.767; FTMAC2 = 0.651; FTMAC3 = 0.749; FTMAC4 = 0.663	0.801	0.503
InvestChar	InvestChar1 = 0.756; InvestChar2 = 0.673; InvestChar3 = 0.678; InvestChar4 = 0.732	0.803	0.505
ExtFactor	ExtFactor1 = 0.732; ExtFactor2 = 0.714; ExtFactor3 = 0.700; ExtFactor4 = 0.703	0.805	0.507
InvestBehav	InvestBehav1 = 0.705; InvestBehav2 = 0.700; InvestBehav3 = 0.683; InvestBehav4 = 0.701	0.791	0.486

Source: SmartPLS 4.0 output; AVE computed from the reported loadings

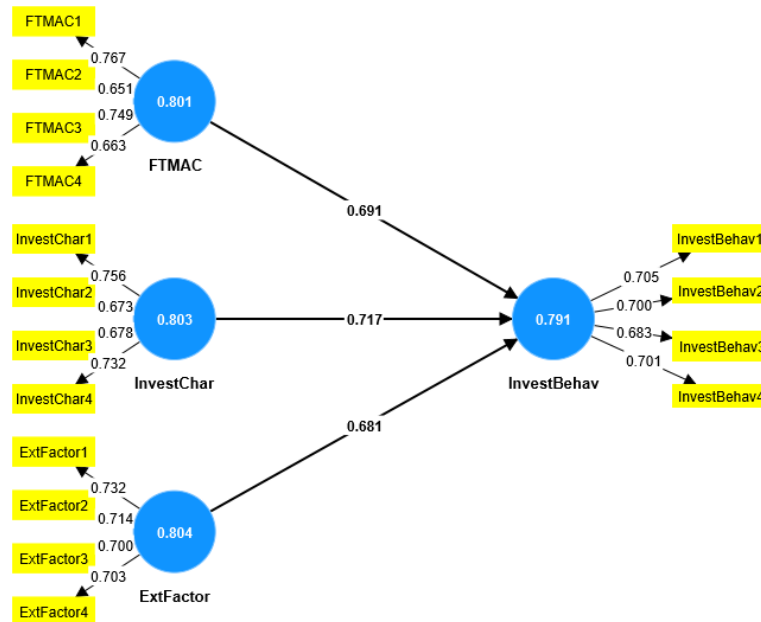


Figure 2: Measurement model (indicator loadings and composite reliability)

Source: SmartPLS 4.0 output. Structural estimates used for hypothesis testing are reported in Figure 3 and Table 5.

6.2 Structural model and hypothesis testing

Bootstrapping results are shown in Figure 3 and Table 5. All three path coefficients are positive and significant at the 0.001 level (SmartPLS reports $p = 0.000$), so H1, H2 and H3 are supported. Investors' characteristics have the largest effect ($\beta = 0.370$), followed by application characteristics ($\beta = 0.300$) and external factors ($\beta = 0.203$). The three predictors together explain 61.1% of the variance in investment behaviour ($R^2 = 0.611$), which is moderate explanatory power rather than very high.

Table 5: Structural model results

Hypothesis	Path	β	p-value	Decision
H1	FTMAC $\rightarrow$ InvestBehav	0.300	< 0.001	Supported
H2	InvestChar $\rightarrow$ InvestBehav	0.370	< 0.001	Supported
H3	ExtFactor $\rightarrow$ InvestBehav	0.203	< 0.001	Supported

R^2 (InvestBehav) = 0.611. Source: SmartPLS 4.0 bootstrapping output

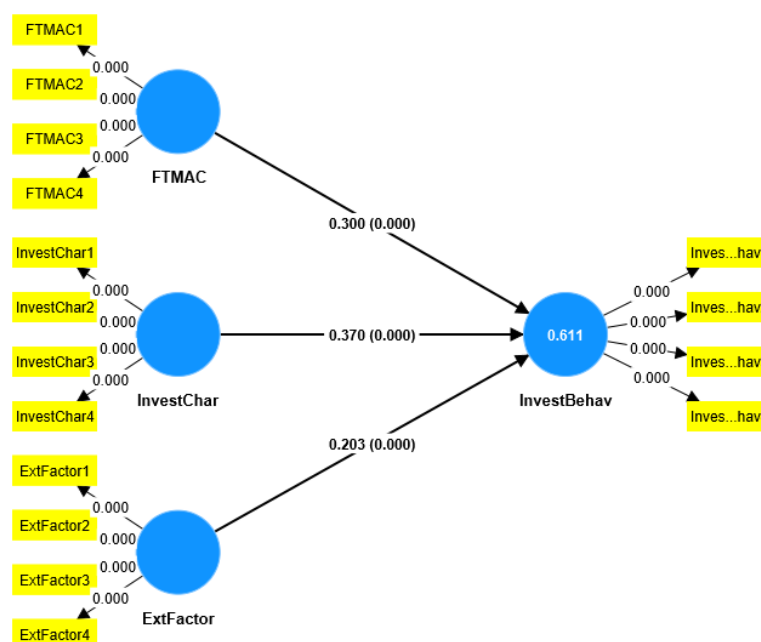


Figure 3: Structural model with bootstrapped path coefficients (p-values in parentheses) and R^2

Source: SmartPLS 4.0 output

A path coefficient is a standardised effect size, not a percentage of variation. The coefficients should therefore be read as the expected change, in standard deviations, in investment behaviour for a one-standard-deviation change in the predictor, other predictors held constant.

7. DISCUSSION

The results show that app characteristics, investor characteristics and external factors each contribute to investment behaviour, and that the model explains a moderate share of its variance. Three points stand out.

First, investors' characteristics had the largest effect. This agrees with behavioural finance research, which gives a central place to individual differences such as overconfidence and experience (Barber & Odean, 2001b; Daniel et al., 1998), and with evidence that demographic, psychological and sociological factors shape investment behaviour (Mak & Ip, 2017). Technology does not act on a blank slate: who the investor is affects how the app is used.

Second, application characteristics had a sizeable effect ($\beta = 0.300$). This is in line with research showing that smartphone trading raises attention and trading intensity (Cen, 2021), changes asset choices (Kalda et al., 2021) and that interface design can steer behaviour (Barber et al., 2022; Kulkarni & Chaudhry, 2021). The present data are self-reported perceptions, so the study shows association, not the causal effect found in studies that observe trades before and after app adoption.

Third, external factors had the smallest but still significant effect ($\beta = 0.203$). Investors' behaviour appears to respond to the broader environment, though less strongly than to their own attributes and the tools they use.

The remaining 38.9% of variance is not explained by the model. Other factors, such as peer influence, social media and personality traits, may also matter.

8. IMPLICATIONS

For app providers. Because app characteristics shape behaviour, providers can design features that support informed decisions, such as clear fee disclosure, risk information at the point of trade and tools for long-term goals, rather than features that encourage frequent trading.

For investors and educators. The strong effect of investor characteristics points to the value of financial literacy and investor education, particularly for new investors who start trading through a smartphone.

For regulators. The findings support attention to interface design, fee transparency, data privacy and cybersecurity in app-based investing (Anagnostopoulos, 2018; Gomber et al., 2018).

9. LIMITATIONS AND FUTURE RESEARCH

The study has several limitations. Snowball sampling is non-probabilistic, and the sample covers only the NCR, so results cannot be generalised to all Indian investors. The data are cross-sectional and self-reported, which limits causal inference and may involve common-method bias. Each construct was measured with four indicators, and some loadings were below 0.70. The model tested direct effects only.

Future research could use probability samples from several regions and compare cultural contexts; examine long-term investment strategies and financial planning; study vulnerable groups such as novice and elderly investors and those with low financial literacy; address ethical and social issues such as privacy and algorithmic bias; and investigate in more detail how specific app design patterns affect decisions. Researchers could also test whether investors' characteristics moderate the effect of app characteristics on behaviour, and could combine survey data with actual trading records.

10. CONCLUSION

This study examined how financial trading mobile application characteristics, investors' characteristics and external factors influence the investment behaviour of 350 retail investors in the NCR. The measurement model showed acceptable composite reliability, and all three determinants had positive, significant effects on investment behaviour, with investors' characteristics the strongest ($\beta = 0.370$), followed by application characteristics ($\beta = 0.300$) and external factors ($\beta = 0.203$). The model explained 61.1% of the variance in behaviour. The findings suggest that app design, investor capability and the market environment work together, and that policy and product decisions should consider all three. Further research with broader samples and behavioural data can test these relationships more rigorously.

REFERENCES

- Anagnostopoulos, I. (2018). Fintech and regtech: Impact on regulators and banks. *Journal of Economics and Business*, 100, 7–25.
- Antonczyk, R. C., & Salzmann, A. J. (2014). Overconfidence and optimism: The effect of national culture on capital structure. *Research in International Business and Finance*, 31, 132–151.
- Arner, D. W., Barberis, J., & Buckley, R. P. (2015). The evolution of Fintech: A new post-crisis paradigm? *Georgetown Journal of International Law*, 47(4), 1271–1319.
- Barber, B. M., Huang, X., Odean, T., & Schwarz, C. (2022). Attention-induced trading and returns: Evidence from Robinhood users. *The Journal of Finance*, 77(6), 3141–3190.
- Barber, B. M., & Odean, T. (2001a). The Internet and the investor. *Journal of Economic Perspectives*, 15(1), 41–54.
- Barber, B. M., & Odean, T. (2001b). Boys will be boys: Gender, overconfidence, and common stock investment. *The Quarterly Journal of Economics*, 116(1), 261–292.
- Benos, A. V. (1998). Overconfident speculators in call markets: Trade patterns and survival. *Journal of Financial Markets*, 1(3–4), 353–383.
- Bollaert, H., Lopez-de-Silanes, F., & Schwienbacher, A. (2021). Fintech and access to finance. *Journal of Corporate Finance*, 68, 101941.
- Caballé, J., & Sákovic, J. (1998). *Overconfident speculation with imperfect competition* [Working paper]. Universitat Autònoma de Barcelona.
- D'Acunto, F., Prabhala, N., & Rossi, A. G. (2019). The promises and pitfalls of robo-advising. *The Review of Financial Studies*, 32(5), 1983–2020.
- Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under- and overreactions. *The Journal of Finance*, 53(6), 1839–1885.
- De Bondt, W. F. M., & Thaler, R. (1985). Does the stock market overreact? *The Journal of Finance*, 40(3), 793–805.
- Demirgüç-Kunt, A., Klapper, L., Singer, D., & Ansar, S. (2022). *The Global Findex Database 2021: Financial inclusion, digital payments, and resilience in the age of COVID-19*. World Bank.
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50.
- Frost, J. (2020). *The economic forces driving fintech adoption across countries* (BIS Working Papers No. 838). Bank for International Settlements.
- Gomber, P., Kauffman, R. J., Parker, C., & Weber, B. W. (2018). On the Fintech revolution: Interpreting the forces of innovation, disruption, and transformation in financial services. *Journal of Management Information Systems*, 35(1), 220–265.
- Greenwood, R., & Shleifer, A. (2014). Expectations of returns and expected returns. *The Review of Financial Studies*, 27(3), 714–746.
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2–24.
- Kahneman, D., & Tversky, A. (1982). Variants of uncertainty. *Cognition*, 11(2), 143–157.
- Kalda, A., Loos, B., Previtero, A., & Hackethal, A. (2021). *Smart(phone) investing? A within investor-time analysis of new technologies and trading behavior*.
- Kulkarni, C., & Chaudhry, S. (2021). *Design patterns of investing apps and their effects on investing behaviors*.
- Mak, M. K. Y., & Ip, W. H. (2017). An exploratory study of investment behaviour of investors. *International Journal of Engineering Business Management*, 9, 1–12.
- Maldonado, M., & B. S. (2019). Fintech. In *Encyclopedia of Business and Professional Ethics* (pp. 1–7).
- Miah, M. A., & H. A. (2019). FinTech and its impact on the financial industry. *Journal of Financial Risk Management*, 8(3), 137–151.
- Nakamoto, S. (2008). *Bitcoin: A peer-to-peer electronic cash system*.

- Philippon, T. (2019). *On fintech and financial inclusion* (NBER Working Paper No. 26330). National Bureau of Economic Research.
- Ritter, J. R. (2003). Advances in behavioral finance. *Pacific-Basin Finance Journal*, 11(4), 429–437.
- Sahay, R., von Allmen, U. E., Lahreche, A., Khera, P., Ogawa, S., Bazarbash, M., & Beaton, K. (2020). *The promise of fintech: Financial inclusion in the post COVID-19 era* (IMF Departmental Paper No. 20/09). International Monetary Fund.
- Shashidhar, H. S., & Shiva Shankar, K. C. (2017). A study on technology and its impact on investment behaviour.
- Thakor, A. V. (2020). Fintech and banking: What do we know? *Journal of Financial Intermediation*, 41, 100833.
- Varma, P., Nijjer, S., Sood, K., Grima, S., & Rupeika-Apoga, R. (2022). Thematic analysis of financial technology (Fintech) influence on the banking industry. *Risks*, 10(10), 186. <https://doi.org/10.3390/risks10100186>
- Vives, X. (2019). Digital disruption in banking. *Annual Review of Financial Economics*, 11, 243–272.
- Welch, I. (2022). The wisdom of the Robinhood crowd. *The Journal of Finance*, 77(3), 1489–1527.
- Zoglami, A., & Matoussi, H. (2009). A survey of the Tunisian investors' behaviours.

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