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MESSAGE FROM THE VICE CHANCELLOR – WAYAMBA UNIVERSITY OF SRI LANKA



It is with great pleasure that I extend my warm greetings and best wishes on the occasion of the 6th Annual International Undergraduate Finance Research Conference (IUFRC) 2026, hosted in hybrid mode by the Sri Lanka Finance Association and Wayamba University of Sri Lanka on 27 November 2026.

The successful continuation of this conference reflects a shared commitment to promoting research, encouraging intellectual engagement, and creating valuable opportunities for students and scholars to exchange knowledge and ideas. IUFRC will enable undergraduate researchers to present their work, learn from one another, and engage with contemporary issues in finance.

This year's theme, "Emerging Frontiers in Finance: Integrating Technology, Sustainability, and Governance for Global Competitiveness," is both timely and significant. Rapid technological changes, growing sustainability priorities, and rising expectations for sound governance are reshaping the global financial landscape. Together, these forces present new opportunities and challenges for financial institutions, businesses, policymakers, and communities. Research and evidence-based decision-making are essential to understanding these changes and developing responsible, innovative, and practical solutions.

I hope participants will engage in constructive discussions, share their perspectives, and explore how technology, sustainability, and governance can contribute to a more competitive and resilient financial sector. I extend my sincere appreciation to the Sri Lanka Finance Association, Wayamba University of Sri Lanka, the conference organizers, and all those whose dedication has made this event possible. I also acknowledge the valuable contributions of the authors, reviewers, session chairs, invited speakers, and participants.

I encourage everyone to make the most of this opportunity: share your research, welcome constructive feedback, and build academic and professional connections. I particularly hope that our undergraduate researchers will be inspired to pursue their inquiries with curiosity, confidence, and a strong sense of responsibility to society.

May IUFRC continue to grow as a distinguished forum for undergraduate finance research and contribute meaningfully to advancing global competitiveness through technology, sustainability, and good governance. My best wishes for a successful and engaging conference.

Professor EMP Ekanayake
The Vice-Chancellor
Wayamba University of Sri Lanka

MESSAGE FROM THE DEAN – FACULTY OF BUSINESS STUDIES AND FINANCE, WAYAMBA UNIVERSITY OF SRI LANKA



It is with great pleasure that I extend my greetings to the 6th Annual International Undergraduate Finance Research Conference (IUFRC) 2026, hosted in hybrid mode by the Sri Lanka Finance Association and Wayamba University of Sri Lanka.

The theme of this year's conference, "Emerging Frontiers in Finance: Integrating Technology, Sustainability, and Governance for Global Competitiveness," reflects the growing importance of adapting to a rapidly changing financial landscape. Technological advances, sustainability priorities, and strong governance practices are reshaping financial systems around the world. Research and innovation in finance play a vital role in understanding these changes and developing insights that support responsible decisions, effective practices, and global competitiveness.

IUFRC 2026 provides a valuable platform for nurturing research and academic inquiry among undergraduate students and researchers. It offers participants an opportunity to broaden their perspectives, exchange knowledge, and engage with emerging issues in finance. These experiences can contribute significantly to the academic and professional development of future researchers and practitioners. I hope that IUFRC 2026 inspire curiosity, meaningful discussion, and continued contributions to the field of finance.

I extend my sincere appreciation to the Sri Lanka Finance Association, Wayamba University of Sri Lanka, the conference chair, the organizing committee, and all academic, administrative, and non-academic staff for their dedication and collective efforts in organizing this conference.

Finally, I offer my heartfelt congratulations and best wishes to all the emerging researchers presenting their work at this distinguished academic forum.

Proffessor SK Gamage
Dean
Faculty of Business Studies and Finance
Wayamba University of Sri Lanka

MESSAGE FROM THE PRESIDENT - SRI LANKA FINANCE ASSOCIATION



I am pleased to extend my warm greetings to all participants of the 6th Annual International Undergraduate Finance Research Conference (IUFRC 2026), organized by the Sri Lanka Finance Association (SLFA) in collaboration with the Wayamba University of Sri Lanka.

Established in 2016, the Sri Lanka Finance Association is committed to advancing finance education, promoting high-quality research, encouraging sound financial policies and practices, and strengthening financial literacy. Through conferences, publications, seminars and educational initiatives, the Association fosters engagement among academics, practitioners, policymakers and students. The Annual International Undergraduate Finance Research Conference is a key initiative, providing aspiring researchers with a platform to develop their research capabilities, share findings, exchange ideas and contribute to the advancement of financial knowledge.

The theme of this year's conference, "Emerging Frontiers in Finance: Integrating Technology, Sustainability, and Governance for Global Competitiveness", is both timely and significant. Technological advancements are reshaping financial markets and institutions, while sustainability and governance have become increasingly central to financial decision-making and long-term value creation. These developments present both opportunities and challenges for Sri Lanka and other emerging economies in the region. I believe this conference will provide a valuable opportunity to explore these emerging developments and their implications for the future of finance.

I am particularly delighted to welcome our keynote speaker, Associate Professor My Nguyen, Deputy Head of Finance at the School of Economics, Finance and Marketing, RMIT University, Australia. With her distinguished academic contributions and research expertise spanning banking, corporate finance and entrepreneurial finance, she brings valuable international perspectives to this conference. On behalf of the Sri Lanka Finance Association, I wish to express my sincere appreciation to her for graciously accepting our invitation to deliver the keynote address and share her insights with our participants.

I also wish to convey my sincere gratitude to the Wayamba University of Sri Lanka, particularly its Vice-Chancellor, the Dean of the Faculty of Business Studies and Finance, and the academic and administrative staff involved in organizing this conference. I wish to place on record my special appreciation to Hiranya Dissanayake, Co-Chair of the Conference, for her leadership, dedication and efforts in coordinating the conference. I deeply appreciate the University's willingness to host this year's conference and the collaborative efforts of the organizing committee in bringing this important academic event to fruition.

Finally, I extend my best wishes to all presenters, participants and distinguished guests for a fruitful conference. I sincerely hope that this gathering will provide an enriching experience for our emerging researchers, enabling them to share their research outputs, exchange ideas, receive constructive feedback and, most importantly, build lasting academic and professional networks that extend beyond the conference.

Professor Manjula K. Wanniarachchige
President
Sri Lanka Finance Association (SLFA)

MESSAGE FROM CONFERENCE CO-CHAIRS





It is with great pleasure that we extend a warm welcome to all participants, presenters, reviewers, our keynote speaker, and distinguished guests at the 6th Annual International Undergraduate Finance Research Conference (IUFRC 2026). This prestigious event is proudly organized by the Department of Business Studies and Finance, Wayamba University of Sri Lanka, in collaboration with the Sri Lanka Finance Association. The conference will be held in hybrid mode on 27 November 2026.

This year's theme, "Emerging Frontiers in Finance: Integrating Technology, Sustainability, and Governance for Global Competitiveness," underscores the vital role of finance in building a sustainable and globally competitive future. At a time when economies worldwide are navigating significant challenges and opportunities, it is essential to explore emerging technologies, embrace sustainable practices, and strengthen governance.

The conference serves as a valuable platform for undergraduates and recent graduates to showcase their research, exchange ideas, and receive constructive feedback from accomplished academics and industry professionals. We are honoured to welcome our keynote speaker, Assoc. Prof. My Nguyen, Deputy Head of Finance and Associate Professor of Finance at the School of Economics, Finance and Marketing, College of Business and Law, RMIT University, Australia. We look forward to the insights she will share.

We express our heartfelt gratitude to the organizing committee, reviewers, faculty members, and everyone whose commitment and hard work have made this conference possible. We also extend our congratulations to all participants for their dedication and encourage you to make the most of this opportunity as a foundation for your future academic and professional endeavours.

We wish you an engaging, insightful, and inspiring conference experience.

Conference Co-Chair
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MESSAGE FROM THE CONFERENCE CO-SECRETARIES





It is with immense pleasure and pride that we welcome you to the 6th Annual International Undergraduate Finance Research Conference (IUFRC 2026), organized by the Sri Lanka Finance Association (SLFA).

This year's conference is centered on the timely theme, "Emerging Frontiers in Finance: Integrating Technology, Sustainability, and Governance for Global Competitiveness." In an era defined by rapid digital transformation and evolving economic landscapes, IUFRC 2026 serves as a vital platform for emerging scholars to bridge theoretical knowledge with real-world financial challenges. Our primary goal remains empowering undergraduate researchers from Sri Lanka and around the world to showcase their analytical rigor, engage in meaningful academic dialogue, and take their first steps toward peer-reviewed publication.

Organizing a virtual international conference of this scale requires seamless coordination and collective dedication. We extend our sincere gratitude to the President and Executive Committee of the Sri Lanka Finance Association, the Conference Co-Chairs, our distinguished keynote speakers, and the panel of reviewers whose expertise ensured the high academic quality of the papers featured in this proceedings volume.

Above all, we thank our undergraduate presenters and their academic supervisors for their hard work and enthusiasm. We hope that the insights shared during today's sessions inspire continued curiosity, collaboration, and innovation in the field of finance.

We wish all participants a rewarding and intellectually enriching conference experience.

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Contemporary Trends and Issues in Finance

Understanding Investment Behaviour: The Interplay between Personality Traits and Financial Literacy

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ABSTRACT

Investment has become the basic essential of one's life. Investment without knowledge causes confusion. So, financial literacy plays a vital role in investment. Financial literacy is essential for controlling rising living costs and reaching the desired quality of life. As a result, investments are essential to a person's life. The objective of the current study is to observe how variations in the Big Five personality traits influence financial literacy and intention to invest. The study used both primary and secondary data for analysis. Samples were collected from 125 respondents from Begur, Bangalore, India. Using Structural Equational Model, the collected data was analyzed and the interpretations were drawn accordingly. The findings of the study revealed that personality traits have a positive effect towards the intention to invest by the investors and further financial literacy mediates the association between personality traits and intention to invest by the investors. This study also provides managers and policymakers with a foundational understanding and a place to start as they adapt their investment strategies and market surveys to attract investors from the market and monitor the market's degree of financial literacy. There are many different personality types, however, when making financial decisions connected to investments, these personalities are influenced by both high and low financial literacy.

Keywords: *Personality Traits, Investors, Financial Literacy, Investment Behaviour*

JEL code: G41

1. INTRODUCTION

According to the efficient market hypothesis, no one can profit abnormally since the market is efficient. This conventional method disregards the investor's inherent humanity. According to behavioural finance, psychology takes a significant effect on how savers make financial choices. A cognitive mistake has an impact on our financial judgments since psychology influences our investing choices. The ambiguous circumstances we encounter in life have an impact on our decision-making. Our personality affects how we behave. The personality, information interpretation, risk and return, and emotional reaction of the investor all have an impact on their conduct.

Numerous earlier research has shown that an individual's psychographic traits have a significant impact on how they invest. There is some risk involved in investing. The combination of personality qualities someone possesses can influence how they perceive risk. According to research on the psychological characteristics of individual investors, a successful investing strategy could be derailed by emotions. Finance studies usually ignore the decision-making process employed by individual investors when making financial investment decisions. To investigate the reasons prompting individual depositors' financial executive processes and the reasons prompting individual depositors' behaviour, a behavioural paradigm must be built. An investor's predisposition for taking risks can change based on their personality when making investment decisions.

Personality Traits can be used to determine an individual's character. It is a broadly believed concept that describes how different people differ in their personalities along five dimensions. The five dimensions are extraversion, Openness, Conscientiousness, Neuroticism, and agreeableness. First, those with neuroticism are prone to worry, anxiety, and hesitation. They typically feel sad, isolated, and defeated. Second, an extrovert is someone who enjoys social gatherings and is kind and caring toward others. They are assertive in the majority of situations, which draws them in. Third, someone with openness is imaginative and a daydreamer. Their level of originality is average. Fourthly, someone who is agreeable is simple to trust. Allport & Odbert created the “Big-Five Model of personality traits” in 1936. He contends that personality is the most important psychological feature that affects how people behave. Neuroticism, conscientiousness, openness, extraversion, and agreeableness are some of the personality traits.

1.1. Conscientious

People who are conscientious are committed, organized, trustworthy, persistent, and punctual. Additionally, they are less impulsive and take more chances. People who are conscious actively participate in the decision-making process. (B. Widagdo & K. Roz, 2022). Conscientious people trade more to reach their objectives and have a good association with their investment behavior (Sadykov, O. 2022). Without depending on delusions, conscientious investors make wise investment choices

(Baker et al., 2023). This ability makes them pickier about the investments they make. Consequently, the theory is

H01 – Conscientious positively influences intention to invest by investors

1.2. Agreeableness

Collaboration, empathy, and generosity are characteristics of agreeableness that are demonstrated by the capacity to get along with others. People who are agreeable avoid becoming involved in other people's disputes. They accept the information provided by others without critically analyzing it (Sadykov, O. 2022). Cooperative investors follow market herd behavior and engage in intensive stock trading, according to their investing habits. Reputable people rely on the expertise of financial experts since they find it difficult to make their own financial judgments (Hasib, A. 2020). The theory has been formulated as a result.

H02– Agreeableness positively influences intention to invest by investors

1.3. Openness

Individuals that are receptive to new experiences are typically creative, resourceful, and tolerant. Those who possess the trait of being open to new experiences are more likely than others to take risks. The unusual recommendations suggested while making financial decisions are more likely to be accepted by more receptive people (Sachdeva, M., & Lehal, R. 2023). These people are positively correlated with readiness to invest in stocks and risk tolerance (Widagdo, B., & Roz, K. 2022).

H03 – Openness positively influences intention to invest by investors

1.4. Extraversion

"Active, upbeat, thrill-seeking, and inclined to socialize in large crowds" are characteristics of an extravert. Financial decision-making is influenced by extraversion, which only contains positive information. Brown, S., and Taylor, K. (2014) investigated the relationship between personality traits and financial decision-making. This leads us to the conclusion that financial assets and extroversion are closely associated. In order to optimize their gains or returns, extraverted persons appear to take more risks (Durand, R. B., et al. 2008). The theory has been formulated as a result.

H04 – Extraversion positively influences intention to invest by investors

1.5. Neuroticism

People that are neurotic are more pessimistic, depressed, anxious, and fear ambiguity and uncertainty. They would rather avoid uncertainties and steer clear of dangerous products (Niszczota, P. 2014). Analytical, critical thinking, cognitive, and conceptual understanding capabilities are all lacking in people with neuroses. Because of these 48 flaws, neurotic individuals frequently feel anxious and afraid of

failing when taking risks (De Raad, B., & Mlacic, B. 2020). The theory has been formulated as a result.

H05 – Neuroticism positively influences intention to invest by investors

1.6. Financial Literacy

According to Sugiyanto et al. (2019), "an individual's knowledge and understanding of financial concepts" is the definition of financial knowledge. Financial literacy is essential to the development of the financial industry and people's use of it (Sudalai & Vijayalakshmi, 2013). A person's level of financial literacy influences their capacity to make prudent financial decisions since people with less financial literacy are less likely to purchase equities and participate in the stock market. Investors tend to overestimate their level of financial expertise and confidence (Bellofatto et al., 2018). People have a strong sense of self-assurance and financial literacy (Barber & Odean, 2001). Additionally, it has been demonstrated that financial literacy increases a person's propensity to do financial transactions (Hassan et al., 2024). According to Bellofatto et al. (2018), investors who consistently report high levels of financial literacy online make wiser investments.

H06 – Financial Literacy mediates the relationship between personality traits and intention to invest by investors

This study is based on the Big Five personality theory. It is a hierarchical model of psychological traits that has been established through experimentation and is separated into five groups, known as the "Big Five." Numerous recognized qualities have been identified and described by trait theorists. Allport (1937) hypothesized four thousand personality traits, and Cattell (1943) listed sixteen of them. According to Zuckerman et al. (1999) and Kumar et al. (2023), traits include cognitive (brain-based cognitive functions that regulate and control our behavior), motivational (motivating traits are thought to influence behavior through self-control and task-specific motivation), and emotional components (influence how a person generally experiences and expresses emotions in various situations). The five-factor theory, which describes essential attributes and offers the theoretical basis for personality traits, was created in response to criticism that these theories were overly complicated (Soto, 2018). The Big Five personality hypothesis developed by Allport and Odbert (1936) is the most widely accepted, despite the fact that many research has tried to predict personality traits. It is a well-known hypothesis that identifies five personality-related characteristics that distinguish individuals from one another. Agreeableness, extraversion, openness, conscientiousness, and neuroticism are the five characteristics. People's decision-making processes are influenced by their personalities, particularly when making financial decisions (Crysel et al., 2013).

2. REVIEW OF LITERATURE

Investors' opinions of different investment options were examined by Velmurugan et al. (2015). The results highlighted that bank savings and post office investments

are preferred by the elderly and those with large incomes for safe investment purposes. According to Bhavik O. Swadia (2017), the goal of saving is for the children's retirement, healthcare, and education, among other things. The impact of behavioral factors on investment intentions for both short-term and long-term investments was noted by Sashikala et al. (2018). The study comes to the conclusion that behavioral factors influence stock investors' long-term and short-term investing intentions. Investors' personalities, values, emotions, and social surroundings all have an impact on how capable they believe they are of making wise financial decisions. People's psychographic situations have a big impact on how they invest, and the dangers associated with their decisions are interwoven. (2020) Sarwar et al. Decision-making is frequently and consistently influenced by emotions. (2020, Priyadharshini). While anxiety and other negative emotional states have the opposite effect, excitement and other positive emotional states motivate people to take chances and have faith in their abilities to evaluate investment prospects (Kuhnen & Knutson, 2011). One important factor influencing investments in general was emotional stability. Compared to other variables, returns and emotional stability were found to have a larger association with equity. Christie and Isidore (2017). Perceptual constructs may be based on personality variables or an individual's inherent characteristics when forecasting their behavioral intention. Lai (2019). Danish Sarwar et al. (2020) found that while neuroticism has a negative correlation with an investor's intention to invest, extraversion, agreeableness, risk aversion, openness to new experiences, and consciousness all significantly positively connect with an individual's inclination to invest. Cheng-Po Lai (2019) looked into how individual investors' personality factors affected their stock market investments. The findings demonstrate that individuals with aggregable personalities devote their energies to maintaining interpersonal relationships. High and low self-monitors only accept medium risks (Varadharajan & Vikkraman, 2010). The empirical results of this study indicate that the relationship between extroversion and perceived behavioral control is strongly influenced by age. Individuals with a high level of openness are typically self-reliant and make sensible choices in difficult situations. (Awan and Sahar, 2021).

3. RESEARCH GAP

Numerous studies have looked at the relationship between investment behavior and personality qualities, but the results have been conflicting and inconsistent. According to studies on the subject, personality traits are important while making financial decisions, which is backed by utility and theory. It is widely acknowledged that a person's financial behavior may be accurately predicted by their "Big Five" personality traits. Numerous studies on the relationship between personality qualities and investing behavior have been carried out (Rahman & Gan, 2020 & Lai, 2019); nevertheless, the focus on the financial literacy in relation to personality traits remains unexplored. Thus, this study focuses on the unfocused area.

4. OBJECTIVE AND RESEARCH QUESTION

To spot out how investor's personality traits influence the intention to invest and the financial literacy mediating effect towards intention to invest by the investors the focus of this study. It has not yet been determined how personality qualities affect the intention to investment. It poses a number of queries. Do personality characteristics affect how investors make investments? Does Financial Literacy mediate the personality traits and Intention to invest? This study has attempted to investigate the untapped areas with an emphasis on financial literacy in order to obtain insight into the most popular investment paths and the influence of personality traits on investors' investment behavior. An investor may run a profitable platform and have a stronger investment portfolio by understanding personality qualities.

5. CONCEPTUAL FRAMEWORK

The relationship between the constructs used in the investigation is envisioned by the conceptual framework. The model's Schematic representation (Figure 1) explains how variables are connected, and the reader can visualise the theory being given as a result. The personality traits (Conscientious, Agreeableness, Openness, Extraversion and Neuroticism) are taken as the control variables whereas Financial Literacy is the mediating variable and intention to invest is taken as the dependent variable.

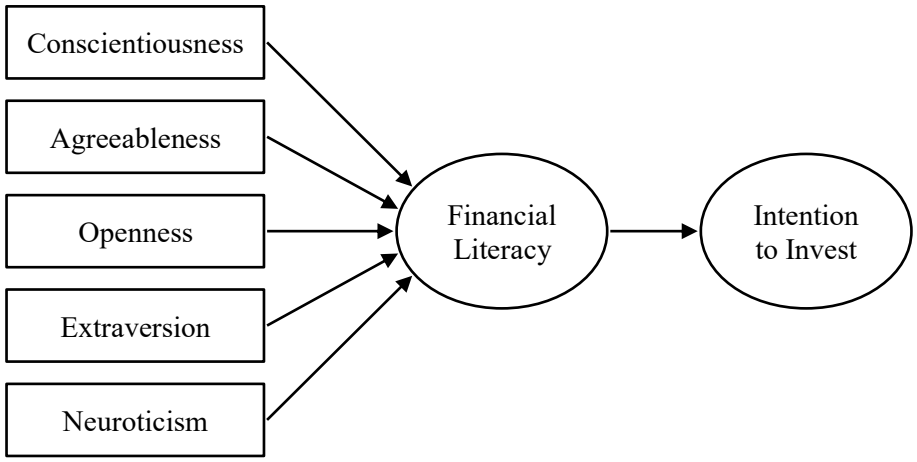

Figure 1. Influence of Big Five Personality Traits

6. RESEARCH METHODOLOGY

6.1. Data Collection

The Big Five Factor Model's personality qualities were included in a well-structured questionnaire (Allport and Odbert, 1936). "The domain of personality descriptors is nearly entirely accounted for by five robust factors if a large number of rating scales are used and the scope of the scales is very broad" (Costa, Paul & McCrae, R.R.,

1999). The data was gathered by convenient sampling. As a result, this method was used to get responses from investors from Begur, Bangalore. 150 investors were given the questionnaire, and 125 of them provided valid answers.

6.2. Data Analysis

All statistical analysis was done using SPSS and AMOS software. The reliability test was carried out, to find whether the variables are reliable to carry out the study. Thus, the test was carried out for the traits and the values are shown in Table 1.

Table 1. Reliability Test

Particulars	Items	Values
Conscientious	5	0.752
Agreeableness	5	0.831
Openness	5	0.801
Extraversion	5	0.729
Neuroticism	4	0.797
Financial Literacy	3	0.817

Source: Processed data

The Cronbach's Alpha value of conscientiousness is 0.752 which is more than the suggested value 0.7 (Peterson, R. A., 1994). Openness Cronbach's Alpha value is 0.801 which is above 0.7. The value of extraversion is 0.729 which is reliable. The values for Agreeableness and Neuroticism are 0.831 and 0.797 which fall above the suggested value 0.7. Hence, the reliability of the question is proved (Peterson, R. A., 1994). The Kolmogorov-Smirnov test is used to determine if a collection of data originates from a normal distribution, which is the null hypothesis (Kolmogorov, A. N., 1983). The test statistics generated by the Kolmogorov-Smirnov test are used to check for normality. The KS test was done for 125 samples and it was found that the distribution was normal. Thus, the parametric test was used for analysing the data It is clear that the value of the Kolmogorov-Smirnov statistics p-value is more than 0.05 (at a 5% level of significance). Thus, it indicates that there is a normal distribution.

7. RESULTS AND DISCUSSION

In this section, the main results of the study are presented and discussed in detail. The results presented in this section correspond to the research questions and objectives of the study. The results have been analyzed using appropriate statistical methods and are presented in the subsequent sections with the corresponding descriptions, emerging patterns, relations and findings. The major characteristics of the sample studied are presented through percentage descriptions in Table 2.

Table 2. Socio-Economic Profile of the Investors

Particulars	Category	Percentage
Gender	Male	56
	Female	44
Age	25 - 35 years	23
	36 – 45 years	36
	46 – 55 years	21
	Above 56 years	20
Qualification	School	12
	Undergraduate	41
	Postgraduate	23
	Professional	24
Annual Income	Below Rs. 2,00,000	14
	Rs. 2,00,000 – Rs. 6,00,000	67
	Above Rs. 7,00,000	19

Source: Primary data

Male investors comprise the largest percentage of participants in the study area. Among them, the investors of age 35 – 45 years are most active in the investment field. This group comprises individuals holding under graduate degrees and with an annual income of more than INR 2,00,000 and up to INR 6,00,000.

7.1. Factors Influencing the Intention to Invest

Several methodologies are used to measure the factors that influence the intention to adopt by investors. It is calculated to reduce the data using the Eigenvalue. The "Kaiser- Meyer- Olkin Measure is an index that determines the appropriateness of sampling. The KMO test" result, which is greater than 0.5 and can be regarded as acceptable and legitimate for use in data reduction procedure, is 0.960.

7.2. Model for Investment Intention

To verify the model fit, the structural model method adheres to common best practices. The computed value for the structural model under the intention to invest is shown in Table 3.

Chi-square, RMSEA, NFI, and CFI have respective values of 32.415, 0.072, 1.511, and 1.119. The minimum fit chi-square statistic was discovered to be significant; as a result, the model could be regarded as ideal and implied that the model is suitable and approved. It was evident that the numbers fell inside perfectly specified SEM analysis range.

Table 3. Model of Intention to Invest

Model Fit Indices	Accepted Value	Model Value
Chi-Square		32.415
Root Mean Square Error of Approximation (RMSEA)	< 0.10	0.072
Goodness of Fit Index (GFI)	> 0.90	0.950
Adjusted Goodness of Fit Index (AGFI)	> 0.90	1.003
Normed Fit Index (NFI)	> 0.90	0.999
Comparative Fit Index (CFI)	> 0.90	1.009
Relative Fit Index (RFI)	> 0.90	0.982
Incremental Fit Index (IFI)	> 0.90	0.927
Root Mean Square Residual (RMSR)	≥ 0	0.002
Parsimony Comparative of Fit Index (PCFI)	> 0.50	1.070
Parsimony Normed Fit Index (PNFI)	> 0.50	1.066

Source: Processed Data

To determine the relationship, a model has been created using SPSS-AMOS. If the GFI indices, Normed Fit Index (NFI), and CFI are all higher than 0.90, the model is deemed appropriate (Hair et al., 2012). Furthermore, if the RMSEA was between 0.05 and 0.08 and the RMR was less than 0.05, the model was deemed appropriate (Hair et al., 2012). GFI is 0.950, NFI is 0.999, CFI is 1.003, RMSR is 0.002, and RMSEA is 0.072, all of which are acceptable values for the model displayed in Table 3. Expectations of the investors cannot be always achieved by them. Even though "personality traits" is a "psychological construct" plays a vital role in determining the individual's investment decision.

8. SUGGESTIONS

Understanding the factors influencing investors' decision to invest is made possible by the study. Based on the results, the following recommendations were made.

- People should be aware of both favourable and unfavourable effects on personality attributes. Being conscious of one's own personality qualities can help one make better investment decisions.
- Individuals can adjust their investment plans to match their talents and weaknesses.
- To gain knowledge about the different investment alternatives, a variety of investment-related seminars should be held.
- It is necessary to start digital services in rural areas so that more households may learn about investments.

9. LIMITATIONS

The limitations of the study are:

- The sample size is limited to 125 respondents
- The study area is limited to Begur, Bangalore
- Only selected constructs were used for the study

10. CONCLUSION AND FUTURE SCOPE

A person's unique features are the result of a variety of circumstances, including their upbringing environment, their moral principles, their religious convictions, and social conditioning elements specific to the many social groups they identify with. The study concludes that there is a positive effect of personality traits towards intention to invest by investors and "financial literacy mediated the relationship between personality traits and" intention to invest by investors. This study also provides managers and policymakers with a foundational understanding and a place to start as they adapt their investment strategies and market surveys to attract investors from the market and monitor the market's degree of financial literacy. There are many different personality types, however, when making financial decisions connected to investments, these personalities are influenced by both high and low financial literacy. Prospective researchers are strongly encouraged to conduct the same research in other countries and to employ different factors, such as behavioural biases and emotional intelligence, in maximising the generalizability of these findings.

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Artificial Intelligence in Financial Risk Management: A Proposed Machine Learning Framework for Predicting Financial Market Stress in an Emerging-Market Context

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ABSTRACT

Artificial intelligence (AI) and machine learning (ML) are used in financial risk management, and Gartner (2024) predicted that 90% of finance functions would deploy at least one AI-enabled solution by 2026. Traditional autoregressive models, however, remain widely used to forecast financial market stress. Though they struggle to capture nonlinear and regime-dependent dynamics. Recent central bank evidence shows that tree-based ML models predict stress in US Treasury, foreign exchange and money markets more accurately than traditional time-series approaches. This paper does not report empirical results. It proposes a research framework for testing whether ML models outperform autoregressive benchmarks in forecasting stress in the equity, foreign exchange, money and government bond markets of an emerging economy, using Sri Lanka as the reference case. The framework fixes the stress measure, data, forecast horizons, chronological validation scheme, evaluation metrics and hypotheses before estimation. It also embeds model risk management and explainability in the design, drawing on supervisory model-risk guidance and explainable-AI research. The expected contribution is a replicable protocol and a governance-oriented evaluation approach for early-warning systems in data-limited emerging markets.

Keywords: *Artificial Intelligence, Machine Learning, Financial Market Stress, Early-Warning Systems, Model Risk Management, Emerging Markets*

JEL Classification: C53, G17, G32, E44

1. INTRODUCTION

Financial markets are closely interconnected through cross-border capital flows, financial innovation and technology. A shock in one segment, such as equities, can quickly spread to exchange rates, interest rates, credit spreads and liquidity. Early identification of market stress is therefore essential for financial institutions, central banks and supervisors. Financial market stress denotes conditions in which markets function abnormally or with unusual uncertainty, visible in sharp price movements, higher volatility, wider spreads, reduced liquidity and weaker investor confidence. Because several indicators typically move together, stress is multidimensional, which is why composite indicators such as the Composite Indicator of Systemic Stress (CISS) aggregate stress across market segments (Holló et al., 2012).

Autoregressive (AR) models are transparent and capture the persistence of stress, but they impose a fixed functional form and may deteriorate under nonlinearities, structural breaks and interactions among many predictors. ML methods can learn such patterns directly from data (Mullainathan & Spiess, 2017; Gu et al., 2020). Random forests (Breiman, 2001) average many decision trees and handle interactions without prespecification. Aldasoro et al. (2025) show that tree-based models significantly outperform traditional time-series approaches in predicting the distribution of market conditions in key US markets. Related central bank work finds that random forests also outperform logit models in early warning of fiscal stress, correctly predicting 70–80% of stress events and tranquil periods (Jarmulska, 2020).

Evidence concentrates on advanced economies, while emerging markets have shorter and noisier data, more frequent structural change and thinner liquidity, so transferability of ML advantages is uncertain. Second, adoption in finance has advanced faster than governance: a model that forecasts well but cannot be explained, validated and monitored is unsuitable for supervisory use (Board of Governors of the Federal Reserve System, 2011; Rudin, 2019). This is a conceptual and methodological paper presenting a pre-specified research protocol. It contains no estimated results, and statements about ML performance describe hypotheses, not findings.

2. AIMS/OBJECTIVES

The primary aim is to specify and justify a protocol for testing whether ML models forecast financial market stress in an emerging economy more accurately than autoregressive benchmarks.

1. Do ML models forecast stress more accurately than AR benchmarks at horizons of 1, 3, 6 and 12 months?
2. Do ML models provide earlier and more reliable warnings of high-stress episodes, at acceptable false-alarm rates?
3. Which predictors drive forecasts, and are they stable across regimes?

4. What model-risk and explainability controls are needed to deploy such models responsibly?

3. HYPOTHESES

H1: Random forests achieve lower out-of-sample forecast loss than AR benchmarks, with larger gains in the upper tail of stress and at longer horizons.

H2: Random forests give longer warning lead times than AR and logit benchmarks at comparable false-alarm rates.

H3: Predictive gains are larger in high-stress regimes than in calm periods.

4. THEORY

The financial instability hypothesis holds that stability breeds risk-taking and leverage that eventually produce abrupt, nonlinear adjustments (Minsky, 1986). This implies threshold effects and interactions, for example funding-liquidity strains combined with currency depreciation, which linear AR specifications represent poorly and tree-based models, such as random forests (Breiman, 2001), can approximate. Portfolio-theoretic stress indices add that systemic stress rises when stress is correlated across market segments (Holló et al., 2012), which motivates multi-market predictors. Empirically, Gu et al. (2020) show that tree-based and neural methods capture nonlinear predictor interactions in asset-pricing forecasts. Aldasoro et al. (2025) use Shapley value analysis to identify funding liquidity, investor overextension and the global financial cycle as important predictors of future tail realisations of market conditions. Evidence for frontier and emerging markets remains scarce.

For model risk, supervisory guidance defines model risk as the potential for adverse consequences from decisions based on incorrect or misused models and calls for sound development, independent validation and ongoing monitoring (Board of Governors of the Federal Reserve System, 2011). Explainable-AI research offers post hoc attribution through Shapley values (Lundberg & Lee, 2017) while cautioning that interpretable models should be preferred in high-stakes settings where they perform comparably (Rudin, 2019). Regulation of high-risk AI also emphasises documentation, human oversight and robustness (European Parliament & Council, 2024).

5. METHODS

The reference case is Sri Lanka, an emerging economy that has recently experienced pronounced external, sovereign and currency stress. The proposed sample is monthly observations from January 2010 to December 2025, subject to data-availability checks. If Sri Lankan series prove too short or discontinuous, the protocol allows a robustness extension to a panel of comparable emerging markets.

Stress is measured by a composite index built in the CISS tradition (Holló et al., 2012) from four segments: equity, foreign exchange, money market and government bonds. Each segment subindex averages three raw stress measures (Table 1), each transformed with an empirical cumulative distribution function computed recursively on an expanding window, so no future information enters. Subindices are aggregated using time-varying cross-correlations. The continuous index is the target for regression forecasts. The binary target equals 1 when the index exceeds its recursively estimated 80th percentile (sensitivity: 75th and 90th percentiles). Forecasts are made h months ahead, with h in {1, 3, 6, 12}.

Table 1. Proposed Stress Measures and Predictors

Segment	Stress measures (target index)	Additional predictors
Equity	Negative return of the All-Share Price Index, realized volatility, maximum drawdown	Trading volume, market capitalisation change
Foreign exchange	LKR/USD depreciation, realised exchange-rate volatility, reserve change	Current account, external debt service, VIX, US policy rate
Money market	Overnight/policy-rate spread, short-term rate volatility, interbank spread	Liquidity injections, reserve money growth
Government bonds	Yield change, term spread, yield volatility	Sovereign spreads, credit growth, inflation, output proxy

Note. Variable lists are proposed and will be finalized after data-availability checks.

Sources: Central Bank of Sri Lanka, Colombo Stock Exchange, and international databases for global factors.

All predictors are lagged so that only information available at the forecast origin is used. Series are transformed to stationarity, standardized using training-window moments only, and checked for missing values (forward fill limited to one month; otherwise, exclusion). Outliers are retained and assessed through minorized robustness checks, because extremes are the object of interest. Benchmarks are (i) AR(p) with p chosen by the Bayesian information criterion up to 12 lags, (ii) AR with exogenous macro-financial variables, and (iii) for the binary target, penalised logistic regression. ML models are random forest (primary; regression and quantile versions), gradient-boosted trees and an elastic net as a low-complexity control. Including several algorithms tests whether any gain is specific to random forests. ML models use 1, 3 and 6 monthly lags of each predictor plus the lagged target.

Data are split chronologically: initial training 2010–2017, expanding-window monthly re-estimation, and an out-of-sample test period 2018–2025 that includes major stress episodes. Hyperparameters are tuned by time-series cross-validation

inside the training window, with purging and an embargo of h months between training and validation folds to prevent leakage from overlapping horizons (López de Prado, 2018). Random shuffling is not used, and grids and seeds are reported.

Point forecasts are evaluated with mean absolute error and root mean squared error, and tail forecasts with quantile loss at the 50th, 90th and 95th quantiles. Accuracy differences against the AR benchmark are tested with the Diebold–Mariano test (Diebold & Mariano, 1995). Binary forecasts are evaluated with ROC-AUC, precision, recall, F1 and precision–recall curves. Early-warning value is measured by warning lead time, false-alarm rate and missed-event rate, reported separately for stress episodes and calm periods. Variable importance uses permutation importance and Shapley values (Lundberg & Lee, 2017), interpreted as predictive, not causal.

Governance is operationalized in four testable elements: (1) documentation of purpose, data lineage, assumptions and limitations in a model card; (2) independent validation through replication by a second analyst, back-testing and benchmark comparison; (3) explainability through global and local Shapley explanations, regime-stability tests of rankings and an interpretable challenger model; and (4) monitoring of forecast errors, data drift and predictor-importance shifts, with predefined thresholds triggering review, human override and recalibration. Costs are made explicit through a loss function that weights missed stress events more heavily than false alarms.

6. RESULTS

No empirical results are reported, because the protocol has not yet been executed. Table 2 shows the output that the completed study will report, so that reviewers can see how hypotheses H1–H3 will be judged. No value in this paper should be read as a finding.

Table 2. Illustrative Household Sorting Outcomes

Output	Content	Hypothesis
Forecast accuracy	MAE, RMSE and quantile loss by model, market segment and horizon; Diebold–Mariano p-values vs AR	H1
Classification	ROC-AUC, precision, recall and F1 for the binary stress target; ROC and precision–recall curves	H1, H2
Early-warning value	Warning lead time, false-alarm and missed-event rates for each stress episode	H2
Regime analysis	Metrics in high stress versus calm periods	H3
Explainability	Shapley and permutation importance rankings; stability across regimes	RQ3

7. DISCUSSION

Because no estimation has been performed, this section describes how outcomes would be interpreted. If H1–H3 hold, they would extend evidence from advanced-economy markets (Aldasoro et al., 2025) to an emerging market. If they fail, the finding would be equally informative: it would indicate that short samples and structural breaks limit ML advantages and that simple benchmarks remain adequate.

Some challenges are foreseeable. Complex models can overfit when observations are few relatives to predictors, so inference rests on out-of-sample results and on comparison with the elastic net and boosted trees. Foreign exchange stress in small open economies is strongly driven by external shocks, so global factors are included. Money-market stress may reflect policy intervention, which can weaken historical relationships. Segments are therefore evaluated separately before generalizing.

8. IMPLICATIONS AND LIMITATIONS

The protocol allows a central bank or supervisor to compare ML and AR early-warning tools under identical, leakage-free conditions and to judge them on lead time, false alarms and explainability, not accuracy alone. For practice, human oversight, local calibration and sensitivity analysis should complement algorithmic forecasts where data are short or structural change is frequent. For theory, the design provides a test of whether nonlinear, interaction-based mechanisms of instability are detectable in an emerging market.

The study is not yet implemented and presents no evidence of ML superiority. It depends on the availability and consistency of Sri Lankan data for 2010–2025, relies on one country, and uses a constructed stress index whose thresholds involve judgement. Predictor importance does not imply causation. Future work should execute the protocol, report full empirical results, extend it to other emerging markets and compare additional explainable-AI methods.

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Artificial Intelligence Adoption, Circular Material Use, and Resource Productivity in the European Union

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ABSTRACT

This study examines whether enterprise artificial intelligence (AI) adoption and circular material use are associated with resource productivity across the 27 European Union Member States. Although digital technologies may support resource optimization, their diffusion does not necessarily translate into measurable circular-economy outcomes. Using a harmonized 2024 cross-section from six Eurostat datasets (N = 27), we estimate ordinary least squares models with HC3 heteroskedasticity-robust standard errors. Resource productivity (euros per kilogram) is related to enterprise AI adoption, circular material use, gross fixed capital formation as a share of GDP, research and development expenditure, and, in sensitivity specifications, GDP per capita. An AI × circular-material-use interaction tests the proposed complementarity. In the baseline model, circular material use is positively associated with resource productivity ($\beta = 0.1016$, HC3 $p = 0.0043$), whereas AI adoption is not statistically significant ($\beta = 0.0789$, $p = 0.177$). Investment intensity has a negative baseline coefficient ($\beta = -0.1786$, $p = 0.0285$), contrary to the directional hypothesis. The interaction is positive but not significant in the full model ($\beta = 0.00260$, $p = 0.402$), and leave-one-country-out tests do not overturn that conclusion. The analysis supports a conditional association between circular material use and resource productivity but does not establish an independent AI effect or AI-circularity synergy. The findings are associative, not causal; they do not directly measure green finance or competitiveness.

Keywords: *artificial intelligence, circular economy, resource productivity, sustainable finance, European Union*

JEL Classification: O33, Q56, O47, E22

1. INTRODUCTION

The transition from a linear economic model toward a circular economy has become an important component of contemporary sustainability strategies. The traditional linear system of production and consumption relies on continuous extraction of natural resources, transformation into products, consumption, and disposal. In contrast, the circular economy seeks to retain the value of products, materials, and resources for as long as possible by slowing, narrowing, and closing resource flows. Circular strategies include reuse, recycling, repair, maintenance, refurbishment, remanufacturing, and other mechanisms that reduce dependence on virgin resources and minimize waste generation (Hofmann & Jaeger-Erben, 2020).

The circular economy is not limited to waste management. It requires changes in production systems, organizational practices, business models, investment decisions, and innovation processes. Lindgreen et al. (2020) argue that one of the central ambitions of circularity is to decouple economic development from finite resource consumption while simultaneously reducing environmental pressures and maintaining economic value creation. Their review also shows that circular-economy assessment approaches remain highly diverse and that only a relatively limited number integrate environmental, economic, and social dimensions simultaneously. The issue of measurement is particularly important because circularity cannot be evaluated solely through individual recycling or waste indicators. Helander et al. (2019) show that many circular-economy indicators focus on single activities and do not necessarily capture the broader environmental pressures associated with economic activity. They therefore recommend complementing activity-based circular-economy indicators with broader measures related to resource use and environmental pressure. This observation supports the use of resource productivity as an outcome variable because it connects the economic value generated by an economy with its material-resource consumption.

Evidence from European economies also indicates that circularity is closely related to innovation and economic development. Šverko Grdić et al. (2020) analyse circular-economy indicators in EU countries and emphasize the relevance of indicator groups covering production and consumption, waste management, secondary raw materials, competitiveness, and innovation. Their study confirms the usefulness of national-level indicators for analysing differences in circular-economy performance and its relationship with economic development. Hysa et al. (2020) provide an important empirical foundation by examining circular-economy indicators and economic growth in European countries. Their model includes environmental taxes, recycling, private investment and employment in circular-economy sectors, patents

related to recycling, and trade in recyclable raw materials. Using fixed-effects panel estimation and an Arellano-Bond dynamic model, they report positive relationships between circular-economy dimensions, innovation, investment, and economic growth. Their findings further indicate that resource productivity and environmental innovation are relevant for explaining differences in economic growth across EU economies.

At the same time, artificial intelligence has become a major component of digital transformation. AI is increasingly considered a general-purpose technology capable of influencing tasks, organizational processes, business models, and innovation systems. Jöhnk et al. (2021) stress that AI can create new business opportunities and competitive advantages, but successful adoption depends on organizational readiness and the capacity to integrate AI into core activities. Their research identifies strategic alignment, organizational resources, knowledge, culture, and data as central categories of AI readiness.

This distinction is important because AI should not be treated as an automatic source of productivity. Technological adoption requires complementary capabilities. Shi et al. (2020), examining knowledge transfer in AI industry innovation networks, show that innovation performance depends on factors such as network characteristics, organizational culture, willingness to receive knowledge, and absorptive capacity. Thus, technological diffusion and productive outcomes are mediated by organizational and knowledge-related conditions. The relationship between AI and circularity becomes especially relevant when information is considered. Bianchini et al. (2019) identify information availability as a key condition for implementing circular business models. Information about resource condition, material and energy flows, asset use, and product location can support predictive maintenance, process optimization, reuse, remanufacturing, and the identification of previously unexploited circular opportunities. The authors also argue that technologies associated with Industry 4.0 can support continuous data collection, processing, and exchange, thereby improving circular-economy implementation and reducing uncertainty in circular investment decisions.

The financial dimension is also central to sustainable transformation. Ziolo et al. (2019) argue that finance can act as a driver of sustainability when financial systems incorporate environmental, social, and governance considerations into decision-making and risk assessment. Their framework expands the traditional financial-system perspective beyond efficiency and stability to include sustainability and ESG integration. De Lucia et al. (2020) further show that ESG practices and environmental innovation are associated with financial

performance among European public enterprises, although they also note that sustainability-related investments may require long-term financial commitments and may produce different short- and medium-term effects.

Previous studies of EU economies have examined the relationships between circular-economy indicators, innovation, and economic growth (Hysa et al., 2020; Šverko Grdić et al., 2020), while research on AI has primarily focused on organizational readiness and the capabilities required for successful technology adoption (Jöhnk et al., 2021). However, these research streams have largely been examined separately, leaving limited empirical evidence on whether enterprise AI adoption and circular material use are jointly associated with resource productivity across EU Member States, particularly whether AI adoption strengthens the circularity-resource productivity relationship. This study addresses this gap by examining their individual associations and interaction using harmonized Eurostat data for all 27 EU Member States in 2024.

2. AIMS, RESEARCH QUESTIONS, AND HYPOTHESES

The main aim of this study is to examine how artificial intelligence (AI) adoption and circular-economy performance are associated with resource productivity across the 27 European Union Member States. Building on previous research linking circular-economy indicators with economic performance and research examining the organizational conditions of AI adoption, the study investigates whether these two dimensions are independently associated with resource productivity and whether AI adoption strengthens the relationship between circular material use and resource productivity.

To achieve this aim, three specific objectives are established:

- To assess the association between enterprise AI adoption and resource productivity across EU Member States.
- To examine the relationships between circular material use, investment intensity, and resource productivity, accounting for differences in innovation capacity and economic development.
- To investigate whether enterprise AI adoption moderates the relationship between circular material use and resource productivity.

These objectives are addressed through the following research questions:

RQ1: How is enterprise AI adoption associated with resource productivity across EU Member States?

RQ2: How are circular material use and investment intensity associated with resource productivity across EU Member States?

RQ3: Does enterprise AI adoption positively moderate the relationship between circular material use and resource productivity across EU Member States?

Drawing on the theoretical arguments concerning technological capabilities, circular-economy transformation, and investment, the following hypotheses are formulated:

H1: Enterprise AI adoption is positively associated with resource productivity across EU Member States.

H2a: Circular material use is positively associated with resource productivity across EU Member States.

H2b: Investment intensity is positively associated with resource productivity across EU Member States.

H3: Enterprise AI adoption positively moderates the relationship between circular material use and resource productivity, such that the positive association between circular material use and resource productivity is stronger in Member States with higher levels of AI adoption.

3. THEORETICAL BACKGROUND

The study draws on the general-purpose technology perspective (Bresnahan & Trajtenberg, 1995) and a complementary-capabilities interpretation of organizational resource use. AI can potentially be deployed across many activities, but its benefits depend on data availability, skills, management, and investment in complementary systems. Jöhnk et al. (2021) identify these readiness conditions, while Shi et al. (2020) demonstrate the relevance of knowledge-transfer capacity in AI innovation networks. Accordingly, an observed country-level AI adoption percentage is a measure of diffusion rather than an index of implementation quality.

Circular material use represents a distinct operational dimension: the share of overall material use supplied by recovered materials. It can rise through collection, sorting, processing, reuse, and substitution, but these activities do not necessarily occur in the same enterprises that adopt AI. The proposed moderation mechanism requires a connection between digital information capabilities and actual circular processes. Bianchini et al. (2019) argue that information about material flows and product conditions can enable circular business models. That mechanism motivates H3, without guaranteeing a positive national-level interaction.

Investment and R&D expenditure capture broader enabling conditions. Aggregate gross fixed capital formation measures economy-wide capital formation, not sustainable finance, and may reflect construction, machinery, or other activities with different resource implications. R&D intensity is a proxy for innovation capacity, not a direct measure of circular innovation. The model thus tests associations between observable macroeconomic proxies rather than direct effects of AI-enabled circular projects or green-finance instruments. Gross fixed capital formation can support resource productivity when new capital replaces inefficient machinery or improves production technology, but the opposite association is plausible where investment expands construction or material-intensive infrastructure. Accordingly, the investment hypothesis is directional rather than mechanically assured. Ziolo et al. (2019) provide a sustainability-oriented financial framework, but INV does not operationalize sustainable finance and cannot identify green investment.

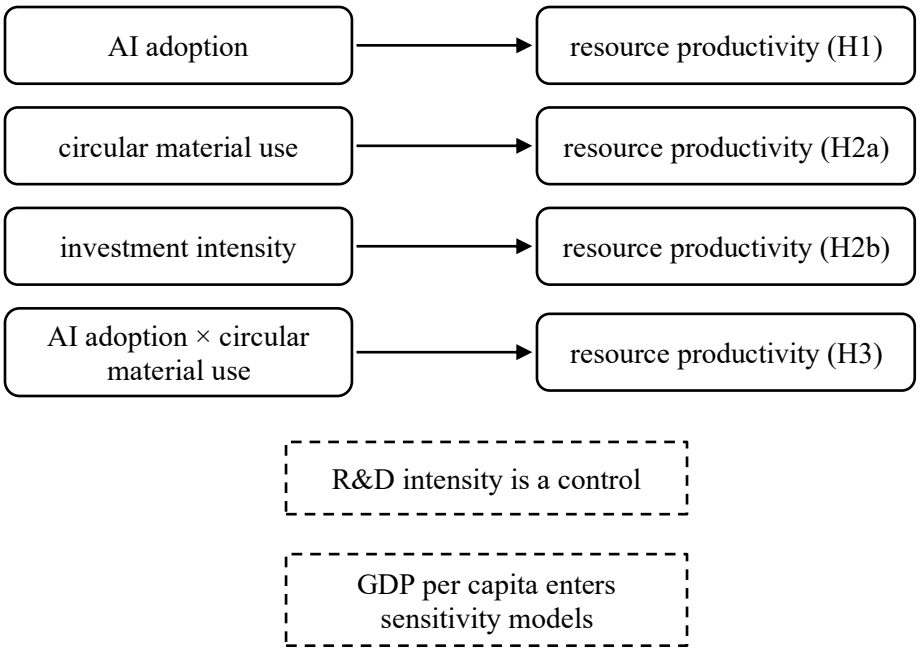

Figure 1. Conceptual Pathways (Hypothesized)

4. METHODS

The unit of observation is the EU Member State in 2024. The final balanced cross-section includes all 27 Member States (N = 27), with no missing values in the selected series. The year was chosen because the enterprise AI indicator

is available for the same reference year as the circularity and national-accounts indicators, avoiding unsupported assumptions about a longer annual panel.

Table 1. Variable Definitions, Measurement Units, and Eurostat Data Sources

Variable	Eurostat code	Measurement
RP	cei_pc030	Resource productivity, €/kg; chain-linked volumes (2015)
AI	isoc_eb_ai	Enterprises using at least one AI technology, 10+ persons employed, %
CMU	cei_srm030	Circular material use rate, %
INV	nama_10_gdp	Gross fixed capital formation / GDP × 100, current-price million €
GDPpc	nama_10_pc	GDP per capita, current-price €/person
R&D	rd_e_gerdtot	Gross domestic R&D expenditure, all sectors, % GDP

Note. RP = resource productivity; AI = enterprise artificial intelligence adoption; CMU = circular material use rate; INV = investment intensity; GDPpc = GDP per capita; R&D = research and development expenditure. Resource productivity uses chain-linked volumes (2015), in €/kg. AI and CMU are percentages; INV and R&D are percentages of GDP; GDPpc is current-price €/person. INV = 100 × gross fixed capital formation / GDP. All indicators refer to 2024.

The study uses harmonized Eurostat exports and retains each variable in its documented unit. There is no interpolation, zero-imputation, or averaging across years. Resource productivity is the ratio of GDP to domestic material consumption, expressed here in euros per kilogram using the chain-linked-volume (2015) Eurostat series. Because GDP is also the numerator of GDP per capita, GDPpc is included only in sensitivity specifications and is not treated as an independent validation of the resource-productivity association.

Investment intensity was calculated from two compatible current-price national-accounts series as 100 × gross fixed capital formation / GDP. The interaction was calculated as AI × CMU using the original percentage-point scales; no artificial conversion to a common physical unit was imposed. All coefficients therefore refer to a one-percentage-point increase in the corresponding percentage variable, conditional on other regressors. The RP series is based on chain-linked-volume output, whereas GDPpc uses current-price GDP, which also calls for care when interpreting their association.

$$RP_i = \beta_0 + \beta_1 AI_i + \beta_2 CMU_i + \beta_3 INV_i + \beta_4 R\&D_i + \beta_5 GDPpc_i + \beta_6 (AI \times CMU)_i + \varepsilon_i \quad (1)$$

In Equation (1), i denotes an EU Member State, ε_i is the regression disturbance, and the year index is omitted because the data comprise a single 2024 cross-section. Coefficients for omitted variables are constrained to zero in the reduced specifications.

Four nested ordinary least squares specifications were estimated: M1 includes AI, CMU, INV, and R&D; M2 adds GDPpc; M3 adds AI × CMU to M2; and M4 adds AI × CMU to M1, omitting GDPpc. The full interaction specification includes all explanatory variables, GDP per capita is excluded from M1 and M4, while the interaction term is excluded from M1 and M2. The country subscript i is used because the dataset is cross-sectional rather than longitudinal.

Inference uses HC3 heteroskedasticity-robust standard errors and residual-degrees-of-freedom t tests. Reported tests include Breusch-Pagan and White diagnostics for heteroskedasticity, Jarque-Bera residual-normality tests, RESET specification checks, variance inflation factors, Cook's distance, leverage, studentized residuals, and leave-one-country-out re-estimation. Interaction effects are interpreted using conditional marginal effects with HC3 confidence intervals. Computations were performed using Python (statsmodels and associated numerical libraries), and country-level input values and outputs are retained in the accompanying reproducibility workbook.

A key measurement concern is that resource productivity uses GDP relative to material consumption, while GDPpc also contains GDP. Adding GDPpc may therefore introduce a mechanical association. M1 and M4, which exclude GDPpc, are central robustness specifications. Even without that overlap, simultaneity, reverse causality, sectoral structure, national price levels, and unobserved institutional differences prevent a causal interpretation.

5. RESULTS

Descriptive statistics show considerable variation among Member States. Average resource productivity is 2.181 €/kg (standard deviation 1.380), and mean enterprise AI adoption is 14.279% (standard deviation 7.177). The full sample contains 27 countries, with no missing observations. The Pearson correlation between AI adoption and RP is 0.534, while the CMU-RP correlation is 0.639. These positive bivariate associations are not equivalent to conditional regression effects.

The baseline model explains 63.8% of cross-country variation in RP (adjusted $R^2 = 0.572$). CMU is positively associated with RP ($\beta = 0.1016$, $p = 0.0043$), while AI is positive but not significant ($\beta = 0.0789$, $p = 0.177$). Investment intensity is negative ($\beta = -0.1786$, $p = 0.0285$), contrary to H2b. Adding GDPpc increases R^2 to 0.832, but this must be considered alongside the GDP-overlap concern. The full interaction model has $R^2 = 0.841$ (adjusted $R^2 = 0.794$), only a modest improvement over M2.

Table 2. Descriptive Statistics for the EU-27 Sample, 2024

Indicator	N	Mean	SD	Min	Max
RP_EUR_kg	27	2.181	1.380	0.386	5.739
AI_pct	27	14.279	7.177	3.070	27.580
CMU_pct	27	10.919	7.629	1.300	32.700
INV_pctGDP	27	21.275	2.745	16.627	26.620
RD_pctGDP	27	1.798	0.933	0.460	3.530
GDPpc_EUR	27	41855.185	25879.020	16340.000	128710.000

Note. N = number of countries; SD = standard deviation; Min = minimum; Max = maximum. RP is €/kg; AI and CMU are percentages; INV and R&D are percentages of GDP; GDPpc is current-price €/person. The sample covers all 27 EU Member States in 2024, without missing observations.

Table 3. Ordinary Least Squares Regression Results for Resource Productivity, EU-27, 2024

Term	M1	M2	M3	M4
AI_pct	0.0789	-0.0342	-0.0646	0.0646
	(p=0.177)	(p=0.184)	(p=0.063)	(p=0.384)
CMU_pct	0.1016	0.1077	0.0637	0.0790
	(p=0.004)	(p<0.001)	(p=0.352)	(p=0.446)
INV_pctGDP	-0.1786	-0.0949	-0.0927	-0.1784
	(p=0.029)	(p=0.110)	(p=0.090)	(p=0.032)
RD_pctGDP	-0.0511	0.2014	0.2381	-0.0352
	(p=0.898)	(p=0.311)	(p=0.259)	(p=0.932)
GDPpc_EUR	—	0.00003494	0.00003573	—
		(p < 0.001)	(p < 0.001)	
AI_x_CMU	—	—	0.0026	0.0013
			(p=0.402)	(p=0.782)
R^2	0.638	0.832	0.841	0.641
Adjusted R^2	0.572	0.792	0.794	0.555
N	27	27	27	27

Note. Dependent variable: RP (€/kg). M1 includes AI, CMU, INV and R&D; M2 adds GDPpc; M3 adds AI × CMU to M2; M4 adds AI × CMU to M1

without GDPpc. Parentheses report HC3-robust p-values from residual-degrees-of-freedom t tests. N = 27 in all models. AI, CMU, INV and R&D are in percentage points; GDPpc is €/person. The interaction uses original percentage-point scales. Statistical significance is assessed at 5%.

The AI × CMU coefficient in M3 is positive but not significant (β = 0.00260, p = 0.402; HC3 95% CI [-0.00373, 0.00892]). In M4, which excludes GDPpc, the interaction remains non-significant (β = 0.00133, p = 0.782). Thus the data do not establish the predicted complementarity. The sign of the AI main effect changes when GDPpc and the interaction are included; in an uncentered interaction model this main coefficient refers to the AI association at CMU = 0 and should not be interpreted as an overall AI effect.

For M3, the conditional AI marginal effect equals -0.06465 + 0.002598 × CMU. At the 10th, 50th, and 90th percentiles of CMU (2.60%, 9.40%, and 20.94%), the estimated effects are -0.0579 (p = 0.064), -0.0402 (p = 0.200), and -0.0102 (p = 0.852) €/kg per one-percentage-point increase in AI adoption. None is significant at 5%. At the median AI adoption rate (11.31%), the conditional CMU effect is 0.0931 €/kg per percentage point (p = 0.016). The positive conditional CMU association does not imply that AI significantly strengthens it.

Diagnostic tests did not reject homoskedasticity in the four specifications: Breusch-Pagan p-values range from 0.406 to 0.811 and White-test p-values from 0.230 to 0.630. However, Jarque-Bera tests reject residual normality for M2 (p = 0.0002) and M3 (p = 0.0016). RESET tests do not reject the examined functional forms at 5%, although their power is limited in a sample of 27. Cook's distance in M3 exceeds the conventional 4/N screening threshold for Estonia (0.264), Italy (0.234), and Luxembourg (0.151). These observations are retained rather than automatically excluded. Across 27 leave-one-country-out re-estimations of M3, the interaction estimate remains positive but is never statistically significant at 5%. The diagnostics therefore support caution rather than a claim of model certainty.

Table 4. Summary of Hypothesis Testing Results

Hypothesis	Coefficient	HC3 p-value	Decision
H1: AI → RP	0.0789	.177	Not supported
H2a: CMU → RP	0.1016	.0043	Supported in M1
H2b: INV → RP	-0.1786	.0285	Not supported
H3: AI × CMU → RP	0.00260	.402	Not supported

Note. H1, H2a, and H2b are evaluated using M1; H3 is evaluated using M3. Statistical significance is assessed at the 5% level. Coefficients represent associations, not causal effects. Source: Authors' calculations based on Eurostat data for 2024.

Multicollinearity was assessed using variance inflation factors (VIFs). The maximum VIF values, excluding the intercept, were 3.07 in M1 and 4.46 in M2, suggesting no severe multicollinearity in the additive specifications. Higher values were observed in the interaction models, with maximum VIFs of 11.99 in M3 and 11.86 in M4, both associated with the AI × CMU interaction term. Circular material use also exhibited elevated VIFs in these models (7.70 and 7.66, respectively). These results indicate substantial collinearity between the interaction term and its constituent variables, potentially increasing standard errors and reducing the precision of individual coefficient estimates. Accordingly, the interaction results are interpreted cautiously, particularly given the small cross-sectional sample.

6. DISCUSSION

The findings provide a qualified picture of the digital and circular transitions. The baseline positive association between circular material use and resource productivity is consistent with the idea that recovering and reusing materials can coexist with greater economic output per unit of material input. Yet the national indicators are not mechanically equivalent: circular material use measures the role of secondary materials, while resource productivity combines economic output and domestic material consumption. The estimated relationship is therefore empirically informative, although it cannot isolate the contribution of individual circular practices.

The absence of a statistically significant AI coefficient cautions against equating enterprise-level technology diffusion with economy-wide resource-efficiency improvements. The AI indicator records whether an enterprise uses at least one technology, not whether that technology targets material flows or whether the implementation is effective. This distinction is compatible with the organizational-readiness literature (Jöhnk et al., 2021). It also leaves open the possibility of time lags, heterogeneous industry effects, and complementary investments that are not observed in the aggregate data. A non-significant coefficient is not proof that AI has no effect; rather, the study does not detect a reliable independent association conditional on the chosen covariates.

The negative investment coefficient in M1 is not evidence that investment damages circular performance. Gross fixed capital formation includes many

asset types and may coincide with material-intensive construction or expansion, especially in economies undergoing capital deepening. It does not distinguish green from conventional investment. The sign and statistical sensitivity of this coefficient therefore reveal the limits of aggregate investment intensity as a proxy for transition-related financing, rather than a causal relationship between investment and resource productivity.

The interaction result is particularly relevant to the paper's original argument. Although the M3 point estimate is positive, its confidence interval includes zero and the marginal-effect pattern is not statistically decisive. The same conclusion holds when GDPpc is omitted and when individual countries are removed. The proposed synergy between AI diffusion and circular material use remains a plausible organizational mechanism, but it is not demonstrated by this EU-27 cross-section. Future work should use sector-level AI applications, circular investment data, and longer observation windows to test the mechanism more directly.

7. IMPLICATIONS AND LIMITATIONS

For policymakers, the results support examining circular material use alongside broader material-efficiency outcomes rather than relying on AI adoption rates as a sufficient indicator of progress. Digitalization policies may need to focus on applications, skills, interoperability, and measurement of resource outcomes. These are interpretations consistent with the empirical limitations, not causal policy-effect estimates. The 2020 EU Circular Economy Action Plan and the Digital Decade policy program provide relevant institutional context for this question (European Commission, 2020; European Parliament & Council of the European Union, 2022).

For finance and investment decision-makers, the evidence suggests that aggregate capital formation cannot stand in for sustainable finance. The model contains no taxonomy-aligned investment, green bonds, sustainability-linked lending, or firm-level financing data. Consequently, this paper does not estimate the impact of green finance on resource productivity, and the title has been narrowed accordingly. Resource productivity is also only one component of economic performance and does not directly measure international competitiveness, profitability, or welfare.

Several limitations constrain generalization. First, the 2024 cross-section is small and cannot identify dynamic responses or country-specific unobserved factors. Second, AI adoption is an extensive-margin indicator and omits intensity, quality, and purpose of use. Third, circular material use is a partial measure of circularity; material trade, composition, and environmental burden

are not fully captured. Fourth, GDPpc shares an output component with RP, motivating models without GDPpc. Fifth, non-normal residuals in the GDP-controlled models, influential countries, possible multicollinearity, and limited statistical power complicate inference. Finally, reverse causality and omitted variables, including industrial structure, institutions, energy prices, and innovation ecosystems-may affect both the regressors and resource productivity. Robust standard errors and sensitivity checks do not resolve these identification problems. The Eurostat enterprise AI indicator covers only recent survey years, limiting opportunities for longer-run evaluation of diffusion effects; results may change as adoption spreads.

8. CONCLUSIONS

This study examined the relationships between artificial intelligence adoption, circular material use, investment intensity, and resource productivity across the 27 European Union Member States using harmonized Eurostat data for 2024. By integrating technological adoption and circular-economy indicators within a common empirical framework, the analysis sought to determine whether AI and circularity are independently associated with resource productivity and whether AI strengthens the relationship between circular material use and resource efficiency.

The findings provide the strongest support for the role of circular material use. Its positive and statistically significant association with resource productivity in the baseline regression suggests that economies with higher circular material use rates tend to generate greater economic value relative to their material consumption, after accounting for the selected explanatory variables. In contrast, although AI adoption was positively correlated with resource productivity, its coefficient was not statistically significant in the baseline model. Thus, the results do not establish that greater AI adoption is independently associated with higher resource productivity across EU Member States. Investment intensity exhibited a statistically significant negative association with resource productivity in the baseline specification, contrary to the initial hypothesis. This finding suggests that aggregate capital formation should not automatically be interpreted as investment in resource-efficient or environmentally sustainable activities. Moreover, the AI-circular material use interaction was positive but statistically insignificant, providing insufficient evidence that AI adoption strengthens the circularity-resource productivity relationship. The marginal-effects analysis and leave-one-country-out robustness checks reinforced this conclusion.

These findings contribute to the discussion on the EU's twin digital and green transition by highlighting the distinction between technological adoption and

measurable resource-efficiency outcomes. From a policy perspective, the results suggest that circular-economy strategies deserve continued attention, while AI-related initiatives should be evaluated according to their actual contribution to material efficiency rather than adoption rates alone. For sustainable finance, the findings underline the importance of distinguishing general capital formation from investments specifically directed toward circular technologies, resource efficiency, and environmental innovation.

Nevertheless, the conclusions are subject to several limitations, including the small cross-sectional sample, potential reverse causality, influential country observations, and the inability of aggregate indicators to capture sectoral differences or the quality of AI implementation. Future research could employ longitudinal and sector-level data, incorporate direct measures of green investment, and examine organizational and institutional conditions through which AI may support circular-economy performance.

Overall, the study finds a positive association between circular material use and resource productivity but does not establish an independent positive AI effect or a significant complementary relationship between AI adoption and circularity. This distinction provides a basis for more targeted research and policy evaluation concerning the contribution of digital technologies to sustainable economic competitiveness in the European Union.

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Digital and Sustainable Public Procurement: Enhancing Governance and Competitiveness in Emerging Economies

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ABSTRACT

Digital transformation, sustainable development, and stronger governance are key factors in modern economic competitiveness. In this context, public procurement serves as a strategic tool through which public authorities can promote innovation, sustainability, and efficient use of financial resources. The aim of this study is to analyze the role of digitalization and sustainable public procurement in boosting the competitiveness of the Republic of Moldova. The research highlights the evolution of the MTender electronic public procurement system, the impact of sustainability principles on the procurement process, and the current challenges in implementing European standards. To carry out the study, the author applied traditional research methods: the monographic method, document analysis, comparison, trend analysis, etc. The conclusions arise as a result of the analysis of international documents, guidelines, and case studies, and reflect that AI in procurement aims to spend public funds on the purchase of products, services, and projects that promote sustainable development. The results show that integrating digital technologies and sustainability criteria can significantly help increase transparency, efficiency, and the competitiveness of the national economy.

Keywords: *Public Procurement, Digitalization, Sustainability, Governance, MTender*

JEL Classification: H57, O33, Q56, D73.

1. INTRODUCTION

Public procurement links public finance to the productive economy. Through purchasing decisions, governments shape demand for goods, works and services, influence the conditions under which firms compete, and can accelerate the diffusion of cleaner and more innovative technologies. Its importance is especially pronounced in emerging economies, where public expenditure is a major source of market demand and where institutional capacity, access to finance and market concentration may constrain private-sector development.

Digital procurement systems can reduce information asymmetries, standardise procedures, widen supplier access and create auditable data trails. Sustainable public procurement (SPP), in turn, broadens the award decision beyond the lowest initial price by incorporating environmental, social and economic considerations, including life-cycle costs (Enachi & Pîrvan, 2025). The strongest policy effects emerge when the two agendas are connected: digital systems make sustainability criteria measurable, traceable and monitorable, while sustainability objectives give procurement data a strategic purpose.

The Republic of Moldova provides a relevant case. Its procurement system has developed around the Law on Public Procurement No. 131/2015 and the MTender electronic platform, while the country has been aligning its institutions and legislation with the EU acquis (Republic of Moldova, 2015). The European Commission's 2025 report recognises progress in legal alignment and professionalisation, but also points to an outdated MTender system, limited administrative capacity and gaps in low-value procurement monitoring (European Commission, 2025). These challenges make Moldova a useful case for examining the gap between formal digitalisation and effective, sustainable procurement.

2. AIMS AND OBJECTIVES

To assess how digitalisation and sustainable public procurement can strengthen governance, market competition and economic competitiveness in the Republic of Moldova, and to identify policy lessons relevant to emerging economies, including Sri Lanka.

The specific objectives of the article are:

- To examine the evolution and structure of public procurement in the Republic of Moldova during 2020–2025.

- To assess the contribution of electronic procurement to transparency, accountability and administrative efficiency.
- To analyse competition indicators, including supplier participation, single-bid procedures and SME involvement.
- To identify opportunities for integrating environmental and social criteria and life-cycle costing into public procurement.
- To examine institutional, regulatory and technological barriers to digital and sustainable procurement.
- To formulate policy recommendations aimed at strengthening governance, competitiveness and sustainable public spending.

The paper addresses three research questions:

1. How did the reported scale and structure of public procurement evolve during the period for which comparable official data are available?
2. What governance and competitiveness constraints are associated with the current digital procurement architecture?
3. Which policy measures can connect e-procurement, sustainability and market openness in emerging economies?

1.3 LITERATURE REVIEW

The literature on public procurement increasingly treats purchasing as a policy instrument rather than a purely administrative transaction. Strategic procurement can support innovation, environmental protection, social inclusion and industrial development, provided that award criteria are transparent, proportionate and linked to the subject matter of the contract. The OECD recommends professional procurement institutions, data-driven performance management and the use of procurement to advance broader policy objectives.

The author used the following documentary sources: Law No. 131 of 3 July 2015 on Public Procurement of the Republic of Moldova; the European Commission's 2025 report on the Republic of Moldova; the EUSTAT methodological datasheet on growth rates; the National Procurement Commission of Sri Lanka's Procurement Guidelines (2024); the Public Procurement Agency's reports on public procurement and sectoral procurement activity for 2023, 2024, and 2025; and the National Programme for the Development of the Public Procurement System for 2023–2026 in the Republic of Moldova. Sustainable procurement requires a shift from

acquisition price to value over the useful life of a product or asset. Relevant criteria may include energy consumption, durability, repairability, recycled content, emissions, waste generation, accessibility, labour standards and local supplier development where legally permissible.

1.4 METHODS

The study analyses factual and theoretical material concerning innovation and sustainable development in the contemporary economy. It uses a literature review and synthesises its findings to develop the theoretical argument. The research also applies document analysis, the monographic method, and comparison. The informational basis consists of specialised literature, legislation, institutional reports, and relevant policy documents. The conclusions are drawn from the analysis of these documents, reports, and case studies.

5. RESULTS

The 2020–2025 period is therefore treated as the institutional observation window, while the main continuous value comparison is restricted to the verified 2021–2023 observations. The 2020 baseline is discussed using published procurement-to-GDP evidence, and 2024–2025 are analysed through verified institutional and EU-monitoring indicators. This conservative approach avoids fabricating missing values or treating differently defined indicators as directly comparable.

The following calculations are used (EUSTAT):

$$AGR_t = \left(\frac{V_t - V_{t-1}}{V_{t-1}}\right) \times 100\% \quad (1)$$

annual growth rate = [(value in year t / value in year t−1) − 1] × 100% (1);

$$PS_i = \frac{V_i}{V_T} \times 100 \quad (2)$$

procurement composition share = (value by procurement object / total reported value) × 100 (2).

All monetary values are nominal and have not been deflated. Accordingly, the results describe nominal market evolution rather than real-volume growth.

Table 1. Evolution of Reported Procurement Value

Indicator	Source / definition	Coverage
Procurement value, 2021–2023	PPA annual reporting; total value of procedures	MDL, nominal
Procurement composition, 2023	PPA annual report; goods, works and services	MDL and share of total
Procurement share of GDP, 2020	Published monitoring analysis based on official statistics	Percentage of GDP
Open tender indicators, 2024	European Commission Moldova Report 2025	Procedure/contract counts
2025 institutional developments	PPA annual report and EU accession reporting	Qualitative; not merged into value series

Source: Public Procurement Agency of the Republic of Moldova. Report on Public Procurement Activity 2021-2023.

Published monitoring evidence places public procurement at approximately 4.38% of GDP in 2020, compared with 4.25% in 2019. In 2021, public authorities purchased goods, works and services worth approximately MDL 8.445 billion. The PPA's annual report for 2022 records MDL 13.682 billion, while its 2023 report records MDL 12.358 billion.

Table 2. Reported Value of Public Procurement Procedures, 2020–2025

Year	Reported value (MDL bn)	Annual change
2020	Not directly harmonised in the value series	-
2021	8.45	-
2022	13.68	+62.01%
2023	12.36	−9.68%
2024	Not inserted into nominal series; EU reports market at 5% of GDP	-
2025	Official annual report published; series reconciliation required	-

Source: Public Procurement Agency of the Republic of Moldova.

The nominal value increased by MDL 5.237 billion between 2021 and 2022, equivalent to 62.01%. In 2023 it decreased by MDL 1.325 billion, or 9.68%, compared with 2022. The three-year pattern indicates substantial volatility. It should not be interpreted as a direct measure of efficiency: changes may reflect inflation, exceptional expenditure, project timing, changes in procedure coverage and the timing of contract reporting.

The 2023 value is reported by the PPA as MDL 12.358 billion across 6,499 procedures and 32,165 contracts and additional agreements. The average value per contract, as reported in the same annual report, was approximately MDL 975,150. The European Commission subsequently estimated the procurement market at 5% of GDP in 2024, maintaining the same share as in 2023 (European Commission, 2025) Differences between the PPA's annual value series and GDP-based estimates underline the need for a clear statistical perimeter, especially for low-value and sectoral procurement.

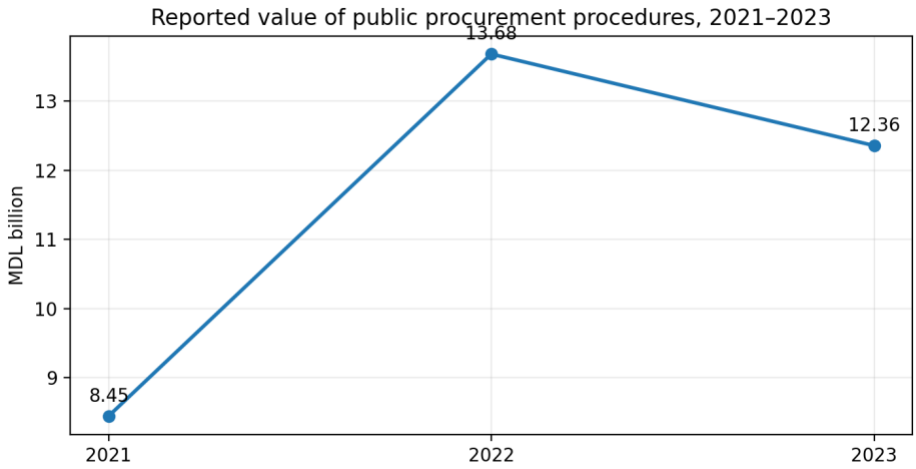

Figure 1. Reported Value of Public Procurement Procedures, 2021–2023 (MDL Billion)

Source: Public Procurement Agency of the Republic of Moldova. (2021-2023).

In 2023, the largest reported category was goods, accounting for MDL 5.559 billion or 44.99% of the total. Works represented MDL 4.515 billion (36.54%), while services amounted to MDL 2.283 billion (18.48%). The distribution suggests that procurement policy has considerable leverage over construction standards, energy performance, material efficiency and the environmental footprint of frequently purchased goods.

Table 3. Structure of Procurement by Object in 2023

Object	Value (MDL bn)	Share of total
Goods	5.56	44.99%
Works	4.52	36.54%
Services	2.28	18.48%
Total	**12.36**	**100.00%**

Source: Public Procurement Agency of the Republic of Moldova (2023).

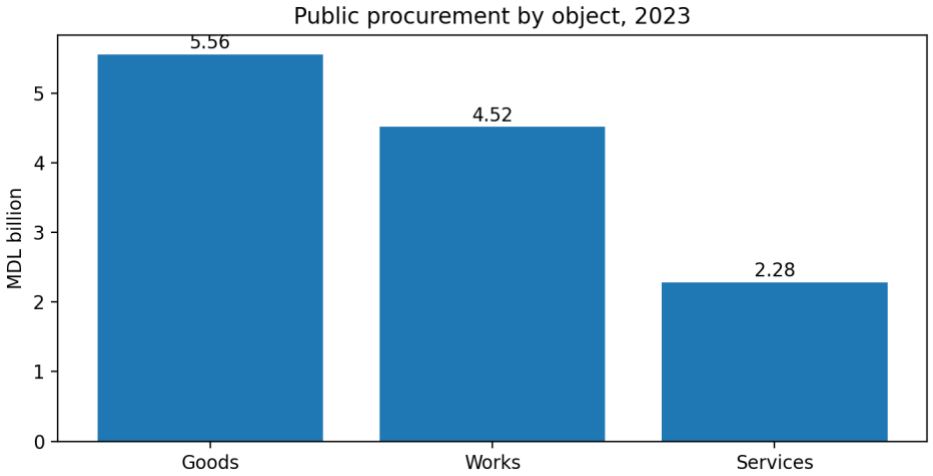

Figure 2. Composition of Reported Public Procurement Value by Object, 2023

Source: Public Procurement Agency of the Republic of Moldova (2023).

For goods, sustainable criteria can be applied to energy-efficient equipment, recycled materials, repairability, packaging and total cost of ownership. For works, the greatest potential lies in energy-efficient public buildings, low-carbon construction materials, climate resilience and whole-life infrastructure costs. For services, criteria can address energy use, accessibility, waste management, labour conditions and service quality.

The 2023 PPA report records 2,733 open-tender notices and 3,306 requests-for-quotations notices. For open tenders, the average number of offers was 4.23; 10.57% of procedures received no offer and 21.34% received only one offer. For requests for quotations, the average was 3.23 offers, while 11.72% of procedures received no offer and 22.34% received one offer. These indicators show that the existence of an electronic publication channel does not automatically ensure robust competition.

The European Commission's 2025 Moldova Report states that 3,432 open tenders in 2024 led to 26,535 contracts, representing 78% of all awarded contracts. It also reports that the procurement market accounted for 5% of GDP (European Commission. (2025). The Commission nevertheless identifies MTender as outdated and unable to support all tools provided by the legislation in force. It further notes the absence of an efficient mechanism to monitor the application and performance of new low-value procurement rules.

These findings point to a distinction between transparency of procedure initiation and transparency across the full procurement cycle. A modern system should publish structured data not only on notices and awards, but also on beneficial ownership, bid participation, contract amendments, delivery milestones, payment performance, sustainability commitments and actual outcomes. Without this information, digital procurement can improve administrative visibility while leaving contract execution and value-for-money assessment underdeveloped.

6. DISCUSSION

The evidence supports three main findings. First, procurement is economically significant but its statistical perimeter remains fragmented. Incomplete coverage of low-value purchases and differences between public and sectoral procurement complicate longitudinal comparisons. A reliable data architecture is therefore a prerequisite for evidence-based governance (OECD, 2022)

Second, competition indicators should be interpreted alongside supplier access and procedural design. A relatively high average number of offers can coexist with a substantial share of tenders receiving one or no offer. This may reflect market concentration, small contract sizes, complex qualification requirements, limited supplier capacity or low attractiveness of the contract. Digital platforms should therefore provide analytics that identify repeated single-bid patterns, concentration by supplier and contracting authority, and barriers faced by SMEs (OECD, 2022)

Third, sustainability requires operationalisation. The presence of a policy commitment is insufficient unless contracting authorities have standard criteria, lifecycle-cost methodologies, model tender clauses, market data and contract monitoring tools. The European Commission reported that Moldova's PPA held two online sustainable-procurement training sessions with 245 participants during the reporting period. This is a useful start, but sustained professionalisation requires systematic training and measurable implementation targets.

7. IMPLICATIONS AND LIMITATIONS

The implications for Sri Lanka are relevant but should be understood as policy transfer rather than a direct statistical comparison. Sri Lanka's Procurement Guidelines 2024, effective from 1 January 2025, include a dedicated chapter on sustainable public procurement. The guidelines define sustainability in economic, environmental, social and institutional terms and refer to lifecycle costing and green procurement principles. They also indicate that detailed SPP parameters are to be introduced through separate guidelines or manuals.

Moldova's experience reinforces the importance of translating high-level provisions into operational templates, digital data fields and performance indicators (Republic of Moldova. (2023).

Table 4. Policy Framework for Strengthening Digital and Sustainable Public Procurement: Reform Priorities and Expected Effects

Reform area	Recommended action	Governance / competitiveness effect
1. Digital infrastructure	Develop an interoperable, end-to-end e-procurement platform with open APIs, structured data and secure bid submission.	Reduces transaction costs; improves auditability and supplier access.
2. Complete market coverage	Integrate low-value and sectoral procurement data and publish a consistent statistical perimeter.	Improves market measurement and risk detection.
3. Sustainable criteria	Introduce standard green and social criteria by category, supported by lifecycle-cost tools and model clauses.	Rewards innovation, resource efficiency and quality.
4. Competition analytics	Monitor single-bid tenders, no-bid procedures, supplier concentration and SME participation.	Identifies barriers and strengthens competitive neutrality.
5. Contract management	Publish amendments, milestones, delivery performance, payment data and sustainability outcomes.	Connects award decisions to actual value for money.
6. Professionalisation	Establish competency standards, certification and continuous training for procurement officials.	Improves decision quality and implementation capacity.
7.Integrity and accountability	Use risk indicators, beneficial-ownership disclosure, audit trails and accessible complaint mechanisms.	Reduces corruption risks and increases public trust.

Source: Author's own elaboration based on OECD (2015,2022), European Commission (2025) and Sri Lanka's Procurement Guidelines (2024).

A phased implementation sequence is recommended. In the first 12 months, authorities should agree on a common data dictionary, identify reporting gaps and publish baseline indicators. In months 12–24, the digital platform should integrate contract-management information and pilot sustainability criteria in

high-impact categories such as construction, vehicles, ICT equipment and energy-consuming goods. In months 24–36, the system should introduce performance dashboards, independent evaluation and expansion of successful criteria across contracting authorities (National Procurement Commission of Sri Lanka, 2024)

A balanced performance dashboard should include: share of procurement value covered by open competition; average number of valid bids; share of procedures with one or no bid; SME participation; percentage of contracts using lifecycle-cost or environmental criteria; contract amendment rate; on-time delivery; payment delays; and verified environmental or social outcomes. Targets should be established only after a reliable baseline has been measured.

8. CONCLUSIONS

The case of the Republic of Moldova demonstrates that digitalisation and sustainable public procurement are mutually reinforcing but not interchangeable reforms. The reported value of procurement increased sharply in 2022 and contracted in 2023, while the structure of 2023 procurement shows substantial potential to influence goods, construction and service markets through sustainability criteria. European Commission evidence for 2024 confirms the economic significance of procurement and the central role of open tenders, but also highlights weaknesses in MTender, institutional capacity and low-value procurement monitoring.

The main contribution of the paper is an integrated governance framework linking digital transparency, competition, sustainability and professional capacity. Its central proposition is that procurement reform should move beyond electronic publication towards full-cycle, data-driven management. Sustainable criteria must be verifiable, linked to lifecycle value and supported by contract monitoring; digital systems must provide complete, interoperable information; and competition indicators must be used to identify barriers to market entry.

For Moldova, the priorities are to accelerate the development of a modern e-procurement platform, improve coverage and quality of procurement data, strengthen professionalisation and operationalise sustainable criteria. For Sri Lanka and other emerging economies, the case illustrates the importance of converting national procurement guidelines into practical implementation instruments, measurable targets and integrated digital monitoring. Future research should construct a harmonised 2020–2025 microdata panel, including low-value and sectoral procurement, and empirically test the relationship

between digital maturity, supplier competition, sustainability criteria and contract performance.

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Behavioural Finance & Corporate Finance

Exchange Rate Fluctuations and Profitability: Evidence from Sri Lankan Apparel and Textile Firms

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ABSTRACT

Exchange-rate movements can affect export-oriented firms through changes in the domestic-currency value of foreign-currency receipts, the cost of imported inputs, and uncertainty surrounding future cash flows. This study examines the relationship between the nominal exchange rate, exchange-rate volatility, and the profitability of apparel and textile firms listed on the Colombo Stock Exchange (CSE). The sample is puristically selected, and the study period is 2014-2024; , there are an 11-year period for 30 firms would yield 330 observations in a balanced panel. Profitability is measured by Return on Assets (ROA), Return on Equity (ROE) and Net Profit Margin (NPM). The explanatory variables include the annual nominal average exchange rate of LKR/USD, exchange rate volatility and inflation as a control variable. Secondary data are drawn from audited annual reports and publications of the Central Bank of Sri Lanka and the Department of Census and Statistics. Descriptive statistics and regression analysis were used to examine the relationships. The nominal exchange rate shows a positive relationship with all three measures of profitability, and the volatility of the exchange rate is negatively related with all three measures of profitability, as reported in the pooled OLS estimates. The model's explanatory power (R-squared) is relatively low at 0.025 in the NPM model. These findings should be interpreted as associations rather than causal effects, and the final statistical conclusions remain subject to verification of the observation count, variable units, panel-data specification, and reported significance levels.

Keywords**:** *Apparel Industry, Colombo Stock Exchange, Exchange rate, firm profitability, Sri Lanka*

1. INTRODUCTION

Exchange-rate fluctuations are a substantial macroeconomic factor that creates uncertainty for firms engaged in international trade, as changes in currency values can affect export revenues, imported input costs, pricing decisions, and ultimately profitability (Sathanantham & Thanabalasingam, 2023). The implementation of the floating exchange rate system following the collapse of the Bretton Woods system in 1973 is generally thought to have increased exchange rate uncertainty (Hall et al., 2010). Excessive fluctuations in exchange rates raise concerns about future exchange-rate movements. Similarly, the exchange rate volatility is frequently viewed as a risk, and an upward trend in volatility may increase costs for risk-averse traders and reduce trade (Jensen & Whitfield, 2022). Furthermore, when payment is deferred after a trade contract is agreed, exchange-rate movements between the transaction and settlement dates can create uncertainty about the value of revenues and costs (Gunarathne et al. (2021).

Against this backdrop, exchange-rate movements have become an important consideration for trade and investment in Sri Lankan context. The Sri Lankan rupee has experienced substantial depreciation over time, while movements in the real exchange rate have not always corresponded with movements in the nominal exchange rate (Arachchi, 2018). Furthermore, Ramanayake (2019) asserts that economies with open capital accounts and flexible exchange rate arrangements can experience considerable exchange-rate variations. Such movements are particularly relevant to export-oriented firms because depreciation can increase the local-currency value of foreign-currency receipts while simultaneously increasing the local-currency cost of imported inputs.

Moreover, the economic crisis faced in 2022 highlighted the complex effects of exchange-rate movements. While the depreciation of the Sri Lankan Rupee allowed the export sector generate higher local-currency revenues from US dollar-denominated receipts, it also resulted in higher production costs because the sector relies heavily imported inputs (Ramanayake, 2019). In addition, Rajapakshe and Chandrasiri (2023) find that increased exchange rate volatility increases the cost of hedging and makes it more difficult to make pricing, budgeting, and business planning decisions. More broadly, exchange-rate regime of Sri Lanka has evolved through several stages, with the country eventually moving towards a flexible exchange-rate arrangement, which has exposed domestic industries to exchange-rate fluctuations. This broader impact is supported by Rathnayaka (2021), who studied the relationship between the exchange rate volatility and the trade, remittance, tourism and stock market activity, and found that exchange-rate

volatility has significant implications for various sectors of the Sri Lankan economy.

The export-oriented apparel sector in Sri Lanka is exposed to exchange rate movements as firms generate foreign-currency export revenues while relying on imported inputs and engaging in other foreign-currency transactions (Ekanayake & Chatrna, 2010). Although the sector plays an important role in the national economy, there is limited consensus about how exchange rate volatility affects the profitability of Sri Lankan apparel exporting firms (Wijekoon et al., 2021). While a depreciation of the Sri Lankan rupee may therefore increase export revenue in local-currency terms, it can also raise production costs through higher costs of imported inputs. Furthermore, exchange rate volatility can additionally increase uncertainty and pose challenges in pricing, sourcing, and hedging decisions. These challenges may become more complex as changes in global trade policies interact with exchange-rate movements, potentially affecting firms' net profitability (Gunarathne et al. (2021).

Accordingly, the relationship between exchange-rate fluctuations and firm profitability remains inconclusive. Prior studies report negative, positive, and statistically insignificant relationships, suggesting that the effects may depend on industry characteristics, trade exposure, input sourcing, pricing flexibility, and financial risk-management practices. Much of the available Sri Lankan evidence has examined. Much of the existing evidence has focused on developed economies or aggregate export performance, limiting the extent to which these findings can be generalized to exporting firms in Sri Lanka Therefore, this study aims to examine how exchange-rate fluctuations affect the profitability of publicly traded apparel and textile exporting firms in Sri Lanka. The present study addresses this gap by examining three firm-level profitability indicators—ROA, ROE, and NPM—among listed apparel and textile firms. It distinguishes the level of the nominal exchange rate, reflects the domestic-currency value of the $1 (due to exchange-rate volatility), which reflects fluctuations in currency values from month to month. The analysis also considers inflation as a macroeconomic control variable.

1.1 Research Objectives

1. To examine the relationship between the NER of the LKR/USD and profitability of listed apparel and textile companies in Sri Lanka.
2. To assess the relationship between the volatility of exchange rate and profitability of firm in terms of ROA, ROE, and NPM.

3. To analyze the association between inflation and profitability of selected firms.

1.2 Research Questions

RQ1: WHAT IS THE RELATIONSHIP BETWEEN the nominal LKR/USD exchange rate and profitability of listed apparel and textile companies?

RQ2: How is the relationship of exchange-rate volatility with ROA, ROE, and NPM?

RQ3: What is the relationship between inflation and profitability of the selected firms

2. REVIEW OF THE LITERATURE

International trade theory and the J-Curve theory can be used to explain relationship between exchange-rate fluctuations and firm profitability, while the hedging perspective provides an additional explanation of how firms can manage exchange-rate exposure (Thevakumar & Jayathilaka, 2022). International trade theory suggests that exchange rate fluctuations can have an impact on export prices, international competitiveness, and the allocation of resources across countries (Upadhyaya et al., 2020). Accordingly, fluctuations in exchange rates can create uncertainty regarding exporters' future revenues and costs and may therefore influence their profitability (Wijekoon et al., 2021).

The J-Curve theory highlights the dynamic nature of this relationship, contending that profit levels may initially drop as import prices rise quickly, but only if the export prices were fixed in the prior period with the current contracts. However, profit levels will improve only once the firms renegotiate the export prices and the export volume in later periods (Hoque & Banerjee, 2012). Building on these theoretical perspectives, the hedging concept builds on these theories and suggests that firms can reduce exchange rate risk by utilizing financial and operational approaches, but the ability to do so is dependent on market access, cost, and managerial capability to hedge (Ethier, 1973; Viaene & de Vries, 1992). Taken together, these theories suggest that exchange rate fluctuations impact profitability through both enhanced revenue and increasing cost, with the overall impact depending on firms' exposure to foreign trade and their risk management strategies.

Empirically, numerous studies have reported a negative relationship between exchange-rate volatility and trade or firm performance because

volatility can increase uncertainty and transaction costs (Kemapirakash & Thanabalasingam, 2023). In contrast, other studies indicate positive associations where companies can reap some benefits from the positive movement of the currency, which can be achieved via pricing flexibility, market diversification and appropriate currency hedging strategies (Wijekoon et al., 2021). Meanwhile, other studies report statistically insignificant effects, indicating that the relationship may vary with economic structure, industry characteristics, trade policies, and financial-market development (Thevakumar & Jayathilaka, 2022). Despite the growing body of global scholarly literature, the Sri Lankan context has received relatively limited empirical attention, particularly regarding how exchange-rate fluctuations affect firm profitability under the country's specific economic and trade conditions (Rajasinghe & Silva, 2025). Overall, these mixed findings indicate that the effect of exchange-rate fluctuations on profitability remains unclear and context-specific, highlighting the need for further empirical investigation, particularly in emerging economies such as Sri Lanka.

Furthermore, macroeconomic conditions such as monetary policy, tariffs, and global demand may influence the transmission of exchange-rate movements to firm performance (Jayasinghe, 2025; Tarasenko, 2021). However, existing Sri Lankan studies have largely examined aggregate export performance rather than firm-level profitability indicators, including ROA, ROE, and NPM. Moreover, limited empirical attention has been paid to the influence of input costs and hedging practices on firm profitability (Dunusinghe, 2022). To address these gaps, the present study examines the effects of exchange-rate movements and exchange-rate volatility on the profitability of apparel and textile exporting companies listed on the Colombo Stock Exchange.

3. METHODOLOGY

This study adopts a quantitative explanatory research design based on secondary firm-level data to examine the relationship between nominal exchange-rate movements, exchange-rate volatility, and the profitability of apparel and textile exporting firms in Sri Lanka. The study covers the period from 2014 to 2024 and collected data from audited annual financial statements of selected listed firms together with macroeconomic data published by the Central Bank of Sri Lanka and the Department of Census and Statistics.

4. ANALYSIS & DISCUSSION

Descriptive statistics for the study variables for the period indicated are provided in Table 2. Net profit margins are somewhat different among firms and over time. The reported nominal exchange-rate figures (between LKR 2.115 and 2.531, with a mean of 2.288) do not seem to be quoted in the conventional manner (LKR per US dollar). If there is a series that has been rescaled, logged, standardized, or transformed in other ways, the authors are responsible for making sure that they have done so and for indicating the units of the series in the comments. The inflation row also needs to be checked because if all four statistics are on the same scale their mean (9.273) and standard deviation (13.400) do not seem to be consistent with the minimum (9.273) and maximum (9.497) reported. The source values, units and transformations presented in Table 1 must be checked against the underlying dataset before interpreting this table.

Table 1: Descriptive Statistics

Variable	Min	Max	Mean	SD	CV
Return on Assets	.039	2.896	1.290	.419	3.079
Return on Equity	-.250	2.830	1.013	.502	2.018
Net Profit Margin	.000	4.743	.565	.756	0.747
Nominal Exchange Rates	2.115	2.531	2.288	.150	15.253
Exchange Rate Volatility	.741	1.774	1.206	.356	3.388
Inflation Rate	-.400	.497	9.273	13.400	0.692

Notes: Min, Max, SD and CV stand for minimum, maximum, standard deviation, and coefficient of variance, respectively
Source: *Author's findings during 2014 to 2024.*

The OLS regression model illustrated in equation 1 was employed to examine the effect of exchange rate fluctuations on profitability of apparel and textile export industry in Sri Lanka deploying annual data on 30 listed companies during the ten years period from 2014 to 2024. Since the firm profitability is measured employing three different measures, a total of three regression models, such as, model 1, model 2, and model 3, were used, considering each profitability measure as the dependent variable.

The Reported R-squared values are .288 for ROA, .114 for ROE and .025 for NPM. Thus, the explanatory variables explain a relatively small amount of the observed variation in NPM for the reported pooled OLS specification. The low R-squared of the NPM regression suggests that the macroeconomic variables included are not a significant driver of the variation in net profit margins;

additional firm-specific factors like product mix, labour and energy costs, intensity of imports, productivity, financing costs, pricing power and the efficiency of operations could also play a role. They are not directly observed in the present model, and must be considered as possible omitted influences, not as tested explanations. It is not possible to get a definite answer from the reported Durbin–Watson statistics (1.244, 1.320, and 1.933) whether the data are without autocorrelation, especially when the dataset is panel. Evaluate the F-statistics and significance levels only after verification of the model degrees of freedom and exact output of software.

Table 3: Regression Analysis

Variables	Description	Model 1 ROA	Model 2 ROE	Model 3 NPM
NER	Nominal Exchange Rate	11.141***	4.104**	5.666**
		(8.766)	(2.428)	(2.122)
ERV	Exchange Rate Volatility	-4.331**	-1.194*	-2.090*
		(-8.110)	(-1.680)	(-1.863)
IR	Inflation Rate	-.014***	-.009***	-.005
		(-8.065)	(-3.766)	(-1.373)
R^2		.288	.114	.025
F Value		43.909***	14.035***	2.859***
Durbin–Watson		1.244	1.320	1.933

Note: ***, ** and * implies statistical significance at 1 percent, 5 percent and 10 percent levels, respectively. *t* statistics have indicated within parentheses
Source: *Author's findings during 2014 to 2024.*

In the reported pooled OLS results, the nominal exchange-rate coefficient is positive for ROA (β = 11.141, t = 8.766), ROE (β = 4.104, t = 2.428), and NPM (β = 5.666, t = 2.122). With the scale of exchange rates and final p-values verified, these estimates suggest that a higher scale of exchange rate (Loquidity Rate in terms of weaker Rupee under the quotation convention) is associated with a positive value of the three profits measures. One possible explanation is that depreciation increases the local-currency value of foreign-currency export receipts. The net benefit depends, however, on the degree of dependence on imported inputs, on the foreign-currency liabilities, on the timing of contract and on the currency of contract. These channels are not separately measured, so should be shown as possible channels rather than established causal channels.

The exchange-rate-volatility coefficients reported are negative for ROA (β = −4.331, t = −8.110), ROE (β = −1.194, t = −1.680), and NPM (β = −2.090, t = −1.863). Based on the For the ROE association, the t-statistic is significant at the 10% level (p ≈ .094) and for the NPM association, the t-statistic is significant at the 10% level (p ≈ .063) with 296 degrees of freedom in the residual. The values obtained from these p-values should be verified from the final model output. The negative numbers reflect the notion that uncertainty brings a challenge to budgeting, pricing, sourcing and cash flow planning. The results do not directly test the J-Curve theory because the models do not estimate short-run and long-run dynamic adjustments in export and import quantities or prices.

The inflation coefficient is negative in all three reported models. The displayed t-statistics suggest statistically significant negative associations for ROA (t = −8.065) and ROE (t = −3.766) and the NPM coefficient is not statistically significant (t = −1.373; approximate p = .171, given 296 residual degrees of freedom). If inflation is higher, it could be linked to rising labour, energy, transport and other operating costs, and thus negatively impact asset and equity returns. The non-significant NPM estimate does not confirm that firms were able to combat inflation by raising prices; it merely suggests that the estimated association is not significantly different than zero at conventional levels in this specification.The findings should be compared with prior studies only after checking that the studies examine comparable outcomes, periods, industries, and methods. The discrepancy with previous studies could stem from the use of different measures of export performance and accounting-based profitability, as well as variations in the sample of the studies and model specification. No description of results as contradictory should be used unless the measures used in the studies cited and the results from those studies have been verified and directly compared.

5. CONCLUSION

This study is a comparative one that investigates the relationship between nominal exchange rate movements, exchange rate volatility and profitability of listed apparel and textile companies in Sri Lanka. Pooled OLS estimates reveal that the nominal exchange rate has a positive influence on ROA, ROE and NPM, and exchange-rate volatility has a negative impact on each of the three profitability measures. All of the reported results indicate negative correlations between inflation and ROA and ROE, but not with NPM. These findings are preliminary since the time period of study, the number of firm-year observations, the unit of variation and the panel regression diagnostics need to be verified. If we are being specific, then 30 firms observed between 2014 and 2024 will result in 330 observations, not 300. Conclusions should be

revised following confirmation of the sample structure and the panel estimates.

The results have implications for export-oriented firms. A lower rupee valuation of foreign currency export receipts is possible, but can be offset by imported-input costs, foreign currency debt and contract terms. Therefore, it may be beneficial for the firms to keep track of its net currency exposure, consider better timing for its pricing and procurement actions and assess appropriate financial or operational risk management strategies to be implemented. Policymakers must be aware that the competitiveness of the exchange rate is not the only element that influences firm profitability; other factors, such as access to imported inputs, macroeconomic stability, productivity and predictable trade conditions are also important.

This study provides some firm level evidence about the relationship between exchange-rate measures and three accounting based profitability measures for companies listed in the apparel and textile industry of Sri Lanka. However, some caveats must be noted. The sample is limited to listed companies and may not be representative of privately-owned exporters. The analysis relies on the annual data, and limited number of macroeconomic variables; firm-level export intensity, currency invoicing, hedging, productivity and firm-specific cost structures are not directly controlled for. It is also important to reconcile the study period with the number of observations, and to reanalyze the pooled OLS results employing panel methods and robust standard errors. Future research can add the private exporters, can add firm-level variables for foreign-currency exposure and hedging, can test on other measures of volatility, and can apply dynamic panel or time-series models if the data allow.

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The Impact of Profit Distribution Policy on Share Price and Cost of Equity: The Bird-in-Hand Theory Perspective

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ABSTRACT

This study examines the association of profit distribution policy with share price and cost of equity among companies listed on the Colombo Stock Exchange (CSE), guided by the Bird-in-Hand Theory. The theory suggests that investors prefer the certainty of dividend income to the uncertainty of future capital gains. Accordingly, a higher dividend payout is expected to be associated with a higher share price and a lower cost of equity. The study adopted a deductive, quantitative approach with a longitudinal design. A balanced panel of 250 firm-year observations for 50 non-financial companies listed on the CSE over 2021–2025 was analysed. Profit distribution policy was measured by the dividend payout ratio (DPO), share price by the year-end market price per share (MP), and cost of equity by the Dividend Growth Model (DG). A modified Wald test indicated groupwise heteroskedasticity, and the Hausman specification test ($p = .327$) did not reject the null hypothesis, so the Random Effects estimator was used with firm-clustered robust standard errors. DPO had positive but statistically insignificant coefficients in both the MP model ($\beta = 0.059$, $p = .689$) and the DG model ($\beta = 0.025$, $p = .594$). Pearson correlations were similarly weak and insignificant (DPO–MP: $r = .053$, $p = .407$; DPO–DG: $r = .034$, $p = .595$). The evidence therefore did not support any of the four hypotheses derived from the Bird-in-Hand Theory. Because the models include no control variables and DPO and DG contain extreme values, the results indicate that no association was detected in this sample; they do not establish that dividend policy is irrelevant. The study contributes evidence from an emerging market by examining both share price and cost of equity within a single Bird-in-Hand framework, and it offers implications for corporate managers, investors, and capital market policy makers.

Keywords: Profit Distribution Policy; Share Price; Cost of Equity; Bird-in-Hand Theory; Colombo Stock Exchange

1. INTRODUCTION

1.1 Background

The main purpose of financial management is to maximise shareholder value by using existing resources efficiently. Dividend policy, also referred to in this study as profit distribution policy, is central in this context because a firm must decide whether to reinvest earnings or distribute them to shareholders as dividends. The decision matters because it affects the firm's cost of financing as well as its credibility with investors (Bahadur Budhathoki & Khadka, 2024).

One of the most debated issues in corporate finance is whether dividends matter for firm value. According to the dividend irrelevance proposition of Miller and Modigliani (1961), in a perfect capital market with no taxes, transaction costs, or information asymmetry, firm value is determined only by the efficiency with which assets are used. Dividend policy therefore has no effect on share price or cost of equity. In contrast, Gordon (1963) advanced the Bird-in-Hand Theory, which holds that risk-averse investors prefer a certain dividend today to an uncertain capital gain in the future. Firms paying higher dividends are therefore perceived as less risky, which implies higher share prices and a lower required rate of return.

Empirical evidence on this issue is mixed. Significant relationships between dividends and share price have been reported for Pakistan (Sharif et al., 2015) and India (Singh & Tandon, 2019), whereas a study of Shariah-compliant firms in Malaysia concluded that dividend policy did not influence the decisions of Shariah-based investors (Raza et al., 2018). Evidence from Sri Lanka is also inconsistent. Mithila and Kengatharan (2025) report that dividend payments are associated with share value among CSE-listed firms, while Margaret (2023) finds no relationship between dividends and market performance. The CSE differs from many developed markets, and the informational content of dividend policy may be higher there because fewer mechanisms exist to identify value stocks (Margaret, 2023).

1.2 Problem Statement

Dividend policy, the decision to retain and reinvest profits or to pay them out to shareholders, is one of the most important decisions a firm makes because it bears on shareholder wealth and firm value (Brealey, 2003). Its influence on

firm value remains contested, particularly in developing economies such as Sri Lanka. Some researchers argue that dividends and firm value are unrelated (Gunarathne et al., 2016), while others argue that dividends enhance value because investors prefer dividends to retained earnings and view them as a signal of lower risk (Gordon, 1963; Lintner, 1956; Raza et al., 2018).

The same inconsistency appears in the CSE literature. Some studies report that dividend policy significantly affects market value and shareholder wealth (Mithila & Kengatharan, 2025), whereas others report no significant relationship between dividend considerations and share price (Samarawickrema & Rathnasingha, 2016). Developing markets such as Sri Lanka are characterised by market inefficiencies, information asymmetry, and distinctive ownership structures. Investor responses to dividends may therefore differ from those in developed markets, and theories developed in mature markets may not fully capture them (Gordon, 1963; Jensen & Meckling, 1976). This uncertainty about how dividend policy is associated with share price and cost of equity on the CSE motivates the present study.

The research problem is therefore as follows: **Is profit distribution policy associated with share price and cost of equity on the Colombo Stock Exchange, as predicted by the Bird-in-Hand Theory?**

1.3 Research Objectives and Questions

Guided by the Bird-in-Hand Theory, the study pursues two objectives. Each is addressed in two complementary ways: (a) a regression-based test of the association between profit distribution policy and the outcome variable, and (b) a bivariate correlation test of the relationship between the two variables.

1) Objective 1: To examine the association between profit distribution policy and the share price of companies listed on the CSE.
2) Objective 2: To examine the association between profit distribution policy and the cost of equity of companies listed on the CSE.

These objectives correspond to two research questions:

1) RQ1: Is profit distribution policy associated with the share price of CSE-listed companies, in regression and in bivariate correlation?
2) RQ2: Is profit distribution policy associated with the cost of equity of CSE-listed companies, in regression and in bivariate correlation?

In this study, “effect” or “impact” refers to the estimated coefficient from the Random Effects regression, whereas “relationship” refers to the bivariate

Pearson correlation. Because the data are observational and contemporaneous, neither is interpreted as evidence of causation.

1.4 Significance of the Study

The study is significant for corporate finance literature because it evaluates the Bird-in-Hand Theory in an emerging market, where support for the theory has been inconsistent. For corporate managers, it indicates the extent to which profit distribution practice is associated with share price and cost of equity, and thereby informs dividend policy decisions. For policy makers, it offers insights for designing disclosure policies, enhancing transparency, and supporting efficient price discovery on the CSE.

1.5 Scope of the Study

The study was limited to the relationship between profit distribution policy, market price per share, and cost of equity among non-financial firms listed on the CSE. The financial sector was excluded because the economics of banking and financial firms differ from those of non-financial firms. The analysis used only the dividend payout ratio as the proxy for profit distribution policy, excluding special dividends, stock dividends, and share repurchases. Cost of equity was estimated with the Dividend Growth Model rather than alternatives such as the CAPM, because the analysis was restricted to dividend-paying firms. Finally, the study did not develop a firm valuation model integrating all determinants of value. Instead, it evaluated the association of profit distribution policy with market price per share and cost of equity using a sample of fifty firms over five years.

2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1 Theoretical Background

2.1.1 Bird-in-Hand Theory

The Bird-in-Hand argument, developed by Gordon (1963) and Lintner (1956), rests on investors' preference for certain dividend income over capital gains. Capital gains are likened to “two birds in the bush,” whereas a dividend is “a bird in the hand.” The theory assumes that investors are risk-averse and that the risk attached to capital gains makes them less attractive than certain dividend income. Firms that pay consistent dividends are therefore seen as reliable and are expected to have a lower cost of equity because of the reduced risk (Pelcher & Bolton, 2017; Sharif et al., 2015). The theory is the main

framework of this study because it yields clear expectations about share price and cost of equity as a function of dividend policy.

The theory is not universally supported. A study of Shariah-compliant firms in Malaysia concluded that dividend policy did not influence Shariah-based investors' decisions, making the Bird-in-Hand argument less relevant for them; the authors attributed this to differences in market conditions and to specific constraints in the development of Shariah-based payout ratios (Raza et al., 2018).

2.2 Empirical Findings

2.2.1. Profit Distribution Policy and Share Price

The relationship between dividends and share price is mixed, both in studies of the CSE and internationally. Kengatharan and Ford (2021) examined eighty-one non-financial CSE firms that survived between 2013 and 2017 and found that dividend variables explained only about twenty-five percent of the variation in share price volatility; dividend yield increased volatility, whereas dividend per share decreased it. Sugathadasa (2018) analysed thirty CSE firms over 2014–2017 and concluded that both the payout ratio and dividend yield reduced share price volatility. More recently, Mithila and Kengatharan (2025), using ninety non-financial CSE firms that survived between 2017 and 2021, found that the payout ratio and dividend per share were positively related to market price per share.

International evidence is also mixed. Singh and Tandon (2019) found that dividend policy had a significant effect on the stock prices of Nifty Fifty firms in India, and Sharif et al. (2015) reported a significant positive relationship between payout ratio and share price for firms listed on the Karachi Stock Exchange in Pakistan. In contrast, Bahadur Budhathoki and Khadka (2024) found a significant negative relationship between payout ratio and share price for microfinance companies in Nepal.

2.2.2. Profit Distribution Policy and Cost of Equity

In contrast to the extensive research on dividends and share price, comparatively little work links profit distribution policy to the cost of equity. Esqueda and O'Connor (2024) found that the spread between the cost of equity and earnings yield significantly predicted the likelihood of adopting a large dividend policy. Mazouz et al. (2023) found that dividend-paying firms had lower systematic liquidity risk, which in turn lowered their cost of equity,

especially where governance was weak or disclosure was limited. Arhinful et al. (2024) analysed non-financial firms listed on the Frankfurt Stock Exchange and found that the cost of equity did not influence dividend decisions, although the cost of debt did. Note that the direction of the relationship examined differs across these studies: Esqueda and O'Connor (2024) and Arhinful et al. (2024) treat the cost of equity as a determinant of dividend policy, whereas the Bird-in-Hand Theory and the present study treat dividend policy as the explanatory variable.

2.3 Research Gap

Prior studies have typically examined the relationship between dividend policy and either share price or cost of equity, not both (Kengatharan & Ford, 2021; Sugathadasa, 2018; Mithila & Kengatharan, 2025; Esqueda & O'Connor, 2024; Mazouz et al., 2023). Moreover, to the authors' knowledge, no study has examined the association of dividend payout with both share price and cost of equity for CSE-listed firms within the same Bird-in-Hand framework. This study addresses that gap by estimating two separate regression models, one for each outcome, under a single theoretical framework. The models are not estimated jointly as a simultaneous system.

2.4 Conceptual Framework and Hypothesis Development

The conceptual framework treats profit distribution policy as the independent variable and share price and cost of equity as the dependent variables, in order to test the Bird-in-Hand Theory. Under the theory, a more generous payout policy reduces the perceived risk of a share, which should be associated with a higher share price and a lower cost of equity. Four hypotheses are derived. H1 and H3 are tested through the Random Effects regressions, and H2 and H4 through Pearson correlations.

H1: Profit distribution policy (DPO) is significantly and positively associated with the share price (MP) of firms listed on the CSE (regression-based test).

H2: DPO has a positive bivariate relationship with MP (correlation-based test).

H3: DPO is significantly and negatively associated with the cost of equity (DG) of firms listed on the CSE (regression-based test).

H4: DPO has a negative bivariate relationship with DG (correlation-based test).

3. METHODOLOGY

3.1 Research Design and Philosophy

The study adopted a positivist philosophy, a quantitative explanatory design, a deductive approach, and a longitudinal time dimension. This design was appropriate because the study tests hypotheses derived from the Bird-in-Hand Theory using objective financial indicators.

3.2 Population and Sample

The population comprised all companies listed on the CSE that provided the necessary financial statements and dividend disclosures. From the 225 listed companies, 50 non-financial companies were selected using convenience sampling. The inclusion criteria were: listing on the CSE during the study period, availability of all required financial statements, availability of dividend information, and availability of the data needed to compute all variables. Banks, insurers, finance companies, and other financial firms were excluded because their capital structures differ markedly from those of non-financial firms. The final sample consists of 250 firm-year observations (50 firms × 5 years, 2021–2025), forming a balanced panel across nine industry sectors.

3.3 Variable Measurement and Operatio3nalisation

The independent variable, profit distribution policy, was operationalised by the dividend payout ratio (DPO), the ratio of dividends to net income. The first dependent variable, share price, was operationalised by the market price per share (MP) at the end of the fiscal year. The second dependent variable, cost of equity, was measured with the Dividend Growth Model (DG), also known as the Gordon Growth Model:

$$re = [D0 \times (1 + g) / P0] + g$$

where re is the cost of equity, D0 is the dividend per share paid in the current period, g is the constant long-term dividend growth rate, and P0 is the current market price per share (Acheampong & Agalega, 2013).

Because P0 appears in the denominator of DG and is also the dependent variable in Model 1, and because dividends enter both DPO and DG, the two measures are mechanically related to the variables they are compared with. This potential mechanical dependence is acknowledged as a limitation in Section 7.3.

3.4 Data Collection and Analysis Techniques

Secondary data were collected from the sample firms' annual reports and financial statements. The data were cleaned and imported into STATA as a balanced panel, with firm identifier and year as the panel indicators. Descriptive statistics (mean, standard deviation, minimum, and maximum) were generated for DPO, MP, and DG, and Pearson correlation analysis was used to assess pairwise relationships. A modified Wald test was used to test for groupwise heteroskedasticity, and the Hausman specification test was used to choose between the Fixed Effects and Random Effects estimators. Given the heteroskedasticity detected, Random Effects regressions with cluster-robust standard errors at the firm level were estimated. Clustering by firm also accommodates serial correlation of errors within firms.

The two models estimated were:

Model 1: $MP(it) = \alpha 0 + \beta 1\ DPO(it) + u(i) + \varepsilon(it)$

Model 2: $DG(it) = \gamma 0 + \gamma 2\ DPO(it) + u(i) + \varepsilon(it)$

where (i) indices' firms, t indexes years, u(i) is the firm-specific random effect, and ε(it) is the idiosyncratic error. Both models were estimated separately; they do not form a simultaneous system. The models contain DPO as the only explanatory variable, which is consistent with the study's aim of testing the Bird-in-Hand prediction in its simplest form, but it means that omitted firm characteristics may bias the estimates.

4. RESULTS AND DISCUSSION

4.1 Descriptive Statistics

Table 1 reports descriptive statistics for the 250 firm-year observations. DPO, the independent variable, has a mean of 28.622 and a standard deviation of 178.946, with values ranging from −2,638.325 to 500.727. This wide range indicates considerable heterogeneity in payout behaviour. A negative DPO arises where a firm reported negative net income but still paid a dividend, and very high values arise where dividends are large relative to small positive earnings. MP has a mean of 205.538 (SD = 465.362; range = 5 to 5,390), reflecting the wide spread of firm sizes and valuations on the CSE. DG has a mean of 40.013 (SD = 132.146; range = −100 to 1,080.573), indicating very large variation in the estimated cost of equity across firms and years. Some of these DG values are economically implausible as required returns and most likely reflect extreme estimated growth rates in the Dividend Growth Model

rather than genuine differences in risk.All 250 observations were retained in the estimations reported below; no trimming or winsorisation was applied**.**

Table 1: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
DPO	250	28.622	178.946	−2,638.325	500.727
MP	250	205.538	465.362	5	5,390
DG	250	40.013	132.146	−100	1,080.573

Note. DPO = Dividend Payout Ratio; MP = Market Price per Share; DG = Dividend Growth Model (cost of equity). **[Author to state the units of DPO, MP (LKR) and DG.]** Source: STATA output.

4.2 Diagnostic Tests

Table 2 presents the diagnostic results. The modified Wald test for groupwise heteroskedasticity rejected the null hypothesis of homoskedasticity for both the market price model ($\chi^2 = 1.22 \times 10^{10}$, $p < .001$) and the cost of equity model ($\chi^2 = 74{,}950.98$, $p < .001$). The extremely large statistic for the market price model is consistent with the very wide dispersion in the data. Standard errors were therefore clustered at the firm level.

The Hausman specification test produced a chi-square of 0.96 with $p = .327$. Because this p-value exceeds the 5 per cent level, the null hypothesis that the Random Effects estimator is consistent is not rejected. The unobserved firm effects are therefore not significantly correlated with DPO, and the Random Effects estimator, which is both consistent and more efficient under the null, was adopted. (The earlier wording that the null was rejected was incorrect.) The Hausman statistic in Table 2 is reported for both models together.

Table 2: Diagnostic Test Results

Test	Model	Statistic	Value	p-value
Modified Wald (heteroskedasticity)	Market Price (MP)	Chi-square	1.22×10^{10}	0.000
Modified Wald (heteroskedasticity)	Cost of Equity (DG)	Chi-square	74,950.98	0.000
Hausman specification test	Both models	Chi-square	0.96	0.327

Note. Source: STATA output.

4.3 Correlation Analysis

Table 3 reports the Pearson correlations. DPO has a very weak positive correlation with MP (r = .053, p = .407) and with DG (r = .034, p = .595). The correlation between MP and DG is close to zero (r = −.001, p = .991). None of the correlations is statistically significant, so the correlation results do not support the Bird-in-Hand predictions.

Table 3: Pearson Correlation Analysis

	DPO	MP	DG
DPO	1		
MP	0.053 (p = .407)	1	
DG	0.034 (p = .595)	−0.001 (p = .991)	1

Note. DPO = Dividend Payout Ratio; MP = Market Price per Share; DG = Dividend Growth Model (cost of equity). Source: STATA output.

4.4 Random Effects Regression

Table 4 presents Model 1 (market price) and Table 5 presents Model 2 (cost of equity). In Model 1, the DPO coefficient is positive but close to zero and statistically insignificant (β = 0.059, SE = 0.147, z = 0.40, p = .689, 95% CI [−0.230, 0.347]). In Model 2, the DPO coefficient is also positive and insignificant (β = 0.025, SE = 0.047, z = 0.53, p = .594, 95% CI [−0.067, 0.117]). The wide confidence intervals include zero and values of both signs, so the data are compatible with a negative, zero, or positive association.

Table 4: Random Effects Regression Results – Model 1 (Market Price)

Variable	Coefficient	Std. Err.	z	p-value	95% CI
DPO	0.059	0.147	0.40	0.689	[−0.230, 0.347]
Constant	203.854	45.099	4.52	0.000	[115.461, 292.247]

Note. Dependent variable: Market Price per Share. Cluster-robust standard errors (firm level). N = 250. Source: STATA output.

Table 5: Random Effects Regression Results – Model 2 (Cost of Equity)

Variable	Coefficient	Std. Err.	z	p-value	95% CI
DPO	0.025	0.047	0.53	0.594	[−0.067, 0.117]
Constant	39.299	8.476	4.64	0.000	[22.685, 55.912]

Note. Dependent variable: Dividend Growth Model (cost of equity). Cluster-robust standard errors (firm level). N = 250. Source: STATA output.

4.5 Hypotheses Testing

Table 6 summarises the hypothesis tests. None of the four hypotheses was supported. H1 predicted a significant positive association between DPO and share price; the Random Effects coefficient was positive but not statistically significant ($\beta = 0.059$, $p = .689$), so H1 was not supported. H2 predicted a positive bivariate relationship between DPO and MP; the correlation was positive but insignificant ($r = .053$, $p = .407$), so H2 was not supported. H3 predicted a significant negative association between DPO and the cost of equity; the coefficient was positive, opposite to the predicted sign, and insignificant ($\beta = 0.025$, $p = .594$), so H3 was not supported. H4 predicted a negative bivariate relationship between DPO and DG; the correlation was positive and insignificant ($r = .034$, $p = .595$), so H4 was not supported. A failure to find statistical significance means the evidence does not support the hypotheses; it does not prove that the true association is zero.

Table 6: Hypotheses Testing Summary

Hypothesis	Test	Estimate	p-value	Decision
H1: DPO is significantly and positively associated with share price	Random Effects regression	$\beta = 0.059$	0.689	Not supported
H2: DPO has a positive relationship with share price	Pearson correlation	$r = 0.053$	0.407	Not supported
H3: DPO is significantly and negatively associated with cost of equity	Random Effects regression	$\beta = 0.025$	0.594	Not supported (sign opposite to prediction)
H4: DPO has a negative relationship with cost of equity	Pearson correlation	$r = 0.034$	0.595	Not supported (sign opposite to prediction)

Note. DPO = Dividend Payout Ratio. Source: STATA output.

5. DISCUSSION

The results do not support the Bird-in-Hand Theory in this sample. They differ from the positive dividend–share price relationships reported by Mithila and Kengatharan (2025) for the CSE, by Sharif et al. (2015) for the Karachi Stock Exchange in Pakistan, and by Singh and Tandon (2019) for Nifty Fifty firms in India. They also differ from Esqueda and O'Connor (2024) and Mazouz et al. (2023), who reported significant links between dividend policy and the cost

of equity, although the first of these treats the cost of equity as a predictor of dividend policy and so is only indirectly comparable.

The results are more consistent with studies that found weak or limited explanatory power of dividend variables, but comparisons should be made with care. Kengatharan and Ford (2021) and Sugathadasa (2018) examined share price volatility rather than the level of share price, and both found some significant dividend effects on volatility, so their evidence is not directly comparable. Likewise, Arhinful et al. (2024) examined whether the cost of equity influences dividend payments in a European market, which is the reverse direction of the relationship tested here.

One possible explanation for the present results is that CSE investors consider many factors in addition to dividends, such as earnings outlook, growth prospects, capital structure, earnings stability, governance quality, and overall market conditions, so dividend policy may be only one of several considerations. This explanation is speculative, because none of these factors was included in the models. The high heterogeneity in payout, including extreme negative and very high DPO values, and the extreme DG values may also have weakened any underlying association by adding noise. The wide confidence intervals in Tables 4 and 5 show that the study has limited precision.

These findings must be interpreted carefully with respect to the theoretical debate. The absence of a significant association between payout and either share price or cost of equity is not inconsistent with the Dividend Irrelevance proposition of Miller and Modigliani (1961), but it cannot be taken as proof of that proposition. The models contain no control variables, the sample is small and was selected by convenience, and the two outcome measures are mechanically related to dividends and price. The results therefore indicate that this study could not detect a Bird-in-Hand effect with the data and specification used, and they should not be read as evidence that dividend policy is irrelevant on the CSE.

6. IMPLICATIONS

6.1 Conclusion

This study tested the predictions of the Bird-in-Hand Theory by examining whether the dividend payout ratio is associated with market price per share and cost of equity. Using Random Effects panel regressions on data for fifty non-financial firms listed on the CSE from 2021 to 2025 (250 firm-year

observations), the study found no statistically significant association between dividend payout and either share price or cost of equity. The DPO coefficients were positive but insignificant in both models, and the Pearson correlations were weak and insignificant. The four hypotheses were therefore not supported. Given the absence of controls, the extreme values in DPO and DG, and the convenience sample, the conclusions are limited to this sample and specification.

6.1.1 Recommendations

The findings have tentative implications for corporate finance practice. For managers, the results do not show that changing the payout ratio alone is associated with a higher share price or lower cost of equity, so dividend decisions may be considered together with profitability, growth prospects, and risk. For investors, the results suggest caution in treating dividend payout alone as a signal of value or risk, and a wider analysis of liquidity, leverage, and growth outlook is advisable. For regulators and policymakers, the results underline the importance of high-quality financial reporting for investors' decision-making. These implications should be confirmed through studies with control variables and larger samples.

6.1.2 Limitations and Suggestions for Future Research

The study has several limitations. First, the sample consists of fifty non-financial firms selected by convenience over five years, so the results may not generalise to all CSE-listed firms or to other markets. Second, each model includes only DPO and an intercept. No firm-level controls (for example size, profitability, leverage, and growth) or year effects were included, so omitted-variable bias is likely and the estimates must not be read causally. Third, DPO and DG contain extreme values, including negative payout ratios for firms that paid dividends despite reporting losses, and these may have unduly influenced the results. Fourth, the Dividend Growth Model is sensitive to the estimated growth rate, and the extreme DG values raise questions about its validity as a measure of the cost of equity. Further, share price enters DG in the denominator and dividends enter both DPO and DG, creating possible mechanical dependence and endogeneity. Fifth, the data are contemporaneous and observational, so reverse causality cannot be excluded. Sixth, the standard Hausman test is not robust to heteroskedasticity and was reported jointly for both models. Seventh, the data rely only on annual reports, and the five-year period includes marked macroeconomic variation that was not modelled.

Future research could expand the sample and period, include control variables and year effects, apply winsorisation or robust estimation methods, and use alternative cost of equity measures such as the CAPM or implied cost of capital approaches. Researchers could also use alternative dividend policy proxies such as dividend yield, dividend per share, or changes in payout, test non-linear specifications, and examine mediating firm-level and market-level factors. Finally, survey or interview evidence from CSE investors and managers could complement these archival findings.

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Impact of Capital Structure on Firm Value: Evidence from Listed Companies in the Materials Sector of the Colombo Stock Exchange

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ABSTRACT

This study examines the association between capital structure and firm value among companies listed in the Materials Sector of the Colombo Stock Exchange (CSE) from 2020 to 2024. Capital structure is measured using the Debt-to-Equity Ratio (DER) and Debt-to-Total Assets Ratio (DTA), while firm value is measured using Tobin's Q. Tobin's Q is calculated as the market value of equity plus the book value of total interest-bearing debt, divided by the book value of total assets. Firm size, measured as the natural logarithm of total assets, and return on assets (ROA) are included as control variables. The study uses a balanced panel of 18 companies and 90 firm-year observations. JAT Holdings PLC was excluded because it was not listed throughout the full study period. Panel regression analysis was conducted, and the Hausman specification test ($\chi^2 = 5.2464$, $p = 0.2629$) supported the random-effects estimator. The results indicate that DER ($\beta = -0.0308$, $p = 0.5234$) and DTA ($\beta = 0.2074$, $p = 0.8136$) are not statistically significant predictors of Tobin's Q. Firm size ($\beta = -0.2444$, $p = 0.0679$) and ROA ($\beta = 2.5023$, $p = 0.0537$) are statistically significant at the 10% level but not at the 5% level. However, the overall regression model is not statistically significant ($p = 0.1108$), and its explanatory power is limited (adjusted $R^2 = 0.0406$). Accordingly, the findings do not provide sufficient evidence that the selected leverage measures explain variations in market-based firm value in the sampled companies during the study period. The results should be interpreted cautiously in view of the sample size, study period, and limited explanatory power of the model.

Keywords: *Capital Structure, Firm Value, Tobin's Q, Materials Sector, Colombo Stock Exchange.*

1. INTRODUCTION

Capital structure is an important corporate financial decision because the mix of debt and equity can affect a firm's financing costs, financial risk and capacity to sustain its operations. This issue is particularly relevant to capital-intensive businesses, which often require substantial investment in plant, machinery and other long-term assets. The operating environment in Sri Lanka changed considerably during 2020–2024, a period that included severe macroeconomic pressures. These pressures included currency depreciation, high inflation, foreign-exchange constraints and sharp increases in lending rates (Central Bank of Sri Lanka [CBSL], 2022, 2023; Weerakoon et al., 2022; Wignaraja et al., 2023). Such conditions may have affected companies' borrowing costs, debt-servicing capacity and investor assessments of risk.

In January 2020, the CSE adopted the Global Industry Classification Standard (GICS), under which the former Manufacturing classification was reorganized, and the Materials Sector was identified as a separate sector. The sector includes businesses involved in producing industrial inputs such as cement, glass, packaging, aluminium, rubber, chemicals, fertilisers and activated carbon. Earlier Sri Lankan studies examined capital structure and firm performance among listed manufacturing companies (Velnampy & Pratheepkanth, 2012; Priya et al., 2015; Chandrasiri et al., 2017). However, evidence specifically examining market-based firm value among companies currently classified in the Materials Sector remains limited.

Prior research has also reported differing relationships between leverage and firm value. In addition, accounting-based measures such as earnings per share and return on equity may not fully capture investors' forward-looking assessments of a company. This study therefore examines the association between two leverage measures and market-based firm value, using Tobin's Q, among CSE-listed Materials Sector companies over 2020-2024. The study focuses on evidence from these five years; it does not attempt to isolate the causal effect of the economic crisis.

2. AIMS/OBJECTIVES

Main Objective:

The overarching objective of this research is to investigate the impact of capital structure on the firm value of companies listed in the Materials Sector of the Colombo Stock Exchange.

Specific Sub-Objectives:

To achieve the main objective, the study addresses two specific sub-objectives:

1. To investigate whether the Debt-to-Equity ratio significantly impacts the firm value of listed materials sector companies of the Colombo Stock Exchange.
2. To investigate whether the Debt-to-Total Assets Ratio significantly impacts the firm value of listed materials sector companies of the Colombo Stock Exchange.

Formulated Hypotheses: Based on corporate finance theory and empirical literature, the following testable hypotheses are specified:

- **Hypothesis 1 (H1):** The Debt-to-Equity Ratio (DER) has a statistically significant negative impact on the firm value (Tobin's Q) of listed Materials Sector companies.
- **Hypothesis 2 (H2):** The Debt-to-Total Assets Ratio (DTA) has a statistically significant negative impact on the firm value (Tobin's Q) of listed Materials Sector companies.

3. THEORY

The theoretical foundation of capital structure originates from Modigliani and Miller's (1958) Capital Structure Irrelevance Proposition. In a baseline market without taxes or bankruptcy risks, Modigliani and Miller established that firm value is determined by physical assets and operating earning power rather than financing mix. Incorporating corporate income taxes, Modigliani and Miller (1963) demonstrated that debt financing can enhance firm value through interest tax shields.

Building upon these propositions, Trade-Off Theory (Kraus & Litzenberger, 1973) posits that an optimal capital structure balances tax-shield benefits against financial distress costs. As leverage increases beyond a threshold, distress costs escalate rapidly, creating a negative relationship between high debt ratios and market value. In developing economies facing interest rate shocks, elevated distress risks are hypothesized to outweigh tax shields, supporting Hypotheses H1 and H2.

Conversely, Pecking Order Theory (Myers & Majluf, 1984) rejects a static optimal debt ratio. Driven by information asymmetry, the theory posits a strict financing hierarchy: internal cash reserves first, low-risk debt second, and external equity last. Highly profitable companies accumulate internal cash and maintain lower debt, predicting a positive relationship between profitability and market valuation, alongside a negative correlation between leverage and profitability.

4. METHODS

The study adopts a quantitative explanatory design using a balanced panel dataset covering five financial years from 2020 to 2024. The target population comprised 19 companies listed in the CSE Materials Sector. Purposive sampling was applied based on continuous listing status and the availability of annual-report disclosures. JAT Holdings PLC was excluded because it was not listed throughout the full study period and did not provide a 2020 listed-company baseline. The final sample therefore consists of 18 companies and 90 firm-year observations.

Firm value is the dependent variable and is measured using Tobin's Q. Market value of equity is calculated using the closing share price on the final trading day of each company's financial year (31 March or 31 December, as applicable) multiplied by the number of ordinary shares outstanding. Total interest-bearing debt comprises short-term bank loans, bank overdrafts, corporate debentures and long-term bank borrowings. Non-interest-bearing trade payables and accrued liabilities are excluded.

Tobin's Q is calculated as follows:

$$Tobin's\ Q = (Market\ value\ of\ equity + Book\ value\ of\ total\ interest - bearing\ debt) / Book\ value\ of\ total\ assets$$

The independent variables are DER and DTA, calculated as:

$$DER = Total\ interest - bearing\ debt / Total\ equity$$

$$DTA = Total\ interest - bearing\ debt / Total\ assets$$

Firm size and profitability are included as control variables. Firm size is measured as the natural logarithm of total assets, while profitability is measured using return on assets (ROA), calculated as net profit after tax divided by total assets.

Because Tobin's Q and DTA both use total assets in their denominators, separate DER-only and DTA-only model specifications were also estimated as sensitivity checks. Outlier screening using studentised residuals and Cook's distance was conducted to examine extreme DER observations. One-percent winsorised re-estimations were reported as producing stable regression parameters. Panel diagnostic procedures included the Breusch–Pagan Lagrange Multiplier test, Hausman test, Modified Wald test and Wooldridge test. The reported Breusch–Pagan LM result supported a panel specification over pooled OLS ($p < 0.001$), while the Hausman test was used to select between fixed and random effects. Huber–White cluster-robust standard errors

were used to address heteroskedasticity and within-firm serial correlation; inference is nevertheless treated cautiously because the panel contains only 18 firm clusters.

The primary panel regression equation is specified as follows:

$$\text{Tobin's Q}_{it} = \beta_0 + \beta_1(\text{DER}_{it}) + \beta_2(\text{DTA}_{it}) + \beta_3(\text{Firm Size}_{it}) + \beta_4(\text{ROA}_{it}) + u_i + \epsilon_{it} \quad (1)$$

5. RESULTS

Table 1 presents the descriptive statistics for the 90 firm-year observations. Mean Tobin's Q is 1.0199, with a standard deviation of 1.0692 and a range from 0.1842 to 8.9866. DER has a mean of 0.4877 and a maximum of 11.2450, indicating variation in the leverage levels of the sampled firms. DTA has a mean of 0.2151. Mean ROA is 0.0945, with observations ranging from −0.1450 to 0.4620. Firm size, measured as the natural logarithm of total assets, has a mean of 22.5784.

Table 1: Descriptive Statistics of Sample Variables (N = 90)

Variable	Mean	Std. Dev.	Median	Minimum	Maximum
Tobin's Q	1.0199	1.0692	0.7434	0.1842	8.9866
DER	0.4877	1.3412	0.2215	0.0000	11.2450
DTA	0.2151	0.1784	0.1820	0.0000	0.7420
Firm Size	22.5784	1.1842	22.4510	20.9142	24.9510
ROA	0.0945	0.1124	0.0780	-0.1450	0.4620

Table 2 reports the Pearson correlation coefficients and variance inflation factors. The correlation between DER and DTA is 0.4125. The largest absolute correlation among the explanatory variables is between DTA and ROA (−0.6791). VIF values range from 1.05 to 1.88, with a mean of 1.48.

Table 2: Pearson Correlation Matrix and Variance Inflation Factors (VIF)

Variable	Tobin's Q	DER	DTA	Firm Size	ROA	VIF
Tobin's Q	1.0000	-	-	-	-	-
DER	-0.0812	1.0000	-	-	-	1.24
DTA	+0.0421	+0.4125	1.0000	-	-	1.88
Firm Size	-0.1942	+0.0821	+0.1241	1.0000	-	1.05
ROA	+0.2415	-0.3124	-0.6791	-0.1142	1.0000	1.76

The Hausman test produced a chi-square statistic of 5.2464 (df = 4, p = 0.2629), supporting the random-effects estimator. The regression estimates are presented in Table 3.

Table 3: Random-Effects Panel Regression Results (Dependent Variable: Tobin's Q)

Variable	Coefficient (β)	Std. Error	t-Statistic	p-Value
Constant	+6.2730	2.9498	2.1266	0.0364
DER (H1)	-0.0308	0.0481	-0.6408	0.5234
DTA (H2)	+0.2074	0.8769	0.2365	0.8136
Firm Size (FS)	-0.2444	0.1322	-1.8495	0.0679
ROA	+2.5023	1.2790	1.9564	0.0537

Source: Author's EViews calculation based on CSE disclosures (2020–2024). Weighted R-squared = 0.0838 (8.38%), Adjusted R-squared = 0.0406, F-statistic = 1.9424 (p = 0.1108).

Model statistics: Weighted R^2 = 0.0838; adjusted R^2 = 0.0406; F-statistic = 1.9424; model p-value = 0.1108.

DER has a negative coefficient (β = −0.0308, p = 0.5234), while DTA has a positive coefficient (β = 0.2074, p = 0.8136). Neither leverage measure is statistically significant at the 10%, 5% or 1% level; therefore, H1 and H2 are not supported. Firm Size has a negative coefficient (β = −0.2444, p = 0.0679), and ROA has a positive coefficient (β = 2.5023, p = 0.0537). Both control-variable coefficients are significant at the 10% level but not at the 5% level. The overall model is not statistically significant (p = 0.1108). The separate DER-only and DTA-only specifications also report non-significant leverage coefficients (p = 0.5120 and p = 0.8210, respectively).

6. DISCUSSION

The results do not indicate a statistically significant association between either leverage measure and Tobin's Q in the sampled Materials Sector companies during 2020-2024. Accordingly, the analysis does not support H1 or H2. This finding should not be interpreted as proof that capital structure is irrelevant to firm value; rather, the selected leverage measures do not provide statistically significant explanatory evidence within this sample and model.

The positive coefficient for ROA and negative coefficient for Firm Size are statistically significant only at the 10% level. Furthermore, the overall regression model is not statistically significant. These individual coefficient estimates therefore provide, at most, tentative evidence of associations and should not be described as strong or definitive determinants of firm value.

One possible explanation for the negative Firm Size coefficient is that larger capital-intensive companies may have faced greater fixed-cost commitments and lower operational flexibility during a period of macroeconomic uncertainty. However, the study does not directly measure capacity utilisation, cost structure, supply-chain flexibility or investment behaviour. This explanation is therefore tentative and requires further investigation using firm-level operational data.

7. IMPLICATIONS AND LIMITATIONS

Practical and Managerial Implications: The findings offer practical guidance for Chief Financial Officers, corporate decision-makers, and equity investors in capital-intensive sectors. Financial managers should refrain from relying solely on leverage adjustments or financial engineering to enhance market valuation. Strategic priority should be directed toward operational cost-structure optimization, operating margin defense, working capital liquidity management, and asset productivity. For equity investors, valuation models should emphasize core operating earnings (ROA) and cash-flow resilience alongside balance-sheet debt metrics during macroeconomic shocks.

Regulatory and Policy Implications: Financial regulators, including the Colombo Stock Exchange and the Central Bank of Sri Lanka, should evaluate corporate sector stability using holistic operating liquidity and cash-flow coverage metrics rather than relying exclusively on debt-to-equity thresholds during economic crises.

Limitations and Future Research Directions: This study is subject to several scope limitations. First, it focuses exclusively on 18 listed firms in the CSE Materials Sector over a five-year study period from 2020 to 2024. The relatively small sample size and limited study period may restrict the generalisability of the findings to other sectors and periods. Future researchers are encouraged to conduct comparative pre-crisis versus post-crisis evaluations, expand sample sizes across multiple CSE GICS sectors, and incorporate additional explanatory variables such as corporate governance indicators, foreign exchange exposure, and dividend payout policies.

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Impact of Behavioral Biases on the Profitability of Cryptocurrency Day Traders in Sri Lanka

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ABSTRACT

Cryptocurrency day trading has grown fast in Sri Lanka, but many day traders lose money. This study examines how three behavioral biases, herding behavior, heuristic biases, and prospect theory-based biases, affect the perceived profitability of cryptocurrency day traders in Sri Lanka. Earlier studies looked at how these biases affect general investment decisions, but no known study looked at how they relate to the profit of day traders in Sri Lanka. The study used a quantitative design. An online questionnaire was shared in cryptocurrency trading groups on social media, and 500 valid responses from active day traders were collected through non-probability sampling. Perceived profitability was measured by the traders' own ratings of their trading results, not by checked account data. The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS 4. All three biases had a positive and significant effect on perceived profitability. Herding behavior had the strongest effect ($\beta = 0.190$), followed by prospect theory-based biases ($\beta = 0.157$) and heuristic biases ($\beta = 0.142$). The three biases together explained 14.9 percent of the variance in perceived profitability. This result does not mean that biases raise real profit. It means that traders with stronger biases rate their own results higher. The heterotrait-monotrait (HTMT) ratio between heuristic biases and prospect theory-based biases was 0.919, so these two biases overlap, and their separate effects should be read with care. The study gives advice to traders, trading platforms, and regulators.

Keywords: *herding behavior; heuristic biases; prospect theory; perceived profitability; cryptocurrency day trading*

JEL Classification: *G11, G40, G41*

1. INTRODUCTION

Cryptocurrency is a digital and decentralized form of money. It does not need a central bank or a third party, such as a bank, to work (Manoj, 2023; Roza et al., 2024). Since Bitcoin started in 2009, the number of cryptocurrencies has grown very fast (Gunasena et al., 2024).

Cryptocurrency has also become popular in Sri Lanka in recent years. The value of the Sri Lankan rupee has fallen, and Gunasena et al. (2024) report that the number of cryptocurrency traders in Sri Lanka grew by 730 percent during the economic recession. They also report that Sri Lanka moved up to 49th place in the 2023 Global Crypto Adoption Index. These figures come from a 2024 source, and they may be different today. Cryptocurrency is still not legally recognized in Sri Lanka, but many traders use it through online platforms such as Binance (Manoj, 2023).

Day trading means buying and selling an asset within the same day. It can bring a big gain or a big loss in a short time (Roza et al., 2024). Studies show that day trading is risky and that only a few traders make a steady profit. Roza et al. (2024) found that 97 percent of traders who day traded for more than 300 days lost money in the end. Abarquez et al. (2025) found that only 44 percent of the cryptocurrency traders in a Philippine-based online community performed better than the market.

Cryptocurrency day trading is therefore an important area to study in Sri Lanka. The market is fast-growing, it is not regulated, and many traders may lose money. A better understanding of trader behavior can help traders, trading platforms, and regulators to make safer decisions.

Behavioral finance explains that investors do not always act in a rational way. Instead, biases in their thinking and their feelings affect them (Gunasena et al., 2024). Three important biases in cryptocurrency trading are herding behavior, heuristic biases, and prospect theory-based biases. Herding behavior happens when traders copy the actions of other traders instead of thinking on their own. Heuristic biases include overconfidence, anchoring, availability bias, representativeness, and the gambler's fallacy. Prospect theory-based biases include loss aversion, regret aversion, and mental accounting.

Gunasena et al. (2024) studied how these three biases affect the investment decisions of 158 Sri Lankan cryptocurrency investors. They found that heuristic biases and prospect theory-based biases had a significant effect, but herding behavior did not. However, their study looked at general investment decisions, not at the profit of day traders. Roza et al. (2024) studied the losses of day traders, but not in Sri Lanka. Abarquez et al. (2025) studied the profitability of cryptocurrency trading in the Philippines, but they did not include behavioral biases. No known study has looked at how these three

biases relate to the profitability of cryptocurrency day traders in Sri Lanka. This study fills that gap.

In this study, profitability means perceived profitability. It is the trader's own view of how profitable his or her trading is. The study does not measure real profit from trading accounts. This point is important, and it is kept clear in the title, the hypotheses, the results, and the discussion. The rest of this paper has six parts: Aims/Objectives, Theory, Methods, Results, Discussion, and Implications and Limitations.

2. Aims/Objectives

The research question of this study is: What is the impact of behavioral biases on the perceived profitability of cryptocurrency day traders in Sri Lanka?

The aim of the study is to examine how behavioral biases relate to the perceived profitability of cryptocurrency day traders in Sri Lanka. There are three specific objectives. The first objective is to examine the effect of herding behavior on the perceived profitability of cryptocurrency day traders in Sri Lanka. The second objective is to examine the effect of heuristic biases on their perceived profitability. The third objective is to examine the effect of prospect theory-based biases on their perceived profitability.

The study is useful for academics, since it adds new knowledge to behavioral finance in a developing country. It is also useful for traders, financial educators, and regulators, since the findings can help them build better tools, lessons, and rules for a market that is fast-growing but still not regulated.

3. THEORY

This study uses behavioral finance as its main theory. Behavioral finance says that investors do not always act in a rational way. Their thinking shortcuts and their feelings can change their choices (Gunasena et al., 2024). The study looks at three groups of biases, and each group is described below.

Herding behavior. Herding theory says that people tend to follow the actions of others instead of using their own judgment, especially when the market is uncertain (Gunasena et al., 2024). In cryptocurrency trading, herding can lead traders to buy or sell at the wrong time only because other traders do the same. Roza et al. (2024) explain that social media plays a big part in herding, since traders often follow influencers and online trading groups. Gunasena et al. (2024) found that herding did not have a significant effect on the investment decisions of general Sri Lankan cryptocurrency investors, and they explained this by the small size of the market and the unclear rules in Sri Lanka.

Heuristic biases. Heuristic biases are mental shortcuts that people use to make fast decisions when they do not have full information. Gunasena et al. (2024)

study five heuristic biases: overconfidence, anchoring, availability bias, representativeness, and the gambler's fallacy. Overconfidence makes a trader believe that he or she is better than the average trader. Anchoring makes a trader depend too much on one reference price. Availability bias makes a trader depend on information that is easy to remember. Roza et al. (2024) argue that these biases are very risky for day traders, since day trading needs fast decisions in a market that changes very quickly.

Prospect theory-based biases. Prospect theory, developed by Kahneman and Tversky (1979), explains that people feel the pain of a loss more strongly than the pleasure of an equal gain. Gunasena et al. (2024) study three biases that come from this theory: loss aversion, regret aversion, and mental accounting. Loss aversion can make a trader hold on to a losing position for too long, hoping that the price will recover. Regret aversion makes a trader avoid decisions that may cause regret later. Mental accounting makes a trader treat money differently depending on where it came from. Roza et al. (2024) report that loss chasing and a false sense of control are important risk factors for cryptocurrency day traders.

Hypotheses. The dependent variable of this study is perceived profitability. It is the trader's own opinion of how profitable his or her trading is, and it is not the real profit from trading accounts. Earlier work shows that these biases are risky for day traders (Roza et al., 2024). However, traders who follow the crowd, trust their own mental shortcuts, or react strongly to gains and losses may feel more sure about their results, and they may rate their own trading higher. For this reason, the study expects a positive effect from each bias on perceived profitability. Based on this, the following hypotheses are proposed:

H1: Herding behavior has a positive effect on the perceived profitability of cryptocurrency day traders in Sri Lanka.

H2: Heuristic biases have a positive effect on the perceived profitability of cryptocurrency day traders in Sri Lanka.

H3: Prospect theory-based biases have a positive effect on the perceived profitability of cryptocurrency day traders in Sri Lanka.

4. METHODS

This study follows a positivist research philosophy, since it measures the relationship between variables using numbers and statistical tests (Gunasena et al., 2024). A deductive approach is used, since the study starts with existing theory and tests specific hypotheses using collected data. A quantitative research strategy is used, since the study collects numerical data through a

questionnaire survey. A cross-sectional time horizon is used, since the study collected data at one point in time.

The target population of this study is active cryptocurrency day traders in Sri Lanka. A day trader is a person who buys and sells cryptocurrency within the same trading day (Roza et al., 2024). Cryptocurrency is not officially regulated in Sri Lanka, so there is no official list of traders, and the exact number of day traders is not known (Manoj, 2023). For this reason, the study could not use a sampling frame, and it could not select respondents by chance. It used non-probability sampling. The link to the questionnaire was shared in cryptocurrency day trading groups and communities on social media, and traders in these groups chose to answer it (convenience sampling). Only people who said that they were active day traders could answer. The number of responses was also watched so that three groups of trading experience were included: less than one year, one to three years, and more than three years (quota sampling). This was done because earlier studies show that trading experience affects trading behavior and profitability (Gunasena et al., 2024; Abarquez et al., 2025). Because of this sampling method, the results apply to the traders who answered the survey, and they cannot be generalized to all day traders in Sri Lanka.

The study received 511 responses. Eleven responses were removed because they were incomplete, were duplicates, or did not pass the day trader screening questions, so 500 valid responses were kept. An estimate shows about 410,000 cryptocurrency owners in Sri Lanka (Triple-A, 2024), but the number of day traders is not known. For a population of this size, Krejcie and Morgan (1970) give a sample size of 384. The sample of 500 is larger than this number. The model also has only three predictor constructs, and a sample of 500 is large for a model of this size.

Data were collected using a structured, self-administered questionnaire. The questionnaire has four sections. The first section asks about the trader profile, such as age, gender, education, income, trading experience, and platform. The other sections measure herding behavior (five items), heuristic biases (10 items), prospect theory-based biases (six items), and perceived profitability (seven items). All items were measured on a five-point Likert scale, from strongly disagree to strongly agree. The items for the three biases were adapted from Gunasena et al. (2024). The items for perceived profitability were adapted from Abarquez et al. (2025) and Gunasena et al. (2024). They cover total investment, total gains, return on investment, consistency of returns, overall performance, ability to cover losses, and satisfaction with trading outcomes. Perceived profitability was measured by the traders' own ratings, and it was not checked against trading account records. A pilot test with 10 respondents checked the clarity and the validity of the questionnaire.

Herding behavior was a first-order reflective construct with five items. Heuristic biases and prospect theory-based biases were second-order constructs, built with a two-stage approach. First, scores were computed for the lower-order constructs: overconfidence, anchoring, availability bias, representativeness, and the gambler's fallacy for heuristic biases, and loss aversion, regret aversion, and mental accounting for prospect theory-based biases. Then these scores were used as indicators of the higher-order construct. This approach was used because an early model, with all 10 and all six items as direct indicators, gave low average variance extracted (AVE) values of 0.283 for heuristic biases and 0.247 for prospect theory-based biases. The same early model gave an AVE of 0.247 for perceived profitability, so the three items with the lowest loadings were removed, and four of the seven items were kept. Perceived profitability shows how a trader rates his or her own trading results. A higher score on each construct means a higher level of that bias or a higher self-rating.

Data were analyzed in two steps. First, descriptive statistics (frequency, mean, and standard deviation) were used to summarize the demographic profile of the respondents and the general pattern of answers. Second, the three hypotheses were tested using Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS 4, since this method works well with small to medium sample sizes and does not need normally distributed data (Hair et al., 2019). The measurement model was checked first, using indicator loadings, Cronbach's alpha, composite reliability (CR), AVE, the Fornell-Larcker criterion (Fornell & Larcker, 1981), and the heterotrait-monotrait (HTMT) ratio. The structural model was checked next, using full collinearity variance inflation factor (VIF) values (Kock, 2015), path coefficients, *t*-values, *p*-values, the coefficient of determination (R^2), adjusted R^2, effect size (f^2), and predictive relevance (Q^2). The full collinearity VIF test was also used to check common method bias, and Harman's single-factor test was used as a second check. The significance of the paths was tested using bootstrapping with a two-tailed test at the 5 percent level, so a *t*-value above 1.96 means a significant path.

5. RESULTS

Out of 511 responses received, 500 were valid and complete, which gives a response rate of 97.8 percent. Four respondents (0.8 percent) gave the same answer to all items. They were kept in the data, because the reliability results changed very little when they were removed. Table 1 shows the sample profile. Most respondents were male (71 percent) and aged between 26 and 35 years (67 percent). The largest group held a General Certificate of Education

(G.C.E.) Advanced Level (43 percent), and most worked part-time (43 percent) or full-time (37 percent).

Table 1: Sample Profile of Respondents

Characteristic	Most Common Group	Respondents (%)
Gender	Male	71
Age	26 to 35 years	67
Education	G.C.E. Advanced Level	43
Employment	Part-time work	43
Monthly income from trading	LKR 50,001 to 100,000	60
Trading experience	One to three years	61.8
Main platform	Binance Futures	58
Trades per day	Four to six trades	57

Note. N = 500. LKR = Sri Lankan rupee; G.C.E. = General Certificate of Education.

Most traders earned between 50,001 and 100,000 Sri Lankan rupees (LKR) per month from cryptocurrency trading (60 percent). By trading experience, 35.4 percent had less than one year, 61.8 percent had one to three years, and 2.8 percent (14 traders) had more than three years. Binance Futures was the main platform for 58 percent of the traders, and Bybit for 39 percent. Most traders (57 percent) made four to six trades a day, and another 40 percent made one to three trades a day. This profile matches the young, active day trader population that this study aims to examine.

Table 2: Reliability and Convergent Validity

Construct	Indicators	Loadings	Cronbach's Alpha	CR	AVE
Herding behavior	Five items	0.795 / 0.709 / 0.700 / 0.649 / 0.741	0.767	0.843	0.519
Heuristic biases	Five lower-order scores	0.715 / 0.757 / 0.740 / 0.774 / 0.765	0.805	0.866	0.563
Prospect theory-based biases	Three lower-order scores	0.755 / 0.741 / 0.734	0.594	0.787	0.553
Perceived profitability	Four items	0.677–0.734	0.681	0.807	0.511

Note. CR = composite reliability; AVE = average variance extracted. For the two second-order constructs, the loadings are those of the lower-order construct scores.

The mean scores of all four constructs were above 4.0 on the five-point scale (from 4.15 to 4.38), so most traders agreed with the statements.

Table 2 shows the reliability and validity results. All indicator loadings were above 0.60. CR values ranged from 0.787 to 0.866, and all AVE values were above 0.50. Cronbach's alpha was 0.594 for prospect theory-based biases and 0.681 for perceived profitability, which is below the usual limit of 0.70. These two constructs have few indicators, and alpha is a strict measure for such constructs, so CR was used as the main reliability measure (Hair et al., 2019). The Fornell-Larcker criterion was met for all pairs of constructs (Fornell & Larcker, 1981).

Table 3 shows the HTMT values. One pair, heuristic biases and prospect theory-based biases, had an HTMT value of 0.919, which is above the strict limit of 0.90 that is often used. The other five pairs were below 0.85 (from 0.329 to 0.470). This study did not compute bootstrap confidence intervals for the HTMT values, so the overlap of these two constructs could not be tested further.

Table 3: HTMT Values

Pair of Constructs	HTMT
Herding behavior – Heuristic biases	0.431
Herding behavior – Prospect theory-based biases	0.329
Herding behavior – Perceived profitability	0.406
Heuristic biases – Prospect theory-based biases	0.919
Heuristic biases – Perceived profitability	0.430
Prospect theory-based biases – Perceived profitability	0.470

Note. HTMT = heterotrait-monotrait ratio.

Table 4 shows the path coefficients, *t*-values, *p*-values, and effect sizes for the three hypotheses. Herding behavior had the strongest effect on perceived profitability, followed by prospect theory-based biases, and then heuristic biases. All three hypotheses were supported. The three biases together explained 14.9 percent of the variance in perceived profitability ($R^2 = 0.149$; adjusted $R^2 = 0.144$). The predictive relevance was small but above zero ($Q^2 = 0.122$; Hair et al., 2019). The f^2 value was 0.038 for herding behavior, which is a small effect. The values for heuristic biases (0.015) and prospect theory-based biases (0.019) are just below the 0.02 limit for a small effect (Cohen, 1988). Full collinearity VIF values ranged from 1.173 to 1.840, which is well under the threshold of 3.3 (Kock, 2015).

Table 4: Path Coefficients and Hypothesis Tests

Hypothesis	β	*t*-value	*p*-value	f^2	Decision
H1: Herding behavior - Perceived profitability	0.190	4.345	0.000	0.038	Supported
H2: Heuristic biases - Perceived profitability	0.142	2.682	0.008	0.015	Supported
H3: Prospect theory-based biases - Perceived profitability	0.157	3.040	0.002	0.019	Supported

Note. β = path coefficient. The dependent variable is perceived profitability.

6. DISCUSSION

This study tested whether herding behavior, heuristic biases, and prospect theory-based biases have a positive effect on the perceived profitability of cryptocurrency day traders in Sri Lanka. The results support all three hypotheses. An important point is that profitability in this study is based on the traders' own opinion about their performance, not on checked numbers from real trading accounts. A positive path therefore means that traders with stronger biases also rate their own trading as more profitable. It does not mean that these biases create higher real profit. One possible reason for this pattern is that biased traders feel more sure about their trades, and they may judge their own results in a better way. This reason was not tested in this study.

The difference between perceived profit and real profit matters. A trader may feel profitable because of a few recent wins, or because the trader compares his or her results with only a few other traders. A trader may also forget past losses. In all these cases, the self-rating can be higher than the real result. Without data from real trading accounts, this study cannot say how large the gap is.

The finding that herding behavior has the strongest effect on perceived profitability is different from Gunasena et al. (2024), who found that herding did not significantly affect general investment decisions in Sri Lanka. The two studies used different samples and different outcome variables, so the results cannot be compared directly. Gunasena et al. (2024) explain their result by the small size of the Sri Lankan market and the unclear rules. A possible reason for the difference is that day traders have very little time to decide, so following other traders becomes a fast and easy way to decide, especially in a market that runs for 24 hours and is strongly shaped by social media (Roza et al., 2024).

The finding on heuristic biases agrees with Gunasena et al. (2024), who also found that heuristic biases significantly affect the decisions of cryptocurrency traders in Sri Lanka. The finding on prospect theory-based biases is in line with Roza et al. (2024), who found that loss chasing and a false sense of control are important risk factors for cryptocurrency day traders. However, Roza et al. (2024) describe these factors as risk factors, while this study links the biases to perceived profitability. Traders who show these biases may not see the risk in their own behavior. This is a possible reason only, and it needs more testing with real trading data.

The explanatory power of the model is low ($R^2 = 0.149$). The three biases explain 14.9 percent of the variance in perceived profitability, so 85.1 percent is explained by other factors. This shows that behavioral biases are only part of the story. Other factors outside this study, such as market conditions, the amount of capital used, and risk management skills, may also play an important role in shaping profitability. The path coefficients are between 0.142 and 0.190, which are low in size, and the effect sizes are very small (f^2 from 0.015 to 0.038). The predictive relevance is also small ($Q^2 = 0.122$). The effects are statistically significant, but their practical size is small, and they should not be read as strong drivers of trader profitability. The mean scores of all constructs were above 4.0 with little spread, so most traders gave high ratings. This may reduce the differences between traders and make the relationships weaker.

The HTMT value of 0.919 between heuristic biases and prospect theory-based biases shows that these two constructs overlap. The Fornell-Larcker criterion was met for all pairs of constructs, but HTMT is a stricter test. Heuristic biases are mainly thinking shortcuts, and prospect theory-based biases are mainly emotional reactions to gains and losses. One possible reason for the overlap is that, in day trading, a trader's fast thinking mistakes and emotional reactions to loss often happen together in the same decision, rather than as two separate steps. This reason is an explanation only, and this study did not test it with statistical analysis. Because of the overlap, the result that the three biases have separate effects should be read with care. The effects of heuristic biases and prospect theory-based biases may not be fully separate from each other. This is a limitation of the study. Future studies can test the two constructs again, and they can merge or revise them if the overlap remains.

These findings apply to the 500 traders in this sample. Because the sample came from social media groups, traders who are active in these groups may be different from traders who are not. The group with more than three years of experience was also small (14 traders), so the results mainly describe traders with up to three years of experience. The findings should therefore be used as a first step, and they should be tested again with other samples.

7. IMPLICATIONS AND LIMITATIONS

For theory, this study adds new knowledge to behavioral finance in a developing country. It shows that, among the traders who answered the survey, herding behavior, heuristic biases, and prospect theory-based biases are all linked with higher perceived profitability. The study also shows that a measure based on self-rating can be different from real profit, so future studies should keep these two ideas apart. The result for herding is different from an earlier study of general investors in Sri Lanka, which suggests that the effect of a bias may depend on the type of trader.

For traders, the findings suggest that feeling profitable is not the same as being profitable. Traders are encouraged to build a clear trading plan with a fixed entry point, exit point, and stop-loss point before they start trading, and to keep a trading journal to track their real results over time. Traders should also base their decisions on checked market information rather than social media trends, and they should spread their trading across different assets instead of risking everything on one position.

For trading platforms, the findings suggest three steps. Platforms are encouraged to add risk warning messages for impulsive or repeated trading, to provide simple educational tools about behavioral biases, and to build performance dashboards that show traders their real trading numbers next to their own self-rating. This is useful because traders with stronger biases rated their own trading as more profitable in this study. Financial regulators and educational bodies are encouraged to run financial literacy and public awareness programs about herding and emotional trading, since cryptocurrency remains an unregulated market in Sri Lanka.

This study has seven limitations. First, profitability was self-reported, so the study cannot say anything about real profit. Second, the study used non-probability sampling in social media groups, so the sample may not represent all day traders in Sri Lanka, and the group with more than three years of experience was small (14 traders, 2.8 percent). Third, the design was cross-sectional, so the study shows links between variables and does not prove cause and effect. Fourth, the HTMT value between heuristic biases and prospect theory-based biases was 0.919, so these two constructs overlap, and the study did not compute confidence intervals for the HTMT values. Fifth, the model explains only 14.9 percent of the variance in perceived profitability. Sixth, all variables came from one self-reported survey, so common method bias and answers that seem more acceptable to the trader are possible. Harman's single-factor test and the full collinearity VIF test did not show a serious problem (all VIF values were below 3.3; Kock, 2015), but these tests cannot remove this risk fully. Seventh, most respondents used Binance Futures (58 percent) or

Bybit (39 percent) as their main platform, and all respondents were traders in Sri Lanka, so the findings may not apply to traders on other platforms or in other countries.

Future research should use real trading account data, follow traders over a longer period, include traders from other platforms and countries, and use probability sampling if a sampling frame becomes available. It should also test the two overlapping constructs again, and it can combine them into one construct if the overlap remains. It should add other factors such as market conditions, the amount of capital used, risk management skills, and financial education.

In conclusion, this study examined how herding behavior, heuristic biases, and prospect theory-based biases affect the perceived profitability of cryptocurrency day traders in Sri Lanka. Using data from 500 active day traders and PLS-SEM analysis, the study found that all three biases have a positive and significant effect on perceived profitability, and herding behavior has the strongest effect. The results do not show that biases improve real profit. They show that traders with stronger biases rate their own trading results higher. The model explains only a small part of perceived profitability, so the results should be read with care.

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Corporate Governance and Sustainability

The Impact of Green Financing on Financial Performance: The Mediating Role of Environmental Performance in Listed Companies in Sri Lanka

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ABSTRACT

With the rise of sustainable development, green financing has become more important in supporting green businesses and promoting corporate and environment sustainability. However, the empirical evidence on the linkage between green financing, environmental performance and financial performance remains limited in Sri Lanka, particularly regarding the mediating role of environmental performance. Therefore, this study examines the relationships between green financing, environment performance and financial performance including the mediating role of environmental performance among listed companies in Sri Lanka. The use of a quantitative research method is due to the use of secondary panel data in the form of 60 listed companies with a number of 180 observations of firm years in 2022 – 2024. The data has been gathered from annual reports, sustainability reports, integrated reports, ESG disclosures, audited financial statements and corporate websites. Financial performance was measured using Return on Assets, while green financing and environmental performance were measured using respective indices based on green investment and financing initiatives, and environmental practices such as carbon reduction, energy conservation, and waste management, respectively. Stata was used to analyze the data using descriptive statistics, correlation analysis, panel regression, diagnostic tests, and Baron and Kenny mediation procedure. The results indicate that green financing has a significant positive impact on both financial performance and environmental performance. When both green financing and environmental performance were simultaneously included in the final regression model, the

effect of environmental performance on financial performance became statistically insignificant, while the direct effect of green financing remained significant. This indicates that environmental performance does not mediate the relationship between green financing and financial performance. The study represents the limited empirical study in Sri Lanka on green financing, and offers implications for companies and policymakers to strengthen the green financing practices and environmental performance monitoring.

Keywords: Environmental Performance, Financial Performance, Green Financing, Listed Companies, Sri Lanka

1. INTRODUCTION

Environmental issues like pollution, resource shortage and climate change have made sustainability a higher priority in business. Green financing is also crucial in enabling green investments, such as renewable energy projects and energy efficiency and pollution control (Wang & Zhi, 2016). According to previous studies, green financing is positively related to financial performance (Li & Lin, 2024). Likewise, Zheng and Siddik (2022) noted that it helps to improve environmental performance, and Friede et al. (2015) found a positive relationship between environmental and financial performance.

However, there is a lack of empirical studies which investigate these three variables simultaneously, especially the role of environmental performance as a mediator in the Sri Lankan context. Hence, the present study aims to explore the effect of green finance on the financial performance and to explore the mediating role of environmental performance between these variables in the listed companies of Sri Lanka.

2. AIMS/ OBJECTIVES

This study is aimed at exploring the effect of green financing on financial performance of listed companies in Sri Lanka and whether the impact of green financing on financial performance is mediated by environmental performance. In particular, the following objectives are set for the study:

1. What is the impact of green financing on financial performance in listed companies in Sri Lanka?
2. What is the impact of green financing on environmental performance?
3. What is the impact of environmental performance on financial performance?
4. Does environmental performance mediate the relationship between green financing and financial performance?

3. THEORY

Stakeholder Theory: An explanation of how green financing supports the company to satisfy stakeholder expectations and to foster trust.

Legitimacy Theory: Describes the role environmental activities play in ensuring social acceptance and corporate legitimacy.

Resource Based View (RBV): Describes how green investments build environmental capabilities, enhance efficiency and create competitive advantages.

Signaling Theory: The theory that describes the way in which green financing and environmental disclosures send a message to investors and other stakeholders about the sustainability commitment by the company.

Institutional Theory: Discusses how regulations, industry standards and social pressures influence companies to take sustainable measures.

These theories provide explanations for company's decision to invest in environmentally responsible financing and sustainability practice, from the perspective of stakeholder expectations, organizational legitimacy, competitive advantages, corporate reputation and institutional pressures.

The conceptual framework considers the relationship between three major variables: green financing, environmental performance and financial performance. Green financing is considered the independent variable, financial performance is the dependent variable, and environmental performance is the mediating variable.

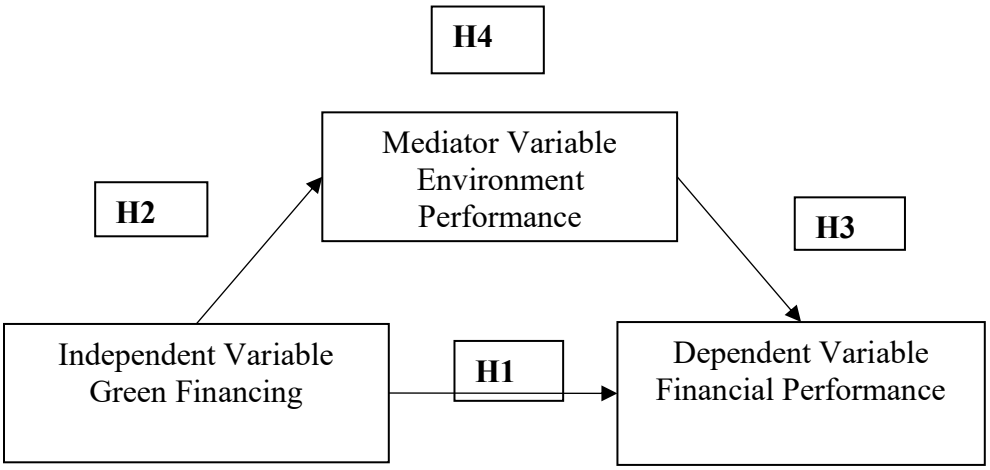

Figure 1. Conceptual Framework

3. METHODS

This study adopted quantitative research method, secondary data analysis, to explore the relationship between green financing, environmental performance and financial performance.

This study has been conducted using the panel data of the 60 listed companies in Sri Lanka for the period of 2022 to 2024, which constituted 180 company-years of data. Secondary data were gathered from the company annual reports, sustainability reports, integrated reports and financial statements.

The Green Financing Index (GFINDEX) was used to measure green financing, and the Environmental Performance Index (EPINDEX) was used to measure environmental performance. The evaluation of financial performance was based on Return on Assets (ROA).

This study used a positivist research philosophy, deductive approach and explanatory research design. The 60 companies were selected in the study using purposive sampling method.

Stata was used for data analysis. The descriptive statistics were used to summarize the variables and to check their relationships by correlation analysis. Using four regression models, four relationships were tested using panel regression analysis. The Hausman test was used to determine the type of panel estimation model to use. Assessment of the regression assumptions was done by conducting diagnostic tests such as normality, multicollinearity (VIF), heteroskedasticity and autocorrelation tests. For the hypothesis test, the Random Effects model with robust standard errors was used. Lastly, Baron and Kenny (1986) mediation method were adopted to explore the mediation effect of environmental performance between green financing and financial performance. The evaluation of hypotheses was done at 5% significance level.

4. RESULTS

Table 1. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
ROA	180	0.074	0.121	-0.161	0.815
GFINDEX	180	0.538	0.183	0.2	0.9
EPINDEX	180	0.536	0.174	0.2	0.9

Note: This table presents descriptive statistics for the main variables. ROA= Return on Asset, GFINDEX= Green Financing Index, EPINDEX= Environmental Performance Index
Source: STATA output

The descriptive statistics show that Return on Assets (ROA) had a mean of 0.074 (SD = 0.121). The mean value of the Mean Green Financing Index

(GFINDEX) was 0.538 (SD = 0.183) and the mean value of the Mean Environmental Performance Index (EPINDEX) was 0.536 (SD = 0.174).

Table 2. Correlation Analysis

Variables	(1)	(2)	(3)
(1) ROA	1.000		
(2) GFINDEX	0.188*	1.000	
	(0.012)		
(3) EPINDEX	0.192*	0.748*	1.000
	(0.010)	(0.000)	

Source: STATA output

Positive and statistically significant correlation between the study variables were found. The financial performance and environmental performance were positively associated with green financing ($r = 0.188$, $p = 0.012$) and ($r = 0.748$, $p < 0.001$), respectively. There is also a positive correlation between environmental performance and financial performance ($r = 0.192$, $p = 0.010$).

Table 3. Panel Regression and Diagnostic Analysis

Variables	Model 1	Model 2	Model 3	Model 4
GFINDEX	0.156	0.713	-	0.137
EPINDEX	-	-	0.138	0.026
Constant	-0.010	0.152	0.000	-0.013
Observations	180	180	180	180
Overall R^2	0.035	0.560	0.037	0.038
Model χ^2	19.164	237.789	11.157	19.373
Model p-value	<0.001	<0.001	0.001	<0.001

Source: Compiled by the author based on the study results.

The results of the panel regression confirmed that green financing is positively associated with financial performance ($\beta = 0.156$, $p < 0.001$), thus supporting the H1. Support for H2 was also obtained with a positive and statistically significant correlation between green financing and environmental performance, $\beta = 0.713$ and $p < 0.001$. When considered separately, environmental performance showed positive and significant association with financial performance ($\beta = 0.138$, $p = 0.001$), thus justifying H3.

The regression analysis results indicated that green financing was still positive and statistically significant ($\beta = 0.137$, $p = 0.004$) when the green financing and environmental performance were included simultaneously in the final regression model, but environmental performance was not statistically significant ($\beta = 0.026$, $p = 0.641$). So, the results did not lend support to the

proposed mediating role of environmental performance and H4 was not supported.

Table 4. Mediation Analysis

Step	Model	Result	Condition
1	Green Financing → Financial Performance	β = 0.156, p = 0.000	Satisfied
2	Green Financing → Environment Performance	β = 0.713, p = 0.000	Satisfied
3	Environmental Performance → Financial Performance	β = 0.138, p = 0.001	Satisfied
4	Green Financing and Environmental Performance → Financial Performance	GFINDEX: p = 0.004 (significant); EPINDEX: p = 0.641 (not significant)	Not Satisfied

Source: Compiled by Author

5. DISCUSSION

Based on the results, it can be seen that there is a positive relationship between green financing and financial performance, which is statistically proved, thus supporting H1. This is in line with the positive correlation that was reported in Nizar (2025) and Li and Lin (2024). Variation between studies may be attributed to differences in companies characteristics, green financing definition, and the time frame examined. In the Sri Lankan context that is explored in this study, the positive coefficient indicates that companies having higher scores in green financing index also exhibited higher ROA scores in the range of 2022-2024.

The findings of a positive and significant relationship between the two variables of green financing and environmental performance support the hypothesis H2. This aligns with the link between green financing and environmental enhancements as mentioned in (Zheng & Siddik, 2022). A possible solution is to provide financing for environmental programs to help the adoption of cleaner technologies, energy efficiency and environmental management. However, the present study has employed an index-based measure so that the outcome should be interpreted as indicative of a relationship between the measured scores rather than of specific environmental improvements resulting from financing.

Examine the individual relationships between environmental and financial performance showed positive and significant relationships, thus confirming H3. This is in line with the broader connection between environmental and economic performance as put forth by (Friede et al., 2015). The combined

regression model, however, did not show environmental performance to be statistically significant, with green financing being significant instead. This is significant as it contrasts the separate model with the combined model: The positive individual association is not an indication of the independent effect of environmental performance in this model.

H4 was not supported by the mediation analysis. Green financing had a significant relationship with environmental performance, both variables had significant association with ROA in the separate models, however, environmental performance was not significant in the final model ($\beta = 0.026$, $p = 0.641$). Hence, the results are not considered as proof that green financing relates to environmental performance as the mechanism. This is not the mediation option mentioned in (Ma et al., 2022). The difference could be due to the different context, variables, measurement methods, or study periods.

Table 5. Hypotheses Testing

Hypotheses	Decision
H1: Green financing has a significant impact on financial performance.	Accepted
H2: Green financing has a significant impact on environmental performance.	Accepted
H3: Environmental performance has a significant impact on financial performance.	Accepted
H4: Environmental performance mediates the relationship between green financing and financial performance.	Rejected

Source: Compiled by Author

The results should be interpreted also taking into consideration the methodological simplifications of the study. First, the analysis is only applied to 60 companies listed on the stock exchange and restricted to 3 years (2022-2024). This gives 180 firm-year observations, however, the short observation period might not reflect future financial gains from environmental investments. Secondly, the study is secondary and uses index based measures. These measures provide a basis for comparing among companies, but may be indicative of the availability and extent of disclosure and of actual practices. Third, the models do not include control variables. The estimated relationships are not limited by the factors such as company size, leverage, industry, and general economic conditions. Lastly, regression results do not necessarily equate to causal relationships. It is therefore important to not read the mediation finding as an indication of a lack of statistical evidence in the tested model, but rather as a finding that environmental performance cannot be considered a mediator in that tested model.

The study in general concludes that there are positive relationships among the listed companies selected in Sri Lanka between green financing, environmental performance and financial performance. But the predictive role of environmental performance was not confirmed by the final regression model. The results provide context specific evidence and raise the need for more extensive samples, extended periods of observation, and models incorporating company characteristics.

6. IMPLICATIONS AND LIMITATIONS

This study is an empirical study on the relationship between green financing and environmental and financial performance for the Sri Lankan situation, which assists the literature. The results confirm the positive association between green financing and financial performance as well as green performance. The presence of the mediating effect of environmental performance was, however, not confirmed, which remains a topic for further research on other possible pathways on how green financing can be found to affect financial performance.

The results of this research provide some useful information for company management, investors, and policy makers. A company may resort to green financing when deciding where to invest, and should assess its financial and environmental impact. Environmental performance disclosures should be included among the financial metrics used to evaluate companies. Policymakers can stimulate green financing by fostering business practices that are environmentally friendly.

The time period for this study was 2022–2024, and the listed companies that were studied were 60. It additionally used disclosure-based indices and secondary data for the measurement of green financing and environmental performance. In addition, only ROA was used to determine financial performance without including control variables. Larger sample size, longer time, direct environmental factors and more financial factors like ROE and ROCE can be considered in future studies. The relationships could also be deeper and more informative if there were inclusion of control variables and also if there were a consideration of other potential mediators.

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Board Characteristics and Environmental Disclosure: Evidence from Sri Lankan Listed Companies

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ABSTRACT

Despite growing scholarly attention to corporate environmental reporting, empirical evidence on the influence of board characteristics on environmental disclosure in Sri Lanka remains limited. Thus, this study aims to examine the effect of board characteristics on environmental disclosure among non-financial listed companies in Sri Lanka. The study uses panel data from 60 non-financial companies listed on the Colombo Stock Exchange (CSE), selected through random sampling, covering the period 2021–2025 and yielding 300 firm-year observations. . Environmental disclosure is measured using a 34-item Environmental Disclosure Index based on the Global Reporting Initiative (GRI), while board characteristics comprise board size, board independence, board gender diversity, and CEO duality. Secondary data are collected from published annual reports, and environmental disclosure is assessed through content analysis. The empirical analysis initially estimates pooled Ordinary Least Squares (OLS), Fixed Effects, and Random Effects models. The Breusch–Pagan Lagrangian Multiplier and Hausman specification tests are subsequently applied to determine the appropriate panel-data model, with the test results supporting the Fixed Effects model for final estimation. The findings indicate an average environmental disclosure level of 31%. Board gender diversity has a positive and statistically significant effect on environmental disclosure, whereas board size, board independence, and CEO duality have no statistically significant effects. The study is limited to a five-year period, 60 companies, and selected board characteristics. Nevertheless, it contributes recent empirical evidence on board-level determinants of environmental disclosure in Sri Lanka and provides practical insights for listed companies, regulators, and policymakers seeking to strengthen board diversity and corporate environmental transparency.

Keywords: Board Characteristics, Environmental Disclosure, Corporate Governance, Sri Lanka

1. INTRODUCTION

Growing concern over climate change, environmental degradation and the environmental consequences of business activities has increased expectations for companies to be transparent about their environmental performance (Nuskiya et al., 2021; Krishnasamy & Keerthana, 2026; Xu et al., 2025). Therefore, corporate reporting has expanded beyond traditional financial information as stakeholders increasingly demand information about firms' environmental responsibilities, practices and impacts. Within this broader reporting environment, corporate environmental disclosure (CED) has become an important means through which companies communicate their environmental policies, practices, performance and impacts to stakeholders (Wilmshurst & Frost, 2000; Nuskiya et al., 2021). Environmental disclosure can improve corporate transparency and provide stakeholders with information needed to assess how firms manage environmental risks and responsibilities (Jamil & Khan, 2024). These developments have increased academic and regulatory attention towards understanding not only the extent of environmental disclosure but also the factors that influence differences in disclosure practices among companies.

Corporate governance has received considerable attention in environmental disclosure research because board characteristics can influence corporate reporting practices (Khaireddine et al., 2020; Nuskiya et al., 2021). In particular, the composition and structure of the board may affect the extent to which companies disclose environmental information (Khaireddine et al., 2020; Xu et al., 2025). Previous studies have therefore examined board size, board independence, board gender diversity and CEO duality in relation to environmental disclosure (Khaireddine et al., 2020; Xu et al., 2025). In the Sri Lankan context, Nuskiya et al. (2021) specifically examined board size, board independence, board meetings and CEO duality as governance determinants of CED. However, findings concerning individual board characteristics and environmental disclosure remain mixed across different institutional and organisational settings (Xu et al., 2025).

International empirical evidence demonstrates these differences. Khaireddine et al. (2020) found that board independence and board gender diversity were positively associated with environmental disclosure among French listed companies. Board size also had a significant positive relationship with environmental disclosure. In India, Kumari et al. (2022) reported positive

relationships between board size, board meetings and environmental disclosure, while board independence, gender diversity and CEO duality were insignificant. Almaqtari et al. (2023) also documented relationships between board attributes and environmental reporting using evidence from Asian and European companies. More recently, Alta'any et al. (2026) found that board size, board independence, CEO duality and board gender diversity did not significantly explain the environmental reporting dimension in an international sample. The variation in empirical findings suggests that the relationship between board characteristics and environmental disclosure may differ according to institutional and organisational contexts.

Sri Lankan evidence also shows variation across different forms of corporate disclosure. Nuskiya et al. (2021), based on 41 listed companies during 2015–2019, found that CED increased over the study period but remained at an early stage compared with developed economies. Board size and board independence were positively associated with CED, while CEO duality was negatively associated with CED. Randunu et al. (2022) subsequently examined carbon-emission disclosure among environmentally sensitive Sri Lankan companies during 2016–2020. Board size had a positive relationship with carbon-emission disclosure, whereas board independence was insignificant. Shamil et al. (2014) also identified associations between board characteristics and sustainability reporting among Sri Lankan firms. More recently, Niresh and Vinsana (2026) found a positive and significant relationship between board gender diversity and integrated reporting disclosure. Nevertheless, carbon disclosure, sustainability reporting and integrated reporting differ from environmental disclosure and therefore cannot fully explain recent CED practices.

Despite the growing importance of environmental transparency, the level of environmental disclosure among Sri Lankan listed companies remains relatively limited. Krishnasamy and Keerthana (2026) reported a mean CED level of only 21% among 100 CSE-listed companies during 2020–2024, suggesting that a considerable amount of environmental information was not disclosed. At the same time, environmental disclosure was found to be positively and significantly associated with firm value, highlighting the economic relevance of such information (Krishnasamy & Keerthana, 2026). This presents an important concern in the Sri Lankan context. Although environmental information appears to be relevant to firm value, the overall level of disclosure remains relatively low. Understanding the factors associated with differences in environmental disclosure is therefore important. In particular, the extent to which board characteristics contribute to such differences remains an area requiring further empirical investigation.

Although previous studies have contributed to understanding corporate environmental reporting in Sri Lanka, recent evidence on the relationship between board characteristics and environmental disclosure remains limited. The most directly relevant Sri Lankan study examined the period from 2015 to 2019 and did not incorporate board gender diversity (Nuskiya et al., 2021). Subsequent studies have focused on related areas such as carbon disclosure, integrated reporting and the consequences of environmental disclosure rather than directly addressing the board-level determinants of CED (Randunu et al., 2022; Niresh & Vinsana, 2026; Krishnasamy & Keerthana, 2026). This gap is particularly relevant given the mixed evidence reported across different institutional settings (Xu et al., 2025; Alta'any et al., 2026). Accordingly, this study examines the relationship between board characteristics and environmental disclosure among Sri Lankan listed companies during 2021 to 2025. By incorporating board gender diversity alongside established board characteristics and examining a more recent period, the study extends existing Sri Lankan evidence and contributes to a better understanding of corporate environmental transparency in an emerging-market context.

2. AIMS/OBJECTIVES

To examine the impact of board characteristics on environmental disclosure among Sri Lankan listed companies.

3. THEORY

The relationship between board characteristics and environmental disclosure can be understood through Agency Theory and Stakeholder Theory, which provide different but complementary explanations of corporate reporting behaviour. Agency Theory originates from the separation of ownership and management, which can create conflicts of interest and information asymmetry between managers and shareholders (Jensen & Meckling, 1976). Within this relationship, the board performs a monitoring function by overseeing managerial decisions and promoting accountability and transparency (Nuskiya et al., 2021). Board structure is therefore important because differences in monitoring capacity may affect the information made available to external users (Khaireddine et al., 2020; Xu et al., 2025). Larger boards may offer a broader range of expertise, while greater independence can enhance objective oversight. Conversely, the concentration of executive and board leadership through CEO duality may restrict independent monitoring (Nuskiya et al., 2021; Xu et al., 2025). However, Agency Theory assumes that stronger monitoring mechanisms should improve transparency, an expectation that is not consistently supported across different institutional settings (Kumari et al., 2022; Xu et al., 2025). More importantly, its emphasis on the

manager–shareholder relationship provides only a partial explanation of environmental reporting because environmental information is relevant to groups beyond shareholders.

Stakeholder Theory broadens this explanation by recognising corporate accountability to employees, customers, regulators, communities and other groups affected by business activities (Freeman, 1984). Environmental disclosure can consequently be viewed as a response to demands for information about corporate environmental responsibilities and performance (Khaireddine et al., 2020; Nuskiya et al., 2021). From this perspective, the relevance of board structure extends beyond monitoring management to the recognition and consideration of diverse stakeholder interests (Xu et al., 2025). A board with broader expertise, independence and diversity may be better positioned to recognise different expectations concerning environmental accountability (Khaireddine et al., 2020; Xu et al., 2025). Nevertheless, Stakeholder Theory does not imply that stronger stakeholder representation will automatically produce greater disclosure because stakeholder groups may differ in influence, priorities and information demands. Neither theoretical perspective therefore provides a complete explanation independently. Agency Theory provides an explanation of the internal governance and monitoring systems that influence disclosure decisions while Stakeholder Theory provides an explanation of the external accountability and information pressures that influence disclosure decisions. Their integration offers a better theoretical framework for the analysis of the effect of the board characteristics on environmental disclosure in the Sri Lankan corporate environment.

Based on Agency Theory, Stakeholder Theory, and previous empirical studies, the following hypotheses are formulated:

H_1: Board size has a significant positive impact on environmental disclosure among Sri Lankan listed companies.

H_2: Board independence has a significant positive impact on environmental disclosure among Sri Lankan listed companies.

H_3: Board gender diversity has a significant positive impact on environmental disclosure among Sri Lankan listed companies.

H_4: CEO duality has a significant negative impact on environmental disclosure among Sri Lankan listed companies.

4. METHODS

This study adopts a quantitative longitudinal research design using panel data to examine the impact of board characteristics on environmental disclosure among non-financial companies listed on the Colombo Stock Exchange (CSE). The study population comprises non-financial listed companies, while financial-sector companies are excluded because of differences in regulatory and reporting requirements. A sample of Sixty companies was selected using random sampling from the eligible population of non-financial listed companies. The selected companies were observed over the five-year period from 2021 to 2025, resulting in a balanced panel of 300 firm-year observations. The panel structure enables variations across companies and over time to be incorporated into the analysis.

Secondary data are collected from the selected companies' published annual reports, which provide corporate governance and environmental disclosure information (Nuskiya et al., 2021; Krishnasamy & Shanthakumar, 2026). Environmental disclosure was measured through content analysis of corporate annual reports using a 34-item Environmental Disclosure Index (EDI) based on the Global Reporting Initiative (GRI) framework, following Tharsika and Keerthana (2025) and Krishnasamy and Keerthana (2026). The checklist covers 11 environmental disclosure categories: materials, energy, water, biodiversity, emissions, effluents and waste, products and services, compliance, transport, overall environmental expenditure, supplier environmental assessment, and environmental grievance mechanisms. Each disclosure item was coded using a binary scoring system, whereby a score of one was assigned if the relevant environmental information was disclosed in the annual report and zero otherwise. The EDI was calculated by dividing the total number of disclosed items by 34, yielding a standardized index ranging from zero to one. The EDI was calculated as follows:

Where:

$$EDI_{it} = \frac{\sum_{j=1}^{n} d_{ijt}}{n} \quad \text{.....(1)}$$

- EDI_{it} = Environmental Disclosure Index of firm *i* in year *t.*
- d_{ijt} = 1 if environmental disclosure item *j* is disclosed by firm *i* in year, and 0 otherwise.
- n = Total number of environmental disclosure items (34 in this study).

An unweighted scoring approach was adopted, assigning equal importance to all disclosure items. The same checklist and scoring procedure were applied throughout the study period (2021–2025) to maintain consistency in measurement across firms and years Board size, board independence, board gender diversity and CEO duality constitute the independent variables, reflecting board attributes commonly examined in environmental disclosure research (Nuskiya et al., 2021; Kumari et al., 2022). The operational measurements are presented in Table 1.

Table 1. Variable Measurement

Variable	Measurement	Supporting Source
Environmental Disclosure Index (EDI)	Number of environmental items disclosed ÷ 34. Each item is coded one if disclosed and zero otherwise.	Krishnasamy & Shanthakumar (2026)
Board Size (BS)	Total number of directors on the board.	Nuskiya et al. (2021); Kumari et al. (2022)
Board Independence (BI)	Number of independent directors ÷ total number of directors.	Nuskiya et al. (2021); Kumari et al. (2022)
Board Gender Diversity (BGD)	Number of female directors ÷ total number of directors.	Kumari et al. (2022)
CEO Duality (CEOD)	Dummy variable coded one when the CEO and board chair positions are held by the same person and zero otherwise.	Nuskiya et al. (2021); Kumari et al. (2022)

Source: Based on Nuskiya et al. (2021), Kumari et al. (2022), and Krishnasamy and Shanthakumar (2026).

Data are analysed using Stata. Descriptive statistics summarise the study variables, while Pearson correlation analysis examines the direction and strength of bivariate relationships. The Variance Inflation Factor (VIF) assesses multicollinearity among the independent variables. Panel-data regression is employed to examine the impact of board characteristics on environmental disclosure. Pooled Ordinary Least Squares (OLS), Fixed Effects (FE), and Random Effects (RE) models are estimated. The F-test compares pooled OLS with FE, while the Breusch–Pagan Lagrange Multiplier (LM) test compares pooled OLS with RE. The Hausman specification test determines the appropriate choice between FE and RE. . Statistical significance is assessed at the 10% level for both regression analysis and panel-model selection. The 10% significance threshold is applied to evaluate the statistical significance of the estimated regression coefficients and to

interpret the Hausman specification test. This threshold is consistent with significance levels employed in previous empirical panel-data research (Hassan & Lahyani, 2020; Dicuonzo et al., 2022).

5. RESULTS

The descriptive statistics provide an initial overview of the distribution and characteristics of the study variables. As presented in Table 2, the mean board size is 8.147 directors, while board independence and board gender diversity report mean values of 0.419 and 0.125, respectively. CEO duality records a mean of 0.190. The EDI has a mean value of 0.310, with observed values ranging from 0.000 to 0.912.

Table 2. Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
BS	300	8.147	2.077	4.000	13.000
BI	300	0.419	0.119	0.180	0.750
BGD	300	0.125	0.135	0.000	0.630
CEOD	300	0.190	0.393	0.000	1.000
EDI	300	0.310	0.265	0.000	0.912

Source: Authors' calculations based on secondary data.

Table 3 reports the Pearson correlation coefficients and Variance Inflation Factors (VIF). The correlations among the independent variables range from -0.249 to 0.391. The VIF values range from 1.03 to 1.29, with a mean VIF of 1.15, indicating that multicollinearity is not a concern in the regression analysis.

Table 3. Correlation Matrix and Variance Inflation Factors

Variable	BS	BI	BGD	CEOD	EDI	VIF
BS	1.000					1.07
BI	- 0.249***	1.000				1.29
BGD	- 0.038	0.391***	1.000			1.20
CEOD	- 0.096*	0.135**	- 0.030	1.000		1.03
EDI	0.311***	- 0.032	0.068	- 0.051	1.000	-

Notes: ****, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. VIF denotes Variance Inflation Factor.*
Source: Authors' calculations based on secondary data.

To determine the appropriate panel-data estimation model, the F-test, Breusch–Pagan Lagrange Multiplier (LM) test, and Hausman specification test were conducted, as presented in Table 4. The F-test and LM test indicated that the Fixed Effects (FE) and Random Effects (RE) models, respectively, were preferred over pooled Ordinary Least Squares (OLS).

Table 4. Model Selection Tests

Test	Statistic	p-value	Decision
F-test (FE vs. Pooled OLS)	F(59, 236) = 16.08	0.001	FE preferred to pooled OLS
Breusch- Pagan LM (RE vs. Pooled OLS)	chibar²(01) = 313.93	0.001	RE preferred to pooled OLS
Hausman (FE vs. RE)	$\chi^2(4) = 9.41$	0.0516	FE preferred at the 10% level

Source: Authors' calculations based on secondary data.

The Hausman specification test yielded a chi-square statistic of 9.41 (p = 0.0516), which was statistically significant at the 10% level but not at the 5% level. Accordingly, the null hypothesis was rejected at the 10% significance level, providing marginal evidence in favour of the FE model over the RE model. Therefore, the FE model was retained for the final regression analysis.

Table 5. Fixed Effects Regression Results

Variable	Coefficient	t-statistic	p-value
Constant	0.287***	2.93	0.004
BS	0.002	0.18	0.860
BI	-0.123	-1.05	0.294
BGD	0.551***	3.78	0.001
CEOD	-0.038	-0.46	0.647
Observations	300		
Number of groups	60		
Within R^2	0.0725		
F-statistic	4.61***		
Prob > F	0.0013		

*Notes: *** indicates statistical significance at the 1% level.*
Source: Authors' calculations based on secondary data.

Following the model selection tests, the Fixed Effects model is used to estimate the impact of board characteristics on environmental disclosure, with the results reported in Table 5. Board gender diversity exhibited a positive and statistically significant association with environmental disclosure (β = 0.551, p = 0.001), supporting H_3. Specifically, a 10% increase in female board representation is associated with an estimated 5.51% increase in environmental disclosure, holding other variables constant. In contrast, board size (β = 0.002, p = 0.860), board independence (β = - 0.123, p = 0.294), and CEO duality (β = - 0.038, p = 0.647) did not exhibit statistically significant associations with environmental disclosure. Therefore, H_1, H_2, and H_4 were not supported. The overall model was statistically significant (F = 4.61, p = 0.0013), with a within R^2 of 0.0725.

6. DISCUSSION

The mean EDI of 0.310 indicates that sampled companies disclose approximately 31% of the environmental items. This is higher than the 21% mean disclosure reported by Krishnasamy and Shanthakumar (2026) for Sri Lankan listed companies during 2020–2024. The finding also reflects the increasing trend in environmental disclosure identified by Nuskiya et al. (2021), although environmental reporting in Sri Lanka was considered to remain at an early stage. Thus, environmental disclosure appears to be improving, but considerable scope for further improvement remains.

Among the board characteristics examined, board gender diversity has a statistically significant impact on environmental disclosure. This finding is consistent with Khaireddine et al. (2020), who reported a significant positive influence of board gender diversity on environmental disclosure. From a stakeholder theory perspective, greater gender diversity may broaden the range of stakeholder interests considered in board decision-making and strengthen attention to environmental accountability. From an agency theory perspective, diverse boards may also strengthen monitoring and encourage greater transparency. However, Kumari et al. (2022) found no significant impact of board gender diversity in India, indicating that its influence may vary across institutional contexts.

In contrast, board size, board independence and CEO duality do not significantly impact environmental disclosure. The board-size finding differs from Nuskiya et al. (2021) and Khaireddine et al. (2020), who reported positive associations with environmental disclosure. The insignificant impact of board independence is consistent with Kumari et al. (2022), but differs from Nuskiya et al. (2021). Similarly, the insignificant impact of CEO duality supports Kumari et al. (2022), whereas Nuskiya et al. (2021) reported a negative association. These findings provide limited support for agency theory, as formal monitoring structures such as board independence and separation of leadership roles do not significantly explain environmental disclosure. Overall, the results suggest that board composition, particularly gender diversity, may be more relevant to environmental transparency than board size, independence or leadership structure in the Sri Lankan context.

7. IMPLICATIONS AND LIMITATIONS

The results have both theoretical and practical implications. Theoretically, board gender diversity has an impact on the board and strengthens consideration for stakeholders' broader expectations, which aligns with the stakeholder theory. The result also offers some confirmation of agency theory,

since greater diversity of the board members might improve monitoring and accountability. The lack of significant impacts from board size, board independence and CEO duality, however, suggests that traditional board composition may not necessarily be associated with increased environmental disclosure. Therefore, the results emphasize the need to take into account the composition and diversity of the board and not just structural governance characteristics.

In practical terms, the results have implications for listed companies, regulators and policymakers in Sri Lanka. Compelling messages for female representation on board can be used as an element of other activities to enhance environmental accountability and transparency. It may also be worth considering encouraging more women to serve on boards and providing guidance for environmental reporting by regulators and policymakers. The average environmental disclosure level of Sri Lankan listed companies is as low as 31%, thus there is ample room for enhancements to the level of disclosure of environmental information.

The study has some limitations that can be addressed in future research. First, the sample is restricted to 60 non-financial listed companies, and the time period is limited to 2021-2025, which may have an impact on generalizability. Further research might involve more individuals and a longer time frame. Second, environmental disclosures are measured with an unweighted 34 item index, measuring how much disclosure rather than how good or bad it is. Research in the future may include disclosure quality, quantitative environmental performance measures, or weighted disclosure measures. Lastly, other governance factors can be investigated in future studies including the quality of the board, board meetings, characteristics of sustainability committees and audit committee, and using alternative econometric methods to overcome endogeneity.

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The Impact of ESG Factors and Behavioral Biases on Investment Decisions: Evidence from Private Sector Employees in North Western Province of Sri Lanka

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ABSTRACT

Environmental, Social, and Governance (ESG) factors and behavioral biases have become important considerations in understanding individual investment decision-making. This study examines the impact of ESG factors and behavioral biases on investment decisions among private sector employees in the North Western Province of Sri Lanka. Specifically, the study investigates the effects of environmental factors, social factors, governance factors, and behavioral biases on investment decisions. A quantitative research approach was adopted, and primary data were collected through a structured questionnaire from 200 private sector employees in the North Western Province, particularly in the Kurunegala and Puttalam districts. The collected data were analyzed using descriptive statistics, reliability and validity tests, Pearson correlation analysis, and multiple regression analysis with SPSS. The findings revealed that environmental factors and governance factors have

significant positive effects on investment decisions, with environmental factors emerging as the strongest predictor, followed by governance factors. However, social factors and behavioral biases did not demonstrate statistically significant individual effects in the multiple regression model. The final regression model explained 88.2% of the variance in investment decisions. The study provides context-specific evidence on the role of ESG factors and behavioral biases in investment decision-making among private sector employees in Sri Lanka and highlights the importance of environmental and governance considerations in investment decisions.

Keywords: *Behavioral Biases; Environmental Factors; Governance Factors; Investment Decisions; Social Factors*

1. INTRODUCTION

Investment decisions influence individual financial security and the allocation of capital across financial and non-financial assets. Traditionally, investors have relied on profitability, expected return, liquidity, and risk. Environmental exposure, social responsibility, and corporate governance can provide additional information about an organisation's sustainability and management quality. Environmental, Social, Governance considerations have consequently become an important topic in corporate finance and investment research (Friede et al., 2015; Gillan et al., 2021). Behavioral finance recognizes that investment decisions may be influenced by psychological tendencies rather than objective analysis alone. Overconfidence, herding, and loss aversion can affect how investors interpret information, assess risk, and make investment choices (Abideen et al., 2023; Islam et al., 2024).

These perspectives are relevant in developing financial markets, where ESG information, disclosure practices, investor experience, and access to financial advice may differ across populations. Sri Lankan studies have examined behavioural biases among household and Colombo Stock Exchange investors, while ESG-related studies have considered corporate reporting, performance, green investment, and investment-management practices. Subramaniam and Velnampy (2017) examined behavioural factors among household investors in the Northern Province, while Lasantha and Kumara (2021) investigated behavioural biases among active Colombo Stock Exchange investors. However, findings from these groups cannot automatically be generalised to private sector employees in other regions or to a model combining ESG factors and behavioural biases.

This study addresses this gap by examining environmental factors, social factors, governance factors, and behavioural biases together in relation to investment decisions among private sector employees in the North Western Province of Sri Lanka.

Despite the growing importance of ESG considerations and behavioral finance in investment decision-making, limited empirical evidence is available regarding how these factors jointly relate to investment decisions among private sector employees in the North Western Province of Sri Lanka. Existing studies have examined behavioral biases and ESG-related investment considerations in different investor groups and contexts; however, examining Environmental, Social, and Governance factors together with behavioral biases within a specific regional population provides an opportunity to extend the existing literature. Private sector employees may differ in their financial knowledge, investment experience, income characteristics, and exposure to financial information, which may influence their investment decisions. Therefore, examining these relationships among private sector employees in the North Western Province can provide context-specific evidence regarding the role of sustainability considerations and behavioral factors in investment decision-making within Sri Lanka.

2. AIMS/ OBJECTIVES

The main objective of this study was to investigate the impact of Environmental, Social, and Governance (ESG) factors and behavioral biases on investment decisions among private sector employees in the North Western Province Sri Lanka.

The specific objectives were:

- To investigate the impact of environmental factors on investment decisions among private sector employees in the North Western Province of Sri Lanka.
- To investigate the impact of social factors on investment decisions among private sector employees in the North Western Province of Sri Lanka.
- To investigate the impact of governance factors on investment decisions among private sector employees in the North Western Province of Sri Lanka.
- To investigate the impact of behavioral biases on investment decisions among private sector employees in the North Western Province of Sri Lanka.

3. THEORY

This study is based on five theoretical perspectives: Modern Portfolio Theory, Prospect Theory, the Theory of Planned Behavior, Behavioral Finance Theory, and Stakeholder Theory. These theories provide a foundation for examining the impact of Environmental, Social, and Governance (ESG) factors and behavioral biases on investment decisions among private sector employees in the North Western Province of Sri Lanka. Modern Portfolio Theory, developed by Markowitz (1952), explains how investors evaluate investment opportunities by considering risk, expected return, and portfolio diversification. In this study, the theory provides a financial perspective for understanding investment decisions, while ESG information offers additional insights into the sustainability and potential risks of investment opportunities. Prospect Theory, introduced by Kahneman and Tversky (1979), explains how individuals evaluate potential gains and losses under uncertainty. This theory is particularly relevant to loss aversion, as investors may give greater importance to avoiding losses than achieving equivalent gains. Therefore, Prospect Theory helps explain how psychological responses to risk may influence investment decisions. The Theory of Planned Behavior, developed by Ajzen (1991), emphasizes the influence of attitudes, subjective norms, and perceived behavioral control on behavioral intentions. In the context of this study, investors' attitudes toward ESG practices and the influence of peers and social environments may affect their investment preferences and decisions. Behavioral Finance Theory explains how psychological and cognitive factors influence financial decision-making. It provides the theoretical basis for examining overconfidence bias, herding behavior, and loss aversion. These biases may affect how investors interpret information, assess risks, and select investment opportunities, potentially causing them to deviate from rational decision-making. Stakeholder Theory, proposed by Freeman (1984), emphasizes the importance of considering the interests of stakeholders, including employees, customers, investors, communities, and society. This theory supports the ESG dimension of the study by explaining why investors may consider companies' environmental responsibility, social practices, and corporate governance when making investment decisions.

The integration of these five theories provides a comprehensive framework for understanding investment decisions by combining financial, psychological, behavioral, and sustainability perspectives. Modern Portfolio Theory explains the role of risk and return, while Prospect Theory and Behavioral Finance Theory explain how psychological biases, particularly overconfidence, herding behavior, and loss aversion, may influence investors’ choices. The Theory of Planned Behavior highlights the importance of attitudes and social

influences, while Stakeholder Theory supports the consideration of environmental responsibility, social practices, and corporate governance. Based on this integration, the present study examines environmental, social, and governance factors and behavioral biases as independent variables influencing investment decisions among private sector employees in the North Western Province of Sri Lanka. This integrated approach enables the study to assess the individual and combined relationships of these factors with investment decisions.

Research Hypotheses

Based on the theoretical framework and the objectives of the study, the following hypotheses were developed:

H1: Environmental factors have a significant positive relationship with Investment Decisions among private sector employees in the North Western Province of Sri Lanka.

H2: Social factors have a significant positive relationship with Investment Decisions among private sector employees in the North Western Province of Sri Lanka.

H3: Governance factors have a significant positive relationship with Investment Decisions among private sector employees in the North Western Province of Sri Lanka.

H4: Behavioral Biases have a significant positive relationship with Investment Decisions among private sector employees in the North Western Province of Sri Lanka.

4. METHODS

The study adopted a quantitative research approach with a deductive research design to examine the impact of Environmental, Social, and Governance (ESG) factors and behavioral biases on investment decisions. The target population consisted of private sector employees in the North Western Province of Sri Lanka, particularly in the Kurunegala and Puttalam districts, who were engaged in investment activities. Since a comprehensive sampling frame was unavailable, convenience sampling was employed. A sample of 200 respondents was selected using convenience sampling because a complete sampling frame of the target population was not available. Respondents were selected based on their accessibility and willingness to participate in the study. Data were collected from private sector employees working in organizations

across the Kurunegala and Puttalam districts. The selection of these respondents was intended to obtain information from individuals with exposure to investment decision-making. Convenience sampling enabled the researcher to collect primary data from the target population within the available time and resources; however, the non-probability sampling approach limits the generalizability of the findings beyond the respondents included in the study.

Primary data were collected using a structured questionnaire consisting of close-ended questions measured on a five-point Likert scale. The questionnaire measured the independent variables, namely environmental factors, social factors, governance factors, and behavioral biases, and the dependent variable, investment decisions. Behavioral biases were examined through overconfidence bias, herding behavior, and loss aversion.

The reliability and validity of the research instrument were assessed using Cronbach's alpha and exploratory factor analysis. The Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity were used to evaluate the suitability of the data for factor analysis. Data analysis was conducted using IBM SPSS Statistics. Descriptive statistics were used to summarize the respondent characteristics and study variables, while Pearson correlation analysis examined the relationships between the independent and dependent variables. Multiple regression analysis was employed to assess the individual impact of the four independent variables on investment decisions. The hypotheses were tested at the 5% significance level.

The multiple regression model was specified as follows:

$$\mathbf{ID = \beta_0 + \beta_1 ENV + \beta_2 SOC + \beta_3 GOV + \beta_4 BB + \varepsilon}$$

Where Investment Decisions (ID) represent the dependent variable; Environmental Factors (ENV), Social Factors (SOC), Governance Factors (GOV), and Behavioral Biases (BB) represent the independent variables; β_0 represents the constant; β_1 to β_4 represent the regression coefficients; and ε represents the error term.

5. RESULTS

The final analysis was based on 200 respondents. Pearson correlation analysis revealed significant positive relationships between all four independent variables and investment decisions. Environmental factors demonstrated the strongest positive correlation with investment decisions ($r = .922$, $p < .001$), followed by governance factors ($r = .900$, $p < .001$), social factors ($r = .877$, p

< .001), and behavioral biases (r = .856, p < .001). These findings indicate that all four variables were positively associated with investment decisions among private sector employees in the North Western Province of Sri Lanka.

5.1 Multicollinearity Assessment

The correlation analysis revealed relatively high positive correlations among the independent variables. Environmental factors were highly correlated with Social factors (r = .885), Governance factors (r = .891), and Behavioral Biases (r = .881). Similarly, Social factors demonstrated a strong correlation with Governance factors (r = .898) and Behavioral Biases (r = .846), while Governance factors were also strongly correlated with Behavioral Biases (r = .884). These findings indicate considerable shared variance among the predictors and raise concerns regarding potential multicollinearity in the multiple regression model.

Although the correlation matrix provides an initial indication of overlap among the independent variables, correlation coefficients alone are insufficient to establish the presence or severity of multicollinearity. Therefore, tolerance values and Variance Inflation Factor (VIF) statistics should be examined to further assess multicollinearity and determine the extent to which the regression coefficients can be interpreted independently. These results should be considered when interpreting the individual contributions of Environmental, Social, Governance, and Behavioral Biases to investment decisions.

Table 01. Multicollinearity Statistics

Predictor	Tolerance	VIF
Environmental Factors	.145	6.915
Social Factors	.158	6.343
Governance Factors	.129	7.729
Behavioral Biases	.175	5.717

Although the correlation matrix provides an initial indication of overlap among the independent variables, correlation coefficients alone are insufficient to establish the presence or severity of multicollinearity. Therefore, tolerance values and Variance Inflation Factor (VIF) statistics were examined to further assess multicollinearity. The tolerance values ranged from .129 to .175, while the VIF values ranged from 5.717 to 7.729. These results indicate considerable multicollinearity among the independent variables, which may affect the stability and interpretation of individual regression

coefficients. Accordingly, the individual contributions of the predictors should be interpreted cautiously.

Multiple regression analysis was conducted to examine the individual impact of environmental factors, social factors, governance factors, and behavioral biases on investment decisions. The regression model demonstrated a strong relationship between the independent variables and investment decisions (R = .939). The coefficient of determination (R^2 = .882) indicated that the four independent variables collectively explained 88.2% of the variation in investment decisions. The adjusted R^2 was .880, while the overall regression model was statistically significant (F = 365.076, p < .001).

Table 02. Multiple Regression Results

Variable	B	SE	β	t	p-value	95% CI	Hypothesis Decision
Environmental Factors	.492	.061	.522	8.079	.001	[.372, .612]	Supported
Social Factors	.109	.057	.118	1.909	.058	[-.004, .222]	Not supported
Governance Factors	.281	.062	.309	4.519	.001	[.159, .404]	Supported
Behavioral Biases	.021	.055	.023	.383	.702	[-.088, .130]	Not supported

Source: Survey Data (2026).

The regression results indicate that environmental factors had a positive and statistically significant impact on investment decisions (B = .492, β = .522, p = .001). Environmental factors were the strongest predictor among the four independent variables. Governance factors also demonstrated a positive and statistically significant impact (B = .281, β = .309, p = .001), making them the second-strongest predictor.

In contrast, social factors did not demonstrate a statistically significant individual impact on investment decisions at the 5% significance level (B = .109, β = .118, p = .058). Similarly, behavioral biases did not have a statistically significant individual impact (B = .021, β = .023, p = .702). Therefore, the hypotheses relating to environmental and governance factors were supported, whereas the hypotheses relating to social factors and behavioral biases were not supported.

Although social factors and behavioral biases showed significant positive correlations with investment decisions, they were not statistically significant in the multiple regression model when the other independent variables were

considered simultaneously. This indicates that their individual contributions were not statistically significant after accounting for the other variables in the model.

5.2 Reliability and Validity Analysis

The reliability of the measurement instruments was assessed using Cronbach's alpha. The results indicated high internal consistency across all five constructs. Environmental Factors recorded a Cronbach's alpha of .947, Social Factors .935, Governance Factors .947, Behavioral Biases .959, and Investment Decisions .956. All values exceeded the commonly accepted threshold of .70, indicating satisfactory internal consistency of the measurement scales.

The suitability of the data for factor analysis was assessed using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity. The KMO value was .908, indicating adequate sampling suitability. Bartlett's Test of Sphericity was statistically significant ($\chi^2 = 1443.527$, df = 10, p \(\lt\) .001), indicating that the correlation matrix was suitable for factor analysis. The communalities obtained through principal component analysis ranged from .879 to .925, while the component loadings ranged from .938 to .962. These results provide evidence of strong shared variance among the examined constructs and support the suitability of the data for further analysis.

6. DISCUSSION

The findings indicate that environmental and governance factors are significant predictors of investment decisions among private sector employees in the North Western Province of Sri Lanka. Environmental factors emerged as the strongest predictor, followed by governance factors. This suggests that respondents place considerable importance on environmental responsibility, energy efficiency, waste management, transparency, and board independence when evaluating investment opportunities. These findings are consistent with Li et al. (2024), who found that retail investors respond to ESG-related information particularly when they consider it financially material to company performance. Similarly, Kräussl et al. (2024) highlighted the importance of investors' expectations, beliefs, and perceptions in understanding ESG investment decisions. However, the findings should be interpreted in the context of the present sample because the previous studies examined different investor populations and research settings.

The significant effect of environmental factors suggests that environmental practices may be relevant to investors' assessments of a company's long-term sustainability and financial prospects. Nevertheless, the present study

measured employees' reported investment decisions rather than actual portfolio transactions. Therefore, the results indicate an association within the study model and should not be interpreted as proof that environmental responsibility directly causes investors to select particular investments. The significance of governance factors also highlights the relevance of transparency and sound corporate oversight. These findings are consistent with the broader ESG literature, which emphasizes the importance of sustainability information and corporate disclosure in investment-related evaluations (Kräussl et al., 2024). Together, the results suggest that environmental and governance considerations deserve attention when examining investment decisions among private sector employees in this Sri Lankan context.

In contrast, social factors showed a strong positive correlation with investment decisions but did not demonstrate a statistically significant unique effect in the multiple regression analysis ($p = .058$). This does not mean that social factors are unimportant to investors. Rather, their independent contribution was not statistically established after environmental factors, governance factors, and behavioral biases were considered simultaneously. One possible explanation is that respondents evaluate social responsibility alongside other aspects of corporate sustainability, creating shared explanatory information among the predictors. Research on ESG investing also indicates that investor responses to ESG information can vary according to the perceived relevance of that information to investment outcomes (Li et al., 2024; Kräussl et al., 2024). Consequently, social factors may remain relevant to investment preferences even though their unique effect was not statistically significant in the present model.

Behavioral biases also demonstrated a strong positive correlation with investment decisions but were not statistically significant in the multiple regression analysis ($p = .702$). This finding contrasts with Abideen et al. (2023), who examined behavioral biases in investment decision-making in the Pakistani equity market. It also differs from Islam et al. (2024), who reported that behavioral biases were related to financial risk propensity and that risk propensity significantly influenced investment decisions. These studies suggest that behavioral influences may operate through different mechanisms and may depend on the variables and analytical models used. In the present study, the non-significant regression result indicates that behavioral biases did not explain a statistically significant additional proportion of investment decisions after the other predictors were controlled for. However, this result should not be interpreted as evidence that behavioral biases have no relationship with investment decisions. Differences in investor populations,

measurements, and model specifications may contribute to variations between studies.

6.1 Interpretation of Regression Model

The multiple regression model demonstrated strong explanatory power, with an R^2 value of .882, indicating that the four independent variables collectively explained 88.2% of the variation in Investment Decisions within the sample. Although this represents a high level of explanatory power, the result should be interpreted cautiously because the study employed self-reported questionnaire data and the independent variables demonstrated strong intercorrelations. The high explanatory power may partly reflect shared variance among the predictors and similarities in respondents' perceptions across the constructs. Therefore, the R^2 value should not be interpreted as evidence of causal relationships. Furthermore, the interpretation of individual regression coefficients requires consideration of the potential multicollinearity identified among the independent variables.

Overall, the findings provide context-specific evidence that environmental and governance factors were the strongest statistically significant predictors of investment decisions among the respondents. Although social factors and behavioral biases were positively correlated with investment decisions, their individual effects were not statistically significant in the regression model. By examining ESG dimensions and behavioral biases together, the study contributes to the limited context-specific evidence on investment decision-making among private sector employees in North Western Province, Sri Lanka. Future research could examine whether financial literacy, risk propensity, and the separate dimensions of behavioral bias help explain these relationships in different investor groups and regions.

7. IMPLICATIONS AND LIMITATIONS

The findings of this study provide practical implications for individual investors, financial institutions, companies, and policymakers in Sri Lanka. The significant influence of Environmental Factors suggests that investors may benefit from greater awareness of environmental performance when evaluating investment opportunities. Financial institutions and investment advisers could provide educational materials that explain environmental disclosures, sustainability risks, resource efficiency, and the long-term implications of environmental practices.

The significant relationship identified for Governance Factors highlights the importance of corporate transparency, accountability, ethical conduct, and

effective governance practices. Companies may strengthen investor confidence by improving the quality of financial and non-financial disclosures, promoting accountability, and maintaining transparent governance structures. Policymakers and regulatory institutions could further support responsible investment by promoting consistent ESG reporting practices and improving investor access to reliable corporate information.

Although Social Factors and Behavioral Biases were not statistically significant unique predictors in the multiple regression model, their strong positive correlations with Investment Decisions indicate that they remain relevant considerations within the study context. Therefore, investor education programs could incorporate social responsibility considerations and behavioral awareness to encourage investors to evaluate investment opportunities more comprehensively and avoid relying solely on a single source of information or market sentiment.

This study has several limitations that should be considered when interpreting its findings. First, the study employed convenience sampling and focused on private sector employees in the North Western Province of Sri Lanka. Therefore, the findings may not be generalizable to all investors in Sri Lanka. Second, the cross-sectional research design examined relationships at a single point in time and does not establish causal relationships between the independent variables and Investment Decisions. Third, the study relied on self-reported questionnaire responses, which may be subject to response bias and common method bias. Fourth, Behavioral Biases were examined as a combined construct incorporating overconfidence, herding behavior, and loss aversion. Consequently, the individual contribution of each behavioral bias was not separately established. Future studies could extend the research to different provinces, employ probability-based sampling methods where feasible, conduct longitudinal investigations, and examine individual behavioral biases separately. Future research could also incorporate additional factors such as financial literacy, investment experience, risk tolerance, and access to financial advice to provide a more comprehensive understanding of investment decision-making.

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Determinants of External Auditors' Behavioral Intention to Adopt CAATs: Evidence from Sri Lanka

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ABSTRACT

The growing use of digital systems in business has changed the way external audits are planned and performed. Auditors increasingly need computer-assisted audit techniques (CAATs) to examine electronic records, analyse large datasets, identify unusual transactions and obtain audit evidence. However, access to audit technology does not automatically lead to its use. This study examines the factors associated with external auditors' behavioral intention to adopt CAATs in Sri Lanka. The model is based on the Unified Theory of Acceptance and Use of Technology (UTAUT) and includes Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Conditions, together with Perceived Risk and Perceived Trust. A quantitative, positivist and cross-sectional survey design was used. Data were collected through an electronic structured questionnaire from external auditors working in Big Four and selected local audit firms. Of 107 responses received, seven were excluded during screening and 100 valid responses were retained. Convenience sampling was used. The data were analysed in SPSS using descriptive statistics, reliability analysis, the Kaiser-Meyer-Olkin measure and Bartlett's test, Pearson correlations and multiple regression. The regression model was statistically significant, $F(6, 93) = 98.285$, $p < .001$, and explained 86.4% of the observed variation in behavioral intention ($R^2 = .864$; adjusted $R^2 = .855$). Effort Expectancy ($\beta = .354$, $p < .001$), Perceived Trust ($\beta = .326$, $p < .001$), Performance Expectancy ($\beta = .279$, $p < .001$) and Facilitating Conditions ($\beta = .177$, $p = .001$) were significant positive predictors. Social Influence ($\beta = .020$, $p = .605$) and Perceived Risk ($\beta = .000$, $p = .998$) were not statistically significant. The findings suggest that perceived ease of use, trust, expected performance benefits and support are associated with auditors' intention to adopt CAATs in this sample. The results should be interpreted cautiously because the study used a convenience sample, self-reported cross-sectional data and a model with unusually high explanatory power. The

Perceived Risk regression result also requires verification against the original SPSS data and coding before it is treated as conclusive.

Keywords: *CAATs; Behavioral Intention; External Auditors; UTAUT; Perceived Trust; Perceived Risk*

1. INTRODUCTION

Digital technology has changed the information environment in which external audits are performed. Organisations increasingly use computerised accounting systems, enterprise resource planning systems, cloud platforms and electronic reporting. Auditors therefore need tools and skills to examine electronic records and obtain sufficient, appropriate audit evidence. Computer-assisted audit techniques (CAATs) help auditors collect, process, test and analyse electronic data. They support transaction testing, sampling, recalculation, identification of unusual items and analytical procedures, and can improve audit coverage and efficiency (Braun & Davis, 2003; Janvrin et al., 2008; Mansour, 2016).

However, the availability of CAATs does not guarantee their use. Adoption may depend on whether auditors believe the tools improve their work, whether they are easy to learn, whether managers and colleagues encourage their use, and whether the firm provides software, training and technical support. Auditors may also consider confidentiality, data integrity, system reliability and the consequences of relying on technology. CAAT adoption therefore involves both individual perceptions and the organisational conditions in which auditors work.

The Unified Theory of Acceptance and Use of Technology (UTAUT) developed by Venkatesh et al. (2003) explains technology acceptance through Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Conditions. This study extends the framework with Perceived Risk and Perceived Trust. These constructs are relevant because audit work involves sensitive financial information and depends on reliable systems. Previous CAAT and technology-adoption studies have also considered user perceptions and organisational readiness (Khalil & Nafti, 2020; Meiryani et al., 2022).

Sri Lanka provides a relevant setting because audit firms include large international networks and local firms that may differ in technology access, training, specialist support and resources. Previous local research has examined CAAT use among internal auditors (Pathmasiri & Piyananda, 2021). Jayasena et al. (2024) more directly examined Sri Lankan external auditors' intention to use CAATs using an extended UTAUT model. Their

work is the closest local study and is recognised here as an important contribution.

The present study does not claim that CAAT adoption by Sri Lankan external auditors has not been studied. It provides an additional examination using 100 auditors from Big Four and local/non-Big Four firms, including supervisors, managers, senior managers and partners. It considers Perceived Risk and Perceived Trust alongside the four UTAUT constructs. The available records do not support a complete side-by-side comparison of measures, sample and period with Jayasena et al. (2024); therefore, no claim of superiority or definitive novelty over that study is made.

The research problem is the need for further context-specific evidence on factors associated with external auditors' intention to adopt CAATs. Internal and external auditors have different roles, and findings from one group cannot automatically be transferred to the other. Findings from other countries may also reflect different technological and organisational conditions. This study therefore examines six factors associated with behavioral intention among external auditors in Sri Lanka.

The study addresses the following research question: What factors are associated with external auditors' behavioral intention to adopt CAATs in Sri Lanka? The dependent variable is behavioral intention. The study does not measure actual adoption behaviour or the frequency with which auditors use CAATs. This distinction is important when interpreting the findings and their practical implications.

2. AIMS/ OBJECTIVES

The main objective is to examine the factors associated with external auditors' behavioral intention to adopt CAATs in Sri Lanka. The specific objectives are to examine the relationships of Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Perceived Risk and Perceived Trust with behavioral intention. The analysis considers both the bivariate relationships and the contribution of each predictor when the six factors are included together in a multiple regression model.

3. THEORY

UTAUT was developed by Venkatesh et al. (2003) by integrating earlier technology acceptance theories. It identifies performance benefits, ease of use, social influence and facilitating conditions as relevant to technology acceptance. This study examines the direct relationships of these factors, together with risk and trust, with external auditors' behavioral intention.

Performance Expectancy refers to the extent to which an auditor believes that using CAATs will improve job performance. In external auditing, this may include completing procedures more efficiently, analysing more transactions, identifying unusual items and supporting audit quality. If auditors believe that CAATs provide clear benefits to their work, they may be more willing to adopt them. Prior studies have linked expected usefulness and performance benefits with auditors' technology use and intention (Bierstaker et al., 2014; Khalil & Nafti, 2020; Meiryani et al., 2022). The study therefore proposes: H1: Performance Expectancy is positively associated with external auditors' behavioral intention to adopt CAATs.

Effort Expectancy refers to the perceived ease associated with learning and using a technology. CAATs may require auditors to learn new software, understand data formats and apply analytical procedures. When the tools are easy to learn and operate, auditors may be more willing to use them. Training and practical experience may also reduce the effort involved. Previous research has identified technological knowledge, training and perceived complexity as relevant to auditors' use of CAATs (Janvrin et al., 2008; Ahmi & Kent, 2013; Jayasena et al., 2024). H2: Effort Expectancy is positively associated with external auditors' behavioral intention to adopt CAATs.

Social Influence refers to the extent to which an individual believes that important people or groups think that he or she should use a technology. In an audit firm, these people may include engagement partners, audit managers, supervisors, colleagues and professional bodies. Their encouragement, expectations and examples may influence an auditor's intention. However, auditors may also make decisions based on their own assessment of the usefulness and suitability of a tool. Previous studies have reported mixed results for social influence in technology adoption (Loraas & Wolfe, 2006; Mansour, 2016). H3: Social Influence is positively associated with external auditors' behavioral intention to adopt CAATs.

Facilitating Conditions refer to the availability of organisational and technical infrastructure needed to use a system. For CAATs, this includes software access, suitable computers, training, guidance and technical support. Although the original UTAUT model also links Facilitating Conditions to use behaviour, this study specifies it as a direct predictor of intention because auditors who know that resources and support are available may be more willing to intend to use CAATs. This is a model-specific choice. Prior auditing studies identify organisational readiness and support as relevant (Mansour, 2016; Pathmasiri & Piyananda, 2021). H4: Facilitating Conditions are positively associated with external auditors' behavioral intention to adopt CAATs.

Perceived Risk represents an auditor's concern about uncertainty or possible negative consequences arising from the use of CAATs. In an audit setting, these concerns may relate to data confidentiality, unauthorised access, inaccurate processing, system failure or over-reliance on technology. If auditors believe that using a tool creates risks that are difficult to manage, their intention to adopt it may be lower. Research on technology adoption has considered risk as a factor that may discourage use, although its influence can vary by context and type of technology (Khalil & Nafti, 2020; Meiryani et al., 2022). H5: Perceived Risk is negatively associated with external auditors' behavioral intention to adopt CAATs.

Perceived Trust refers to an auditor's confidence that CAATs are reliable, secure and dependable for supporting audit tasks. Trust may be important because auditors work with confidential client information and need confidence that the tools will process and present data appropriately. When auditors trust the technology and the controls around it, they may be more willing to consider using it. Previous technology-adoption research has identified trust as a relevant consideration in users' decisions (Meiryani et al., 2022). H6: Perceived Trust is positively associated with external auditors' behavioral intention to adopt CAATs.

The original UTAUT model includes moderators such as age, gender, experience and voluntariness of use. They were not tested here because the study focused on six direct paths and the available sample was 100. Demographic and professional characteristics describe the sample but were not modelled as moderators. Their omission limits the model's scope. The six hypotheses specify the expected directions of the direct relationships with behavioral intention.

4. METHODS

The study adopted a positivist research philosophy and a quantitative research approach. A deductive approach was followed because the hypotheses were developed from UTAUT and previous research and then examined using survey data. A cross-sectional survey design was used, meaning that information was collected from respondents at one point in time. The unit of analysis was the individual external auditor.

The target population comprised external auditors employed in registered audit firms in Sri Lanka. Convenience sampling was used to approach auditors in Big Four and selected local firms. The unit of analysis was the individual auditor, including supervisors, managers, senior managers and partners. The questionnaire was distributed electronically through Google Forms. The final

sample represented nine firms: KPMG, EY, PwC, Deloitte, Accfin Associates, RKLS Associates, KB&G, W.R. Rodrigo & Partners and PBC Associates.

A total of 107 responses were received; seven were excluded during screening, leaving 100 valid cases (93.46% of responses received). This is the valid-case retention proportion, not the survey response rate, because the number invited is unavailable. The model included six predictors, giving approximately 16.7 cases per predictor. However, no a priori power analysis is documented, so the sample cannot be described as having been determined through a formal power calculation. Convenience sampling and the unknown invitation denominator limit generalisability and assessment of non-response bias.

The sample included 39 respondents from Big Four firms (39%) and 61 from local/non-Big Four firms (61%). By position, 56 respondents were supervisors (56%), 29 were managers (29%), eight were senior managers (8%) and seven were partners (7%). In terms of audit experience, 37 respondents had less than three years of experience, 40 had three to five years, 16 had six to ten years and seven had more than ten years. The respondents reported using different audit-related tools: ACL (32%), IDEA (29%), Power BI (19%), Microsoft Excel (11%) and firm-tailored software (9%). These tools provide an indication of the types of computer-assisted applications represented in the sample. The questionnaire examined CAATs in a broad sense and did not provide a separate experimental evaluation of each software package.

Data were collected using a structured questionnaire with demographic questions, items for six independent variables and items for behavioral intention. All items used a five-point Likert scale from 1 (Strongly Disagree) to 5 (Strongly Agree). The operational definitions in the research report describe Performance Expectancy through usefulness, productivity, quality improvement and efficiency; Effort Expectancy through ease of learning, understanding and use; Social Influence through peer and management influence; and Facilitating Conditions through resources and support. Perceived Risk concerns possible negative consequences of CAAT use, Perceived Trust concerns confidence in reliability and security, and Behavioral Intention measures intention to adopt or use CAATs.

The research report identifies Venkatesh et al. (2003), Bierstaker et al. (2014), Janvrin et al. (2008), Mansour (2016), Al-Hiyari et al. (2019) and Jayasena et al. (2024) among the sources used to develop the measurement framework. Items were adapted to the CAAT and external-audit context. The report does not provide a complete item-by-item source map, so this paper does not assign an unverified source to each item. A pilot study with 30 external auditors

assessed clarity and reliability; all pilot alpha values exceeded .70 and no items were reported as problematic. Specific written pilot feedback is not available in the report.

The data were analysed in IBM SPSS Statistics using screening, demographic summaries, Cronbach's alpha, KMO and Bartlett's test, descriptive statistics, normality assessment, Pearson correlations and multiple regression. The reported results below are reproduced from the undergraduate report and submitted manuscript. The original SPSS .sav and .spv files were unavailable for this revision, so the calculations could not be independently rerun or checked against raw data.

5. RESULTS

A total of 107 responses were received and seven were excluded during screening, leaving 100 valid cases for analysis. The final sample included 39 Big Four auditors and 61 auditors from local/non-Big Four firms. Supervisors accounted for 56% of respondents, managers 29%, senior managers 8% and partners 7%. ACL was reported by 32% of respondents, IDEA by 29%, Power BI by 19%, Microsoft Excel by 11% and firm-tailored software by 9%.

The main-study reliability analysis reported Cronbach's alpha values above .88 for all seven constructs. Performance Expectancy (five items) recorded $\alpha = .928$; Effort Expectancy (four items), $\alpha = .918$; Social Influence (four items), $\alpha = .897$; Facilitating Conditions (three items), $\alpha = .887$; Perceived Risk (three items), $\alpha = .917$; Perceived Trust (four items), $\alpha = .926$; and Behavioral Intention (three items), $\alpha = .886$. The KMO value was .907. Bartlett's test of sphericity was significant, $\chi^2(325) = 2166.903$, $p < .001$.

Table 1 presents the descriptive statistics for the study variables. The mean values ranged from 2.6800 for Perceived Risk to 3.8025 for Perceived Trust. Behavioral Intention had a mean of 3.6933 and a standard deviation of .67782.

Table 1. Descriptive Statistics of the Study Variables

Variable	N	Mean	SD
Performance Expectancy	100	3.7560	.75241
Effort Expectancy	100	3.6525	.82335
Social Influence	100	3.4450	.72959
Facilitating Conditions	100	3.7567	.73222
Perceived Risk	100	2.6800	.93434
Perceived Trust	100	3.8025	.82135
Behavioral Intention	100	3.6933	.67782

The normality assessment reported statistically significant Kolmogorov-Smirnov tests for all variables ($p < .05$). Skewness values ranged from -.608 to .329 and kurtosis values ranged from -.652 to .049. These values are reported here as descriptive indicators of distribution shape. The significant Kolmogorov-Smirnov results mean that normality should not be described as formally confirmed by that test. The report did not provide residual plots or other residual-based diagnostics.

Table 2 presents the Pearson correlation matrix. Behavioral Intention was positively correlated with Performance Expectancy ($r = .748$, $p < .01$), Effort Expectancy ($r = .795$, $p < .01$), Facilitating Conditions ($r = .678$, $p < .01$) and Perceived Trust ($r = .766$, $p < .01$). Its correlations with Social Influence ($r = .172$) and Perceived Risk ($r = -.167$) were weak and not statistically significant. The table also shows the correlations among the independent variables. The significance markers follow the original report's convention of one-tailed tests.

Table 2. Pearson Correlation Matrix

Variable	PE	EE	SI	FC	PR	PT	BI
PE	1						
EE	.613**	1					
SI	.158	.083	1				
FC	.452**	.524**	.148	1			
PR	.010	-.127	.074	-.204*	1		
PT	.518**	.538**	.157	.570**	-.277**	1	
BI	.748**	.795**	.172	.678**	-.167	.766**	1

The multiple regression model was statistically significant, $F(6, 93) = 98.285$, $p < .001$. The model summary reported $R = .929$, $R^2 = .864$, adjusted $R^2 = .855$ and a standard error of the estimate of .25824. Thus, the six predictors jointly accounted for 86.4% of the observed variance in behavioral intention in this sample.

Table 3. Multiple Regression Results

Predictor	B	β	t	p
Performance Expectancy	.252	.279	5.376	< .001
Effort Expectancy	.291	.354	6.680	< .001
Social Influence	.019	.020	.519	.605
Facilitating Conditions	.164	.177	3.569	.001
Perceived Risk	.000083	.000	.003	.998
Perceived Trust	.269	.326	6.187	< .001

*Note. ** $p < .01$; * $p < .05$ (one-tailed, as reported in the original analysis).*
Source: SPSS output reproduced from the research report, 2026.

Model summary: $R = .929$; $R^2 = .864$; adjusted $R^2 = .855$; standard error = .25824. ANOVA: $F(6, 93) = 98.285$, $p < .001$.

Performance Expectancy had a positive and statistically significant coefficient ($B = .252$, $\beta = .279$, $t = 5.376$, $p < .001$). Effort Expectancy was also positive and significant ($B = .291$, $\beta = .354$, $t = 6.680$, $p < .001$). Social Influence was not significant ($B = .019$, $\beta = .020$, $t = .519$, $p = .605$). Facilitating Conditions had a positive and significant coefficient ($B = .164$, $\beta = .177$, $t = 3.569$, $p = .001$). Perceived Risk was reported as $B = .000083$, $\beta = .000$, $t = .003$, $p = .998$. Perceived Trust had a positive and significant coefficient ($B = .269$, $\beta = .326$, $t = 6.187$, $p < .001$). The reported standardized coefficients indicate that Effort Expectancy had the largest significant contribution, followed by Perceived Trust, Performance Expectancy and Facilitating Conditions.

The multicollinearity statistics reported tolerance values from .522 to .948 and VIF values from 1.054 to 1.916. These values do not indicate serious multicollinearity under commonly used screening thresholds. However, the available report does not include a Durbin-Watson statistic, residual plots, a formal heteroscedasticity test or confidence intervals for the regression coefficients. Those diagnostics are therefore not reported as having been completed.

6. DISCUSSION

The results indicate that four of the six predictors were positively and significantly associated with behavioral intention in the multiple regression model: Effort Expectancy, Perceived Trust, Performance Expectancy and Facilitating Conditions. Social Influence and Perceived Risk were not statistically significant. These findings relate to the intention to adopt CAATs, not verified actual use. Because the study is cross-sectional and based on self-reported responses, the results show associations and should not be interpreted as proof that any one factor causes auditors to adopt CAATs.

Effort Expectancy recorded the largest standardized coefficient ($\beta = .354$, $p < .001$). Auditors who find CAATs easy to learn and use may be more willing to adopt them, particularly when the tools can be incorporated into routine audit procedures without excessive difficulty. This is consistent with Jayasena et al. (2024), who also reported a positive relationship between Effort Expectancy and Sri Lankan external auditors' intention to use CAATs. The present result adds support for the relevance of usability in this sample.

Perceived Trust was the second strongest significant predictor ($\beta = .326$, $p < .001$). Confidence in the reliability and security of CAATs may matter because external auditors handle confidential client information and rely on technology

to support audit evidence. This result is consistent with research that treats trust as relevant to technology-adoption decisions (Meiryani et al., 2022). The present questionnaire did not separately establish which aspect of trust was most influential.

Performance Expectancy was a significant positive predictor ($\beta = .279$, $p < .001$). Auditors who believe CAATs can improve efficiency, productivity, audit coverage or audit procedures tended to report stronger intentions to adopt them. This is consistent with research highlighting the role of expected usefulness and performance benefits in audit technology use (Janvrin et al., 2008; Bierstaker et al., 2014) and studies in Yemen and Indonesia (Khalil & Nafti, 2020; Meiryani et al., 2022).

Facilitating Conditions had a positive significant coefficient ($\beta = .177$, $p = .001$). The result indicates that access to resources, technical support and organisational assistance was associated with stronger intention in this sample. This is consistent with research identifying organisational readiness and technological support as relevant to CAAT use (Mansour, 2016; Pathmasiri & Piyananda, 2021). It should be interpreted within the direct-predictor specification used in this study.

Social Influence had a weak positive correlation with Behavioral Intention ($r = .172$) and was not significant in regression ($\beta = .020$, $p = .605$). Auditors' intentions in this sample may have been more closely related to their own assessments of usability, usefulness, trust and support than to perceived pressure from others. This is only a possible explanation; the survey did not test the mechanism. The result differs from Loraas and Wolfe (2006), who reported an influence of audit-manager encouragement. Differences in sample, setting and measurement may contribute to mixed findings.

Perceived Risk had a weak negative, non-significant correlation with Behavioral Intention ($r = -.167$). Its regression result was $B = .000083$, $\beta = .000$, $t = .003$, $p = .998$. This coefficient is unusually close to zero and requires checking. The SPSS data and output were unavailable, so reverse coding, item construction, scale calculation, data entry and the regression output could not be verified. The value is retained as reported rather than changed or explained without evidence. It should not be taken as proof that risk is generally unimportant. The authors should verify all three risk items and the computed score against the original SPSS files before publication.

The model's R^2 of .864 is high for a cross-sectional survey with 100 observations and six predictors. VIF values (1.054–1.916) and tolerance values (.522–.948) do not indicate serious multicollinearity among the

composite predictors, but they do not rule out measurement overlap or common-method effects. All constructs were measured through the same questionnaire and response format. Correlations among ease, trust, performance and intention may also contribute to the model's explanatory power. Residual plots, Durbin-Watson and formal heteroscedasticity results were unavailable; therefore, the high R^2 is reported as a sample result, not as evidence that the model will explain the same variation in the wider population.

Jayasena et al. (2024) is the closest local comparison because it also examined Sri Lankan external auditors' intention to use CAATs through an extended UTAUT approach. The present study adds another sample including Big Four and local/non-Big Four firms and examines Perceived Risk and Perceived Trust with the four UTAUT constructs. The current results highlight effort, trust, performance benefits and facilitating conditions. Since a harmonised comparison of measures, sample characteristics and coefficients was not available, the study does not claim to confirm or contradict every result of Jayasena et al. A future study could compare the models using a common questionnaire and sampling procedure.

7. IMPLICATIONS AND LIMITATIONS

The empirical contribution is a further examination of six factors associated with external auditors' behavioral intention to adopt CAATs in Sri Lanka. In this sample of 100 auditors from Big Four and local/non-Big Four firms, Effort Expectancy, Perceived Trust, Performance Expectancy and Facilitating Conditions were significant positive predictors; Social Influence and Perceived Risk were not. These findings are specific to the study design and should not be presented as national estimates.

For audit firms, the findings point to practical training that helps auditors use CAATs in actual audit procedures, including examining electronic ledgers, testing transactions, analysing data and documenting work. The significant Effort Expectancy result suggests that reducing the difficulty of learning and using the tools may support intention. Firms can also demonstrate the benefits of CAATs through realistic audit tasks rather than general technology promotion.

Firms should provide suitable software access, hardware, technical assistance and internal guidance. The Facilitating Conditions result highlights the relevance of resources and support. Firms should also maintain controls over client data, user access, system changes and software reliability. The Perceived Trust result makes it useful to communicate how tools are selected,

secured and monitored. These recommendations are linked to associations in the study; they are not proven causal effects.

Professional accounting and auditing bodies can support technology-focused continuing professional development through workshops, short courses and practical guidance on data analysis, confidentiality, documentation and responsible use of audit technology. Such programmes should recognise that firms differ in size and resources and that training alone may not resolve limited access to software or technical infrastructure.

The study has limitations. Convenience sampling was used, and the number invited to participate is unknown. The sample cannot be treated as a probability sample of all external auditors in Sri Lanka. Although 39% of respondents were from Big Four firms and 61% from local/non-Big Four firms, this does not establish population representativeness. The cross-sectional, self-reported design measures intention at one point in time, not subsequent adoption or actual frequency of use. The sample contained 100 cases and no a priori power analysis is documented.

The same questionnaire and response format were used for all constructs, so common-method effects and overlap between perceptions cannot be ruled out. KMO and Bartlett results support factorability, but complete factor loadings, composite reliability and average variance extracted were not available. Kolmogorov-Smirnov tests were significant, and the report did not provide residual plots or full regression-assumption diagnostics. Finally, the Perceived Risk coefficient needs verification and the high R^2 warrants further investigation.

Future research could use larger stratified or probability-based samples, report the number invited and calculate a true response rate, and conduct an a priori power analysis. Longitudinal work could examine whether intention is followed by actual use. Further studies could compare Big Four and local firms, test UTAUT moderators, examine specific CAAT types separately and use multiple data sources to reduce common-method concerns. A harmonised comparison with Jayasena et al. (2024) would also clarify differences across samples and model specifications.

This study examined six factors associated with external auditors' behavioral intention to adopt CAATs in Sri Lanka. Effort Expectancy, Perceived Trust, Performance Expectancy and Facilitating Conditions were significant positive predictors in the reported regression model, while Social Influence and Perceived Risk were not. The findings point to usability, trust, expected audit benefits and organisational support as relevant factors in this sample. They

should be interpreted cautiously given the sampling and design limitations, the high R^2 and the unresolved need to verify the Perceived Risk coefficient.

AI DISCLOSURE

The authors used ChatGPT (GPT-6) to assist with manuscript restructuring, language editing, readability improvements and preparation of responses to reviewer comments. The authors reviewed and revised the output and take responsibility for the accuracy, originality and final content of this manuscript.

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Financial Literacy and Entrepreneurial Finance

The Impact of Financial Literacy on Individual Investment Decisions: Evidence from North Central Province of Sri Lanka

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ABSTRACT

Financial literacy is important as individuals assume greater responsibility for managing savings, investments, and long-term financial security in an increasingly complex and digital financial environment. This study examines the relationship between financial literacy dimensions and individual investment decisions among income-earning adults employed in private-sector organizations in the North Central Province of Sri Lanka. Specifically, it examines financial knowledge, financial behavior, financial attitude, and digital financial literacy while controlling for monthly income and educational level. A quantitative approach and cross-sectional design were adopted. Primary data were collected using a structured questionnaire from 150 employees in the Anuradhapura and Polonnaruwa districts. Following data screening, 149 valid responses were retained for analysis. Each of the five constructs was measured using six five-point Likert-scale statements. Data were analyzed using descriptive statistics, Cronbach's alpha, the Kaiser–Meyer–Olkin measure, Bartlett's test of sphericity, Pearson correlation, and hierarchical multiple regression. The main-survey Cronbach's alpha values ranged from 0.922 to 0.948, indicating high internal consistency. All four financial literacy dimensions were positively correlated with individual

investment decisions. In the final regression model, financial attitude was the strongest predictor ($\beta = 0.284$, $p < 0.001$), followed by financial knowledge ($\beta = 0.256$, $p = 0.001$), digital financial literacy ($\beta = 0.252$, $p < 0.001$), and financial behavior ($\beta = 0.210$, $p = 0.001$). Monthly income and educational level were not statistically significant in the final model. The model explained 79.8% of the variance in individual investment decisions ($R^2 = 0.798$; adjusted $R^2 = 0.789$). The findings highlight the relevance of traditional and digital financial literacy dimensions to self-reported investment decision-making among private-sector employees in the study area.

Keywords: *Digital Financial Literacy, Financial Attitude, Financial Behavior, Financial Knowledge, Investment Decisions*

1. INTRODUCTION

Financial literacy is important as individuals make decisions about savings, investments, retirement planning, and financial risks. It includes not only financial knowledge but also the attitudes and behaviors needed to apply that knowledge (Huston, 2010; OECD,2023). Financial literacy may help individuals evaluate investment opportunities, risk, return, and diversification (Lusardi & Mitchell, 2014; Van Rooij et al., 2011). Investment decisions influence wealth accumulation and financial security. Van Rooij et al. (2011) linked financial literacy with stock-market participation. The growth of digital financial services also increases the relevance of digital financial literacy (Morgan et al., 2019; Lyons & Kass-Hanna, 2021). Sri Lankan studies have examined different populations: undergraduates in the Western Province (Kumari, 2020), individual investors in Jaffna (Balagobei & Prashanthan, 2022), Colombo Stock Exchange investors (Thilakarathna & Rajakaruna, 2022), and accounting and finance undergraduates (Wijethunga & Yamuna, 2023). The present study focuses on private-sector employees in Anuradhapura and Polonnaruwa and includes digital financial literacy with three traditional dimensions. This is a population- and location-specific contribution, not a claim that digital financial literacy has never been studied in Sri Lanka.

2. AIMS/OBJECTIVES

The main objective was to examine the relationships between financial literacy dimensions and individual investment decisions among income-earning adults employed in private-sector organizations in the North Central Province of Sri Lanka. The specific objectives were to examine the relationships of (1) financial knowledge, (2) financial behavior, (3) financial attitude, and (4)

digital financial literacy with individual investment decisions. Monthly income and educational level were included as control variables to assess whether the relationships remained statistically significant after accounting for these characteristics.

3. THEORY

The Theory of Planned Behavior links attitudes and behavioral intentions with behavior (Ajzen, 1991), supporting the examination of financial attitude. Human Capital Theory views knowledge and skills as resources that support information processing and informed decisions (Becker, 1964). Financial Socialization Theory explains how financial knowledge, attitudes, and behaviors develop through interactions with family, peers, education, workplaces, and financial institutions (Danes & Yang, 2014). Digital services may also contribute to digital financial literacy. In the analytical model, financial knowledge, financial behavior, financial attitude, and digital financial literacy are treated as four parallel independent variables. Digital financial literacy is included as a fourth predictor; the study does not estimate a separate higher-order financial literacy construct. Individual investment decisions are the dependent variable, while monthly income and educational level are control variables.

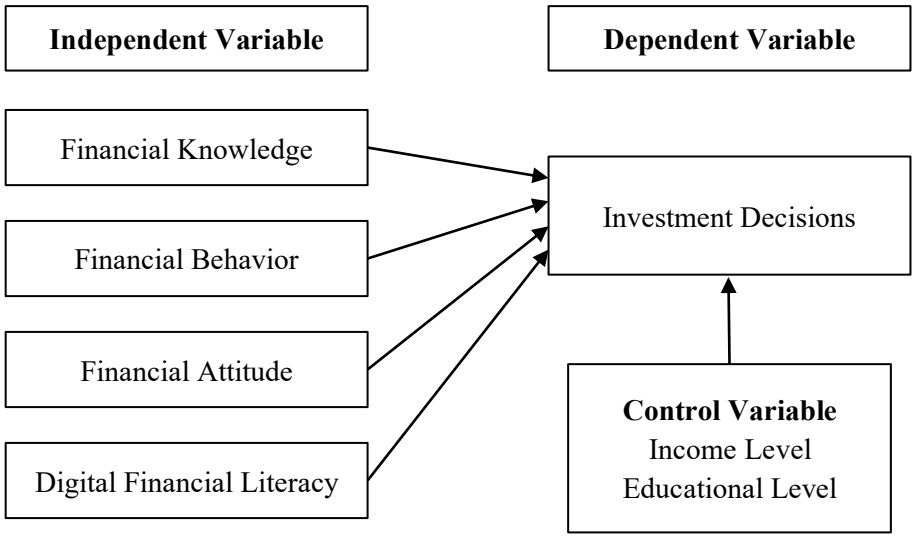

Figure 1. Conceptual Framework

Source: Authors constructed, 2026

The following directional hypotheses were examined:

H_1: Financial knowledge is positively and significantly related to individual investment decisions.

H_2: Financial behavior is positively and significantly related to individual investment decisions.

H_3: Financial attitude is positively and significantly related to individual investment decisions.

H_4: Digital financial literacy is positively and significantly related to individual investment decisions.

4. METHODS

A quantitative approach with a deductive, cross-sectional research design was adopted. The target population comprised income-earning adults employed in private-sector organizations in the North Central Province, with the geographical scope limited to the Anuradhapura and Polonnaruwa districts. Because a comprehensive and updated sampling frame was unavailable, convenience sampling was used. A total of 150 structured questionnaires were collected. One incomplete questionnaire was excluded during data screening, leaving 149 valid responses for analysis.

Each of the five constructs was measured using six statements on a five-point Likert scale (1 = strongly disagree; 5 = strongly agree). Financial knowledge items covered interest rates, inflation, risk and return, diversification, time value of money, and comparison of investment alternatives. These items measured self-assessed knowledge, not objectively scored answers. Financial behavior covered budgeting, saving, expenditure monitoring, planning, emergency funds, and financial review. Financial attitude covered saving preferences, future orientation, discipline, risk, confidence, and the importance of investing. Digital financial literacy covered online banking, mobile payments, digital risks, data protection, digital investment information, and trust in digital platforms. Individual investment decisions were measured through self-reported practices, including analysis of opportunities, risk consideration, diversification, long-term goals, information seeking, and performance review. The dependent variable therefore reflects reported decision-making practices, not verified transactions or actual market participation.

Monthly income was recorded in four categories: below LKR 50,000; LKR 50,000–100,000; LKR 100,001–150,000; and above LKR 150,000. Educational level was recorded as diploma, bachelor's degree, master's degree, professional qualification, or other. These variables were entered as

controls in the regression model. The available research report identifies the response categories but does not provide the SPSS numeric value labels; consequently, no numeric coding scheme is asserted here. Cronbach's alpha assessed internal consistency. Main-survey values were 0.947 (financial knowledge), 0.936 (financial behavior), 0.922 (financial attitude), 0.948 (digital financial literacy), and 0.946 (individual investment decisions), all above 0.70. KMO values ranged from 0.878 to 0.915, and Bartlett's tests were significant (SPSS .000, reported as $p < .001$). These results support factorability; they are not confirmatory factor analysis (CFA), which was not reported.

Table 1. Reliability and Factorability Results for the Main Survey

Construct	Cronbach's alpha	KMO	Bartlett's test
Financial knowledge	0.947	0.878	$p < .001$
Financial behavior	0.936	0.906	$p < .001$
Financial attitude	0.922	0.891	$p < .001$
Digital financial literacy	0.948	0.915	$p < .001$
Individual investment decisions	0.946	0.887	$p < .001$

Source: Authors constructed, 2026

IBM SPSS Statistics Version 25.0 was used for descriptive statistics, Pearson correlation, and hierarchical multiple regression. Model 1 entered income and education; Model 2 added the four financial literacy dimensions. The source research report does not provide full diagnostic outputs (e.g., tolerance/VIF, residual plots, Durbin–Watson, or Cook's distance), so this manuscript does not claim that these assumptions were verified.

5. RESULTS

The final sample comprised 149 respondents. There were 60 males (40.3%) and 89 females (59.7%). In terms of age, 84 respondents (56.4%) were aged 20–29 years, 34 (22.8%) were aged 30–39 years, 24 (16.1%) were aged 40–49 years, and seven (4.7%) were aged 50 years or above. For monthly income, 45 respondents (30.2%) earned below LKR 50,000, 38 (25.5%) earned LKR 50,000–100,000, 19 (12.8%) earned LKR 100,001–150,000, and 47 (31.5%) earned above LKR 150,000. Pearson correlation analysis indicated positive relationships between all four financial literacy dimensions and individual investment decisions. Financial knowledge had the largest correlation ($r = 0.829$, $p < 0.01$), followed by financial attitude ($r = 0.806$, $p < 0.01$), financial behavior ($r = 0.763$, $p < 0.01$), and digital financial literacy ($r = 0.709$, $p < 0.01$).

Table 2. Pearson Correlations with Individual Investment Decisions

Financial literacy dimension	Correlation with IID
Financial knowledge	0.829**
Financial behavior	0.763**
Financial attitude	0.806**
Digital financial literacy	0.709**

*** Correlation is significant at the .01 level (two-tailed)*

Source: Authors constructed, 2026

In the hierarchical regression, Model 1, containing monthly income and educational level, had R = 0.386, R^2 = 0.149, and adjusted R^2 = 0.137; the model was statistically significant, F(2, 146) = 6.391, p = 0.002. After the four financial literacy dimensions were added, Model 2 had R = 0.893, R^2 = 0.798, and adjusted R^2 = 0.789; the model was statistically significant, F(6, 142) = 86.441, p < 0.001. The increase in R^2 was 0.649.

Table 3. Hierarchical Regression Model Summary

Model	R	R^2	Adjusted R^2	F	p
1: Control variables	0.386	0.149	0.137	6.391	0.002
2: Controls + four dimensions	0.893	0.798	0.789	86.441	0.001

Source: Authors constructed, 2026

Table 4. Coefficients of the Final Hierarchical Regression Model (Model 2)

Predictor	B	SE	β	t	p	Decision
Monthly income	−0.037	0.026	−0.062	−1.456	0.148	Not significant
Educational level	0.041	0.025	0.067	1.676	0.096	Not significant
Financial knowledge	0.260	0.080	0.256	3.257	0.001	H1 supported
Financial behavior	0.180	0.052	0.210	3.451	0.001	H2 supported
Financial attitude	0.305	0.072	0.284	4.230	0.001	H3 supported
Digital financial literacy	0.234	0.062	0.252	3.771	0.001	H4 supported

B = unstandardized coefficient; SE = standard error; β = standardized coefficient.

Source: Authors constructed, 2026

In Model 2, financial knowledge (B = 0.260, SE = 0.080, β = 0.256, t = 3.257, p = 0.001), financial behavior (B = 0.180, SE = 0.052, β = 0.210, t = 3.451, p

= 0.001), financial attitude (B = 0.305, SE = 0.072, β = 0.284, t = 4.230, p < 0.001), and digital financial literacy (B = 0.234, SE = 0.062, β = 0.252, t = 3.771, p < 0.001) had positive and statistically significant coefficients. Monthly income (B = −0.037, SE = 0.026, β = −0.062, t = −1.456, p = 0.148) and educational level (B = 0.041, SE = 0.025, β = 0.067, t = 1.676, p = 0.096) were not statistically significant.

6. DISCUSSION

All four dimensions were positively associated with individual investment decisions in the final model. Financial knowledge was significant (β = 0.256, p = 0.001), consistent with Van Rooij et al. (2011) and Shroff et al. (2024). However, this study used self-assessed knowledge rather than an objective quiz, so the measures are not directly equivalent. Financial behavior was significant (β = 0.210, p = 0.001), consistent with a multidimensional view that includes budgeting, saving, expenditure monitoring, and planning (Potrich et al., 2015; OECD, 2023). This is an association in the sample, not proof that each positive practice leads to investment.

Financial attitude was the strongest predictor (β = 0.284, p < 0.001). This aligns with the Theory of Planned Behavior (Ajzen, 1991) and research on attitudes, financial literacy, and stock-market participation (Sivaramakrishnan et al., 2017). Future orientation, discipline, confidence, and views about reasonable risk may therefore be relevant correlates of reported investment decisions. Digital financial literacy was significant (β = 0.252, p < 0.001), consistent with research on digital financial capabilities (Lyons & Kass-Hanna, 2021; Morgan et al., 2019). Because the scale includes online banking, mobile payments, and digital investment information, it measures broad self-reported digital capability rather than investment-platform use alone. Income and education were not significant after the four dimensions were entered. This does not establish that they are irrelevant in other populations. Findings are specific to this convenience sample and should be interpreted cautiously given the cross-sectional, self-reported design and unavailable diagnostic outputs.

7. IMPLICATIONS AND LIMITATIONS

The findings suggest that employee financial education may combine financial concepts, budgeting and saving, long-term planning, and safe use of digital services. Financial institutions may provide accessible guidance on investment risk, return, diversification, and digital security. Employers may consider workplace sessions on budgeting, investment decisions, and retirement planning. These recommendations follow from the observed associations; the study did not test any intervention.

Limitations include convenience sampling and restricted generalizability; a cross-sectional design that cannot establish causality; and self-reported measures that may involve recall, social-desirability, and common-method bias. Financial knowledge was self-assessed, and investment decisions were not verified against actual transactions. The model also omitted possible factors such as risk tolerance, investment experience, behavioral biases, financial self-efficacy, family influence, and access to financial information. The study was limited to Anuradhapura and Polonnaruwa districts.

Future research could extend the geographical and occupational scope, use longitudinal or probability-based designs, employ objective knowledge tests and verified investment measures, and report complete regression diagnostics. Overall, the study provides context-specific evidence of positive associations between the four literacy dimensions and self-reported investment decisions.

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How Does Financial Literacy Influence the Borrowing Behavior of Adults in Jaffna, Sri Lanka? A Multi-Group Analysis of Gender, Income, and Marital Status

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ABSTRACT

Financial literacy (FL) is expected to improve borrowing decisions, yet little is known about whether its association with borrowing differs across socio-demographic groups in post-conflict Sri Lanka. This study examines the relationship between FL and the borrowing behavior (BB) of adults in the Jaffna Divisional Secretariat (DS) Division, where BB denotes prudent borrowing practices, and tests whether gender, income, and marital status moderate it. Survey data were collected in August 2025 from 318 adults aged 18 to 60, randomly selected from household lists across 50 villages (response rate 82.8%), and analysed using partial least squares structural equation modelling (PLS-SEM), with measurement invariance assessed through MICOM and group differences tested by multi-group analysis (PLS-MGA). FL was positively associated with BB ($\beta = 0.379$, $p < 0.001$), explaining 14.4% of the variance in BB. The association was significantly stronger among women ($\beta = 0.503$) than men ($\beta = 0.294$; $p = 0.039$). It was strong among

respondents earning Rs. 150,000 or more per month (β = 0.449, $p < 0.001$) but smaller and not significant among those earning less (β = 0.221, $p = 0.064$), which reflects imprecision rather than evidence of no relationship; the income-group difference was significant ($p = 0.045$). Marital status did not moderate the relationship ($p = 0.096$). FL programs may be most effective when directed at women, and for lower-income earners they may need to be combined with access to affordable formal credit.

Keywords: *Financial literacy, Borrowing behavior, Gender, Income, Marital status*

1. INTRODUCTION

Poorly informed borrowing decisions can lead to higher interest costs, over-indebtedness, and financial distress. Financial literacy (FL), the knowledge, skills, and attitudes needed to make sound financial decisions (OECD, 2018), is commonly seen as a protection against these outcomes (Lusardi & Mitchell, 2014). In this study, borrowing behaviour (BB) refers to the prudence of borrowing practices: comparing credit costs, borrowing within repayment capacity, repaying on time, and avoiding high-cost credit. People with higher FL are better able to compare loan costs and assess their ability to repay, and are less likely to use high-cost or informal credit (Disney & Gathergood, 2013; Huston, 2012; Lusardi & Tufano, 2015).

Evidence from several countries supports this link. In the United Kingdom and Russia, financially literate consumers hold fewer high-cost credit products (Disney & Gathergood, 2013; Klapper et al., 2013), and in rural China, FL is associated with more productive borrowing (Guo et al., 2023). Recent studies extend these findings to digital, peer-to-peer, and student borrowing (Baltazar & Richard, 2026; Khalid et al., 2025; Khan & Rabbani, 2025; Solihati & Indriawati, 2026). However, weak self-control and overconfidence can reduce the benefit of financial knowledge (Gathergood, 2012; Pak, 2018).

Evidence from South Asia is thinner. In India, credit score literacy and psychological traits jointly shape borrowing behaviour (Altaf & Shah, 2025). In Sri Lanka's conflict-affected Northern and Eastern Provinces, the financial behaviour of women microfinance borrowers is associated with financial socialisation and social capital (Domingo & Buvanendra, 2023), and most surveyed households in Jaffna, Kilinochchi, and Mullaitivu were indebted, often without knowing their true level of debt (Romeshun et al., 2014).

The FL–BB link may also differ across groups. Women score lower than men on FL in most economies (Klapper & Lusardi, 2020), and social role theory attributes such differences to the different economic roles men and women

play in the household (Eagly, 1987). The same level of FL may therefore lead to different BB for men and women (Mansharamani, 2026). Lower-income earners have less liquidity and weaker access to formal credit and may borrow from any available source (Lusardi & Tufano, 2015), whereas higher-income earners have more room for knowledge to guide their choices. Married people share household obligations and often make borrowing decisions jointly.

Sri Lanka is a useful setting for these questions: only about 35% of its adults were classified as financially literate (Klapper et al., 2015), and households in Jaffna have long depended on informal lenders, microfinance, and gold loans. Northern Province studies describe indebtedness or focus on women microfinance borrowers; none, to the authors' knowledge, tests whether the FL–BB relationship differs by gender, income, and marital status in the general adult population after formally establishing measurement invariance.

2. AIMS/OBJECTIVES

Hence, the objectives of this study are to examine the relationship between FL and BB among adults in Jaffna and to determine whether gender, income, and marital status moderate this relationship. Based on the literature above, the following hypotheses were tested:

H1: FL is positively and significantly associated with BB.

H2: Gender significantly moderates the relationship between FL and BB.

H3: Income significantly moderates the relationship between FL and BB.

H4: Marital status significantly moderates the relationship between FL and BB.

3. METHODS

3.1 Research Design and Sample

The study adopted a positivist, deductive approach and a quantitative, cross-sectional survey design. The Jaffna DS Division, the administrative and commercial centre of Jaffna District, was selected for its accessibility. It contains 28 Grama Niladhari (GN) divisions and 50 villages, with a population of 54,159 as of June 30, 2025 (Divisional Secretariat, Jaffna, 2025). The target population is adults aged 18 to 60. Krejcie and Morgan (1970) recommend a minimum sample of 381 for this population, a conservative requirement given that the population aged 18 to 60 is smaller. In August 2025, 384 questionnaires were distributed across all 50 villages. Households were randomly selected from lists obtained with assistance from GN officers, and

one eligible adult was surveyed in each selected household. A total of 318 usable responses were received (response rate 82.8%).

Under the inverse square root method (Kock & Hadaya, 2018), the minimum sample needed to detect a path coefficient of 0.20 at the 5% level with 80% power is:

$$n_{\min} > \left(\frac{2.486}{|p_{\min}|}\right)^2 = \left(\frac{2.486}{0.20}\right)^2 \approx 155 \quad \text{.....(1)}$$

A G*Power analysis (Faul et al., 2009) for $f^2 = 0.15$, $\alpha = 0.05$, and power = 0.95, with one predictor, yields 89. The sample exceeds both thresholds; subgroup precision is reported in Section 4.3.

3.2 Measurement of Variables

FL was measured with nine items adapted from Lusardi and Mitchell (2007) and the OECD (2018), and BB with six items adapted from Yeo (2024), Brown and Graf (2013), and the OECD (2018). The BB items capture comparing loan costs, borrowing within repayment capacity, timely repayment, and avoiding high-cost credit. All items were positively worded; none were reverse-coded. Items were rated on a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree), so higher scores indicate higher self-assessed FL and more prudent BB. The questionnaire was translated into Tamil and back-translated into English by an independent bilingual academic to confirm equivalence. It is available from the corresponding author on request. The FL and BB items had no missing values. Gender was not reported by five respondents, and income by three; these cases were excluded only from the comparison in question.

Respondents were grouped by gender, marital status (married, single), and personal monthly income, measured at the respondent rather than the household level. The income cut-off of Rs. 150,000 is the personal income tax-free threshold, effective from April 1, 2025 (Ada Derana, 2025). It provides an official, policy-relevant dividing line between respondents outside the income tax net and taxable earners.

3.3 Model Specification and Analysis

Both constructs are reflective. The full-sample structural model (H1) is Equation 2. For H2 to H4, the model is estimated separately for the two groups of each moderator (Equation 3), and each hypothesis tests the difference between group-specific path coefficients (Equation 4):

$$\text{BB} = \beta_0 + \beta_1 \text{ FL} + \zeta \quad \text{.....(2)}$$

$$\mathrm{BB}^{(g)} = \beta_1^{(g)}\,\mathrm{FL} + \zeta^{(g)},\ \ g = 1, 2 \quad \text{.....(3)}$$

$$H_0: \beta_1^{(1)} - \beta_1^{(2)} = 0;\ \ H_a: \beta_1^{(1)} - \beta_1^{(2)} \neq 0 \quad \text{.....(4)}$$

PLS-SEM was used because the study is prediction-oriented, does not require multivariate normality, and offers an established group-comparison procedure (Hair et al., 2022; Henseler et al., 2016). Data were analyzed in SmartPLS 4. The measurement model was assessed through outer loadings (≥ 0.708), Cronbach's α and composite reliability (≥ 0.70), AVE (≥ 0.50), and HTMT (< 0.85); the structural model through VIF (< 3.3), bootstrapping with 5,000 subsamples (percentile confidence intervals), R^2, and f^2. Measurement invariance was assessed with the three-step MICOM procedure using 1,000 permutations (Henseler et al., 2016), and group differences were tested with PLS-MGA using 5,000 bootstrap subsamples per group and two-tailed tests ($p < 0.05$).

4. RESULTS

Of the valid responses, 167 (53.4%) were female, and 146 (46.6%) were male ($n = 313$); 180 (56.6%) were married and 138 (43.4%) were single ($n = 318$); and 216 (68.6%) earned Rs. 150,000 or more a month and 99 (31.4%) less ($n = 315$).

4.1 Measurement Model

All 15 outer loadings exceeded 0.708 (Table 1), so no items were removed. Cronbach's α and composite reliability exceeded 0.70, and AVE exceeded 0.50 for both constructs. The HTMT ratio was 0.400, and the square root of each AVE (FL 0.792; BB 0.789) exceeded the FL–BB correlation of 0.379. Indicator VIF values ranged from 1.755 to 2.878.

Table 1. Outer Loadings, Reliability, and Convergent Validity

Construct / item	Loading	Cronbach's α	ρA	CR (ρc)	AVE
Financial literacy (FL)		0.926	0.930	0.938	0.627
FL1 / FL2 / FL3	0.780 / 0.772 / 0.819				
FL4 / FL5 / FL6	0.751 / 0.793 / 0.812				
FL7 / FL8 / FL9	0.789 / 0.781 / 0.827				
Borrowing behaviour (BB)		0.879	0.904	0.908	0.623
BB1 / BB2 / BB3	0.742 / 0.822 / 0.885				
BB4 / BB5 / BB6	0.731 / 0.721 / 0.822				

Source: Authors constructed, 2026

4.2 Structural Model

FL was positively and significantly associated with BB (β = 0.379, t = 6.690, p < 0.001; 95% CI [0.274, 0.499]), supporting H1. FL explains 14.4% of the variance in BB (R^2 = 0.144; adjusted R^2 = 0.141), with a medium effect size (f^2 = 0.168).

4.3 Measurement Invariance and Multi-Group Analysis

Configural invariance held for every moderator, and compositional invariance was confirmed, as no permutation p-value was significant (Table 2). Partial measurement invariance was therefore established for all three moderators, allowing path coefficients to be compared (Henseler et al., 2016).

Table 2. MICOM Results

Moderator	Construct	Step 1	Step 2 (p)
Gender	FL	Yes	0.906
	BB	Yes	0.220
Income	FL	Yes	0.918
	BB	Yes	0.070
Marital status	FL	Yes	0.420
	BB	Yes	0.264

Note: Permutation p-values; p > 0.05 indicates invariance.

As Table 3 shows, the FL–BB association was significantly stronger among women than men, supporting H2, and significantly stronger among higher- than lower-income earners, supporting H3. The married–single difference was not significant, so H4 is not supported.

Table 3. PLS-MGA Results

Moderator	Group	n	β	SE	95% CI	p	Diff.	p (Diff.)
Gender	Male	146	0.294	0.081	[0.135, 0.453]	< 0.001	−0.208	0.039
(n = 313)	Female	167	0.503	0.062	[0.381, 0.625]	< 0.001		
Income	Below Rs. 150,000	99	0.221	0.120	[−0.013, 0.455]	0.064	−0.229	0.045
(n = 315)	Rs. 150,000 and above	216	0.449	0.076	[0.300, 0.598]	< 0.001		
Marital status	Married	180	0.448	0.062	[0.327, 0.569]	< 0.001	0.176	0.096
(n = 318)	Single	138	0.272	0.095	[0.085, 0.459]	0.004		

Note: SE = β/t; 95% CI = β ± 1.96 SE; Diff. = first − second group; two-tailed p-values.

The smallest path coefficient detectable at the 5% level with 80% power is $2.486/\sqrt{n}$ (Kock & Hadaya, 2018): 0.250 for the lower-income group ($n = 99$), compared with 0.169 to 0.212 for all other groups. The lower-income estimate (0.221) falls below this threshold and has a wide confidence interval.

5. DISCUSSION

FL was positively associated with prudent BB, consistent with international evidence (Disney & Gathergood, 2013; Guo et al., 2023), although the modest R^2 indicates that other factors, such as self-control (Gathergood, 2012), also matter. The association was considerably stronger among women. One possible explanation, not measured here, is that women in many Jaffna households handle day-to-day finances, pledging jewellery for gold loans and joining microfinance groups and *seettu* (rotating savings groups), so gains in their knowledge may show more directly in borrowing. Men's borrowing may depend more on business needs and social obligations. These explanations remain hypotheses for future research.

Among lower-income earners, the association was weaker and imprecisely estimated, so the data neither confirm nor rule out a smaller association. A plausible but untested explanation, in line with Lusardi and Tufano (2015), is that they often borrow out of immediate need, when knowing that a loan is expensive helps little if no cheaper option exists. Marital status did not alter the relationship, suggesting that FL operates similarly in individual and joint borrowing decisions.

6. IMPLICATIONS AND LIMITATIONS

FL programs run by the Central Bank of Sri Lanka, licensed banks, and microfinance institutions may be more effective if they target women, for example, through women's rural development societies and microfinance groups. For lower-income earners, financial education may need to be combined with affordable formal credit, such as small loans from licensed institutions and cooperative societies. The study has several limitations. Its cross-sectional, self-reported data support associations rather than causal effects, and self-assessed FL may differ from measured knowledge. The data come from a single, largely urban DS division, and FL explains only 14.4% of the variance in BB. The lower-income estimate should be re-examined with a larger sample. Future research could cover rural DS divisions and other Northern Province districts, use household-level income data, and include self-control, debt attitudes, and access to credit.

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Technological Readiness and Perceived Relative Advantage as Drivers of AI Adoption Intention: Evidence from Service Sector SMEs in Gampaha District, Sri Lanka

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ABSTRACT

Although artificial intelligence offers significant advantages, including streamlined service delivery, superior decision-making, faster customer response, and driven innovation, its adoption among small and medium enterprises remains uneven. Many SMEs currently lack the necessary technological systems and internal capabilities to integrate AI tools successfully. Thus, this study examined the impact of technological factors, organizational factors, environmental factors, and perceived relative advantage on the intention to adopt AI in service sector SMEs of Gampaha district in Sri Lanka. The study was designed under the positivist research philosophy, following deductive approach. The study used a quantitative cross-sectional survey to collect data from 126 SME owners and managers. The data were analyzed using Partial Least Squares Structural Equation Modelling. Technological factors played a significant role in determining the intention to use AI, as did the perceived relative advantage. The results highlight that digital readiness and the benefit to the business are key factors in fostering SMEs to adopt AI. At the component level, both IT infrastructure and data availability contributed significantly to technological readiness, with data availability contributing most, whereas employee digital skills and government support were not significant contributors.

Keywords: *Artificial intelligence, AI Adoption Intention, Service-Sector Smes, Technological Readiness, Relative Advantage*

1. INTRODUCTION

Artificial intelligence (AI) is a key contributor to digital transformation, enabling organizations to automate routine tasks, analyze data, improve forecasting, and support decision-making and personalized services. Technologies such as chatbots, recommendation systems, predictive analytics, and intelligent automation create new opportunities for business value. AI also influences service delivery, business models, and management practices, offering benefits in productivity and innovation while creating challenges related to organizational readiness and capabilities (Huang & Rust, 2018; Kaplan & Haenlein, 2019; Dwivedi et al., 2021).

Small and medium-sized enterprises (SMEs) are important contributors to economic development (Deyshappriya & Maduwanthi, 2020). In Sri Lanka, they account for 75% of active enterprises, 45% of employment, and 52% of GDP (National SME Strategy Framework, 2026). However, limited financial, technological, and human resources may restrict their ability to adopt AI, despite its potential to improve efficiency and market responsiveness. Successful AI adoption requires more than access to appropriate software. It also depends on organizational readiness, suitable infrastructure, reliable data, employee skills, management support, financial resources, and a clear business purpose (Nambisan et al., 2019; Chatterjee et al., 2021). In particular, access to high-quality data strengthens an organization's ability to use data-driven technologies effectively (Brynjolfsson & McElheran, 2016).

The Technological – Organizational – Environmental (TOE) framework identifies three contexts that influence innovation adoption (Tornatzky & Fleischer, 1990). The Technological context refers to the attributes of the technology and the firm's IT environment. In addition, prior technology adoption studies show that TOE dimensions should be considered together because technological readiness, organizational resources, and environmental conditions can jointly influence adoption decisions (Oliveira & Martins, 2011; Baker, 2012; Chatterjee et al., 2021). Therefore, the TOE framework is useful for explaining AI adoption intention among SMEs because successful adoption depends on multiple internal and external conditions rather than one factor alone. Further, Rogers (2003) identified several perceived attributes of innovations that influence adoption, including relative advantage, comparability, complexity, trialability, and observability. These attributes refer directly to the degree to which an innovation is perceived as superior to the technology it replaces. Generally, organizations are more willing to adopt innovations quickly when they expect clear benefits such as improved efficiency, quality decision-making, cost reduction, and enhanced customer service or competitive advantage.

Previous studies recognize AI adoption as a multidimensional process influenced by technological, organizational, and environmental factors (Chatterjee et al., 2021). Strategy, resources, knowledge, organizational culture, and data capabilities also contribute to AI readiness (Jöhnk et al., 2021). Perceived value is especially important for SMEs because they must assess the benefits of AI while operating with limited resources. Although SMEs contribute significantly to Sri Lanka's economy, their levels of AI adoption vary considerably. As previous research has mainly focused on developed economies and large organizations, further investigation within the Sri Lankan SME context is required. This study addresses this gap by examining how IT infrastructure, data availability/quality, top management support, employee digital skills, financial readiness, competitive pressure, government support, and relative advantage influence SMEs' intention to adopt AI.

Accordingly, the study seeks to achieve four objectives: first, examine the influence of technological factors; second, investigate the influence of organizational factors; third, assess the influence of environmental factors; and fourth, determine the impact of perceived relative advantage on service sector SMEs' intention to adopt AI.

2. METHODOLOGY

This section explains the research design of the study. This study lies within the positivist research paradigm based on ontological and epistemological assumptions. Hence, the quantitative research method under the deductive approach was utilized. The anticipated relationships among the study variables are depicted in Figure 01. Accordingly, the independent variables were the technological factors, organizational factors, environmental factors, and Relative advantage of innovations. The intention to adopt AI was the dependent variable.

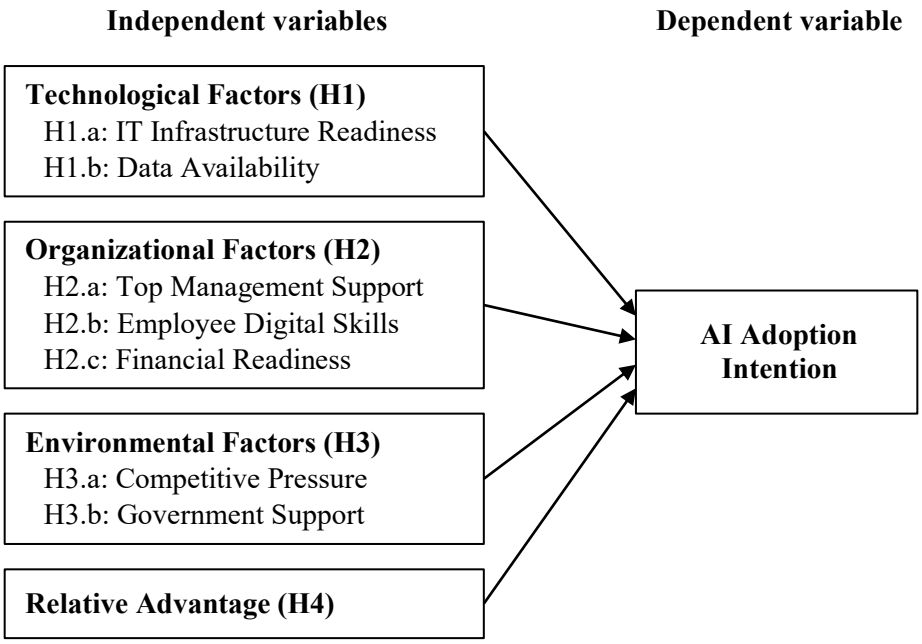

Figure 1. Conceptual Framework

Source: Authors constructed, 2026

Eight hypotheses were formulated and evaluated based on the conceptual framework depicted in Figure 1. Additionally, the corresponding research model was established and tested.

Equations: 1

$$AII = \beta_0 + \beta_1(TI) + \beta_2(DA) + \beta_3(TMS) + \beta_4(EDS) + \beta_5(FR) + \beta_6(CP) + \beta_7(GS) + \beta_8(RA) + \varepsilon \quad (1)$$

Where;

AII = AI Adoption Intention
β0 = Constant (Intercept)
β1=T Infrastructure Readiness
β2=Data Availability
β3 =Top Management Support
β4 =Employee Digital Skills
β5=Financial Readiness
β6= Competitive Pressure
β7=Government Support
β2=Relative Advantage
ε= Error Term

The study's target population consisted of both registered and unregistered SMEs in the services sector in Gampaha District in Sri Lanka. A non-probability convenience sampling method was used since there was no complete list of SMEs that met the inclusion criteria in the sampling frame.

Respondents were the owner's decision makers who had knowledge on their firms' capacity to adopt AI technology. The number of valid responses collected was 126. Prior to full-scale deployment, the instrument was pilot tested with 35 respondents, confirming construct reliability through acceptable Cronbach's alpha values.

Variables used in this research were operationalized through multi-item scales derived from existing literature. Technological variables were operationalized using IT Infrastructure Readiness Scale (Tornatzky & Fleischer, 1990; Bharadwaj et al., 2013) with 4 items and the Data Availability Scale (Brynjolfsson & McElheran, 2016; Gupta et al., 2022). Organizational variables included Top Management Support (Jeyaraj et al., 2006; Hwang & Kim, 2022), Employee Digital Skills (Venkatesh et al., 2012; OECD, 2019), and Financial Readiness (Oliveira et al., 2014; Hsu et al., 2006), all operationalized through 4-item scales. Environmental variables included Competitive Pressure (Porter, 1980; Tornatzky & Fleischer, 1990) and Government Support (Gupta et al., 2022; World Bank, 2025), while Relative Advantage was measured separately (Rogers, 2003; Moore & Benbasat, 1991; Jöhnk et al., 2021). Finally, AI Adoption Intention was operationalized through 5 items. Items used for measuring all these constructs were on 5-point Likert scale where 1 means Strongly Disagree and 5 means Strongly Agree.

Data analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM). To accommodate both first-order reflective and higher-order formative constructs within the model, a two-stage hierarchical component approach was implemented. Because this framework precludes a single-step evaluation, a multi-step procedure was followed to separately evaluate the lower-order measurement properties and the higher-order component relationships (Sarstedt et al., 2019). In the first stage, the reflective measurement model was evaluated through indicator loadings, Cronbach's alpha, composite reliability, average variance extracted (AVE), and discriminant validity. The second stage involved assessing formative collinearity and component weights, followed by testing the structural paths. Hypotheses were evaluated using non-parametric bootstrapping with 10,000 subsamples. Finally, model explanatory power was evaluated using R^2 and effect sizes (f^2), while out-of-sample predictive capability was assessed using PLSpredict, as recommended by Shmueli et al. (2019).

3. FINDINGS AND DISCUSSION

The data contained with no missing values and all the items had valid responses. Numeric checks confirmed all values fell within the 1–5 Likert range and each CaseID was unique. Thus, no imputation or deletion was

necessary. Therefore, all 126 valid responses were retained for the lower-order measurement-model assessment and subsequent higher-order structural analysis. The demographic analysis revealed a few specific features of the selected sample. 78.6% of the sample consisted of micro-enterprises (1-10 employees), and 66.7% of respondents were the owner or manager of these enterprises. Thus, the data primarily reflect high-level managerial and owner perspectives. Further, most of the enterprises have already made use of digital systems. The assessment of normality of the data distribution indicated non-normal behavior, and PLS-SEM was employed for the data analysis. PLS-SEM does not require multivariate normality in the same manner as covariance-based SEM, and statistical significance is commonly assessed using non-parametric bootstrapping, making the method suitable for data that depart from normal-distribution assumptions (Hair et al., 2022; Ringle et al., 2024).

Table 1. Construct Reliability and Validity

Construct	Cronbach's α	Composite Reliability	AVE	Max VIF
AI Adoption Intention	0.895	0.923	0.706	3.631
Competitive Pressure	0.746	0.831	0.552	1.850
Data Availability	0.726	0.830	0.549	1.996
Employee Digital Skills	0.740	0.818	0.547	2.252
Financial Readiness	0.812	0.874	0.635	1.989
Government Support	0.835	0.880	0.648	2.250
IT Infrastructure	0.705	0.820	0.536	1.736
Relative Advantage	0.824	0.884	0.660	3.482
Top Management Support	0.828	0.877	0.644	1.923

Source: Authors constructed, 2026

The results of descriptive statistics reveal that the respondents' attitude towards AI was generally positive: the highest score in favor of AI was revealed for Perceived Relative Advantage (M = 4.442, SD = 0.551), the next was obtained for AI Adoption Intention (M = 4.354, SD = 0.625), followed by Technological Factors (M = 4.140, SD = 0.507). The table 1 shows the construct reliability and convergent validity. For reflective constructs, Cronbach's α, and composite reliability ≥0.70 indicate acceptable internal consistency, and AVE ≥0.50 indicates adequate convergent validity. All nine first-order constructs exceed these thresholds. The weakest reliability is for IT Infrastructure (α = 0.705, CR = 0.820) and Data Availability (α = 0.726, CR = 0.830), which are just above 0.70. The highest reliability is for AI Adoption Intention (α = 0.895, CR = 0.923) and Government Support (α = 0.835, CR = 0.880). All AVEs

exceed 0.536, and no composite reliability or alpha exceeds 0.95, so there is no evidence of indicator redundancy. Thus, all first-order constructs demonstrate acceptable internal consistency and convergent validity (Hair et al., 2022; Fornell & Larcker, 1981).

Discriminant validity was assessed primarily using the Heterotrait–Monotrait ratio (HTMT). HTMT values below 0.90 indicate adequate discriminant validity, with a more stringent threshold of 0.85 when constructs are conceptually very distinct (Henseler et al., 2015; Hair et al., 2022). Table 2 shows the HTMT matrix for the nine reflective constructs. Only one HTMT value exceeds 0.90: HTMT (IT, DA) = 1.046, reflecting a high correlation between IT Infrastructure and Data Availability. This indicates that there could possibly be some conceptual overlap between these two constructs. This is because of the close association between the IT infrastructure of the organizations and the capacity of these organizations to capture, retrieve, and utilize the data. Therefore, discriminant validity for these two constructs was not entirely supported.

Table 2. HTMT Discriminant Validity Matrix

Construct	IT	DA	TMS	EDS	FR	CP	GS	RA	AII
IT	1.000								
DA	1.046	1.000							
TMS	0.451	0.226	1.000						
EDS	0.519	0.182	0.770	1.000					
FR	0.514	0.285	0.632	0.540	1.000				
CP	0.454	0.340	0.507	0.422	0.498	1.000			
GS	0.411	0.297	0.527	0.455	0.555	0.745	1.000		
RA	0.553	0.312	0.505	0.573	0.669	0.646	0.570	1.000	
AII	0.585	0.378	0.514	0.596	0.678	0.586	0.586	0.814	1.000

Source: Authors constructed, 2026

The higher-order constructs Technological Factors (TF), Organizational Factors (OF), and Environmental Factors (EF) were modeled formatively from their component scores. For formative constructs, internal consistency measures (α, CR, AVE) are not interpreted in the same way. Instead, the study focusses on collinearity and the significance of the indicator weights (Becker et al., 2012; Hair et al., 2022). Table 3 shows the variance inflation factors (VIFs) for the components. All VIFs are well below 3.00, indicating no serious multicollinearity among the components of TF, OF, or EF. the outer weight

and significance for each formative component. In Technological Factors, both IT and DA components contribute positively (weights 0.307 and 0.693, $p<0.05$), indicating each is a relevant source of TF. In Organizational Factors, Top Management Support (weight 0.603, $p<0.001$) and Financial Readiness (0.405, $p=0.041$) are significant, while Employee Digital Skills is not (weight –0.118, $p=0.559$). In Environmental Factors, Competitive Pressure has a very strong weight (0.873, $p<0.001$), whereas Government Support's weight (–0.199) is not significant ($p=0.133$). All components align with theoretical expectations.

Table 3. Formative Measurement Model Assessment: Collinearity and Component Weights

Higher-Order Construct	Component	VIF	Weight (β)	t-value	p-value
Technological Factors (TF)	IT Score	1.460	0.307	2.153	0.032
	DA Score	1.460	0.693	3.746	0.000
Organizational Factors (OF)	TMS Score	2.208	0.603	4.201	0.000
	EDS Score	2.208	–0.118	0.585	0.559
	FR Score	1.809	0.405	2.048	0.041
Environmental Factors (EF)	CP Score	1.270	0.873	11.234	0.000
	GS Score	1.270	–0.199	1.505	0.133

Source: Authors constructed, 2026

Where;
VIF = Variance Inflation Factor
IT = IT Infrastructure
DA = Data Availability
TMS = Top Management Support
EDS = Employee Digital Skills
FR = Financial Readiness
CP = Competitive Pressure
GS = Government Support
K

The significant weights ($p<0.05$) suggest that IT and DA jointly form TF, TMS and FR jointly form OF, and CP chiefly forms EF. The insignificance of EDS and GS suggests those components contribute little explanatory variance to their respective HOCs in this sample. However, their removal would change the content of the constructs, so they are retained for completeness. All VIFs in Table 3 were <3.0, confirming that collinearity among components is not problematic (Hair et al., 2022). The structural model's explanatory power for AI Adoption Intention is $R^2 = 0.511$ (adjusted $R^2 = 0.495$), indicating moderate explanatory power for behavioral intention. By conventional PLS guidelines,

R^2 values ~0.50 can be considered moderate to substantial (Hair et al., 2022). A nonparametric bootstrap was used to assess the significance of path coefficients.

Table 4. Hypothesis Testing Summary

Hypothesis	Sub-factor / Variable	Component Weight (β)	t-value	p-value	Decision
H1a	IT Infrastructure	0.307	2.153	0.032	Supported
H1b	Data Availability	0.693	3.746	0.000	Supported
H2a	Top Management Support	0.603	4.201	0.000	Supported
H2b	Employee Digital Skills	-0.118	0.585	0.559	Not supported
H2c	Financial Readiness	0.405	2.048	0.041	Supported
H3a	Competitive Pressure	0.873	11.234	0.000	Supported
H3b	Government Support	-0.199	1.505	0.133	Not supported
H4	Perceived Relative Advantage	0.431	2.769	0.006	Supported

Source: Authors constructed, 2026

Competitive Pressure ($\beta = 0.873$) and Data Availability ($\beta = 0.693$) are by far the most powerful determinants driving AI adoption intent among service sector SMEs. Top Management Support ($\beta = 0.603$), Perceived Relative Advantage ($\beta = 0.431$), Financial Readiness ($\beta = 0.405$), and IT Infrastructure ($\beta = 0.307$) play significant positive roles. Employee Digital Skills and Government Support do not significantly influence the intention to adopt AI in this context ($p > 0.05$). Using the out-of-sample predictive ability, $Q^2 = 0.470$ was generated using PLSpredict. In general, the major direct predictors for the overall level were technological readiness and relative advantage. The level of AI adoption intention was thus largely contingent on whether companies had a credible digital foundation and whether AI would create meaningful value for the company.

4. CONCLUSION

The results reveal that technological readiness and relative advantage are the key determinants of AI adoption intention of service sector SMEs in Gampaha District. Service sector SMEs need a basic level of technical maturity before considering AI integration, though it is not the strongest overall driver. Access to structured, usable data is a primary determinant of AI adoption intention. Since AI relies entirely on

data to train algorithms and extract insights, service SMEs that collect and manage quality data feel significantly more ready and willing to adopt AI tools. Leadership commitment, vision, and resource allocation strongly drive adoption intention. In SMEs, decision-making is highly centralized. If leaders understand AI, the organization is more likely to move forward with adoption. Current employee digital skill levels have no statistically significant impact on the intention to adopt AI. Service SMEs likely view AI tools as user-friendly or expect vendor support/training, indicating existing skill gaps do not act as an immediate barrier to intention. Available budget and financial stability positively influence AI adoption intent. Investing in AI involves upfront software, integration, and maintenance costs. Therefore, SMEs with dedicated financial resources show higher willingness to adopt.

External pressure from market rivals adopting AI is the single strongest driver in the entire model. Service sector SMEs are heavily reactive to market dynamics. Fear of falling behind competitors who leverage AI for efficiency or customer service acts as the primary catalyst for adoption. Government policies, subsidies, or institutional initiatives do not significantly influence adoption intention. Service SMEs rely far more on market forces and internal capabilities than state incentives when considering cutting-edge tech adoption. Recognizing that AI offers clear benefits over existing methods significantly boosts adoption intention. When SME decision-makers perceive tangible value (ex: faster response times, higher productivity, reduced operating costs), they are much more inclined to adopt AI.

There are several limitations in the interpretation of the findings This information should be understood considering the sample of service sector SMEs that were used in the study conducted in Gampaha District. Because the study used non-probability convenience sampling and was limited to one specific region and industry, the findings may not be generalizable to SMEs across Sri Lanka. In addition, because of the cross-sectional nature of the survey and self-reports of intentions and not actual behavior, the information is temporal. Therefore, future research is needed using wider probability-based sampling, comparing sectors and regions, using longitudinal research to follow up the applications of new technology and adopting actual adoption behaviors as a measure, as well as examining mediation or moderation variables. Despite such constraints, the study offers empirical findings indicating that service-sector SMEs are most likely to transition to AI when they have technological readiness, and the belief that AI offers them improved business value is clear.

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The Effect of Digital Financial Literacy on Personal Financial Management Behavior among Career-Entry Undergraduates at Wayamba University of Sri Lanka

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ABSTRACT

Digital financial literacy (DFL) has become an essential competency for young adults in Sri Lanka as financial services move online during the country's post-crisis economic recovery. This study explores the relationship between DFL and personal financial management behavior (PFMB) among career-entry, final-year undergraduates at Wayamba University of Sri Lanka. It examines digital financial awareness (DFA), digital financial skills and knowledge (DFSK), digital financial attitude (DFAT), and digital financial usage (DFU) as dimensions of DFL. Informed by the Theory of Planned Behavior (TPB), the study adopted a quantitative, cross-sectional design, and data were collected through a structured online questionnaire from students of all faculties, selected through proportionally allocated stratified random sampling. Reliability, correlation, and multiple regression analyses were conducted using SPSS. The results indicate significant positive associations between PFMB and digital financial awareness, attitude, and usage, whereas skills and knowledge were not a statistically significant predictor. Awareness had the strongest standardized association, followed by usage and attitude. The findings extend the TPB to the digital financial domain by showing that DFL is not a uniform construct. The results suggest that financial education for graduating students should emphasize risk awareness, attitude formation, and experiential, usage-based learning. Because the data are cross-sectional, drawn from a specific institution, and PFMB is measured with a short scale, the results indicate associations rather than causal effects.

Keywords: *Career-Entry Undergraduates, Digital Financial Attitude, Digital Financial Awareness, Digital Financial Usage, Personal Financial Management Behavior*

1. INTRODUCTION

Digital technology has changed the financial world at a rapid pace, and digital solutions are now part of everyday financial transactions. With the advent of financial technology (Fintech), access to and use of financial services are no longer limited to bank branches but extend to mobile banking, digital wallets, online payment platforms, and peer-to-peer lending (Dewmini et al., 2023; Rahayu et al., 2022). Digital financial literacy has therefore become an important competency for financial well-being. Digital financial literacy (DFL) is the understanding, use, and management of digital financial services together with the risks that accompany them, such as data theft, online fraud, and cybersecurity threats (Lyons & Kass-Hanna, 2021; Prasad et al., 2018). Setiawan et al. (2022) conceptualized DFL through four dimensions, namely awareness, skills and knowledge, attitude, and usage, each representing a distinct way in which people deal with an increasingly digital financial world.

Sri Lanka, like many developing economies, is moving toward a cashless society, and the Central Bank of Sri Lanka (CBSL) has observed growing adoption of mobile banking, online payments, and digital financial services (CBSL, 2021). This shift has taken place during a deep economic crisis marked by high inflation, currency depreciation, foreign currency shortages, and sovereign default in 2022 (Thilakarathna et al., 2024). The financial literacy score of Sri Lankan adults aged 20 and above is 57.9%, but financial risk awareness among young adults aged 18–29 remains weak (CBSL, 2021). Career-entry final-year undergraduates are a particularly vulnerable group within this age band, because they are moving from classroom learning to financial independence and the labor market with little experience of making financial decisions on their own (Kalinga et al., 2024; Perera et al., 2025). Generation Z students are digital natives, yet research indicates that they remain exposed to online fraud and impulsive spending (Goso et al., 2025; Oktaviana & Prasetya, 2026; Senduk et al., 2024), while those with higher DFL tend to budget better, save regularly, and avoid excessive debt (Ratnasari et al., 2025).

The transition from study to work is a formative period for financial behavior, because graduates must make financial decisions without parental guidance. The available evidence suggests that Sri Lankan youth face a real challenge in saving: 76% of youth are working or seeking work, but only 26% save regularly (ILO, 2023), and underemployment after graduation further weakens graduates' capacity to save (Perera et al., 2025).

Despite this, DFL is not evenly distributed among Sri Lankan undergraduates, and a gap remains between DFL and responsible personal financial management behavior (PFMB) among career-entry students. Earlier Sri Lankan studies have concentrated on management faculties or general student populations (Dewmini et al., 2023; Edirisinghe et al., 2017; Thilakarathna et al., 2024), leaving career-entry final-year undergraduates from non-management faculties largely unexamined. The evidence on digital financial attitude (DFAT) is also inconsistent. Dewmini et al. (2023) found no significant effect of attitude among management undergraduates from seven universities ($\beta = -.028$, $p = .745$), whereas Kalinga et al. (2024) found a significant positive effect among final-year undergraduates at the University of Sri Jayewardenepura ($\beta = .175$, $p = .002$). This divergence suggests that the role of attitude may depend on context and may be clarified by analyzing DFL dimension by dimension. This study addresses these gaps by examining the relationship between DFL and PFMB among final-year (career-entry) students from all six faculties of Wayamba University of Sri Lanka.

2. AIMS/OBJECTIVES

The general objective of the study is to examine the relationship between DFL and PFMB among career-entry, final-year undergraduates at Wayamba University of Sri Lanka, using the Theory of Planned Behavior (TPB; Ajzen, 1991) as the theoretical lens. Four specific objectives separately examine the relationship of DFA, DFSK, DFAT, and DFU with PFMB, controlling for the other three dimensions. A further aim is to help reconcile the divergent findings on DFAT reported in earlier Sri Lankan studies. The research question is: To what extent are the four dimensions of DFL associated with PFMB among career-entry undergraduates at Wayamba University of Sri Lanka?

3. THEORY

3.1 Theory of Planned Behavior and the Dimensions of DFL

The study is grounded in the TPB, which Ajzen (1991) developed as an extension of the Theory of Reasoned Action. The TPB holds that behavior follows from behavioral intention, which is shaped by attitude toward the behavior, subjective norms, and perceived behavioral control (PBC). Attitude is a person's evaluation of the behavior, subjective norms are perceived social pressures from family and peers, and PBC is perceived capability, including self-efficacy and skills (Ajzen, 1991; Ajzen & Madden, 1986).

The four DFL dimensions are linked to these components as follows. DFAT corresponds to attitude toward the behavior, because it captures favorable or unfavorable orientations toward saving, expense tracking, and financial responsibility. DFA and DFSK are treated as capability-related resources that inform PBC, because knowing the products, risks, and rights involved in digital finance, and

having the skills to operate digital tools, shape how capable a student feels in managing money. This mapping is an analytical approximation and not a direct operationalization of the TPB constructs. Behavioral intention and subjective norms were not measured, so the study examines TPB-informed antecedents of behavior rather than the full intention-mediated pathway. Ajzen (1991) argues that PBC can predict behavior directly to the extent that it reflects actual control, which supports treating DFA and DFSK as direct predictors.

3.2 The Position of Digital Financial Usage in the Model

DFU, the actual use of mobile banking, e-wallets, and online payments, is not an antecedent in the strict TPB sense. It is specified here as a direct, exogenous antecedent of PFMB for three reasons. First, DFU is a domain-specific behavior (how often students use digital channels), whereas PFMB is a broader set of money-management practices. Using digital channels is a different behavior from managing money well, although the two can reinforce each other. Second, research in the TPB tradition has recognized that past and habitual behavior can predict later behavior over and above intentions (Ajzen, 2002). Frequent use of digital financial tools produces feedback, such as transaction histories, balance alerts, and spending summaries, that can support budgeting and expense tracking. This is the "learning-by-doing" interpretation. Third, earlier Sri Lankan work has modeled usage as a direct predictor of financial behavior (Dewmini et al., 2023).

An alternative reading is that DFU is a mediating component, in which awareness, skills, and attitude shape usage, and usage in turn shapes PFMB. A single-equation regression using cross-sectional data cannot distinguish between the antecedent and mediation accounts. The study therefore specifies DFU as a direct antecedent and leaves the mediation account to future structural modeling (see Section 7.3).

3.3 Hypothesis Development

Digital financial awareness (DFA) is knowledge of digital financial products and services, the risks involved, and consumer rights (Azeez & Akhtar, 2021; Rahayu et al., 2022). Prasad et al. (2018) showed that awareness has a significant positive effect on the practical use of digital platforms in daily financial activities ($p < .05$), and Dewmini et al. (2023) found that DFA significantly and positively influenced the financial behavior of Sri Lankan management undergraduates ($\beta = .165$, $p = .039$). Rahayu and Suryadi (2026) similarly found DFA to be a significant predictor of personal financial management among Indonesian e-commerce users, while Rahim et al. (2022) reported that awareness of digital transaction risk contributed less than other DFL dimensions among students. Based on this evidence, the following hypothesis is proposed.

H1: DFA has a significant positive relationship with PFMB among career-entry final-year undergraduates at Wayamba University of Sri Lanka.

Digital financial skills and knowledge (DFSK) refer to the practical skills needed to use digital financial tools, such as using a mobile banking application, together with basic financial concepts (Edirisinghe et al., 2017; Lyons & Kass-Hanna, 2021). Dewmini et al. (2023) found financial skills to be a strong positive predictor of financial behavior ($\beta = .322$, $p < .001$). Ratnasari et al. (2025) reported that financial skills predicted saving behavior among fresh graduates in Indonesia ($\beta = .153$, $p = .007$), and Perera et al. (2025) reported a strong effect among fresh graduates in Sri Lanka ($\beta = .569$, $p < .001$). Accordingly, the following hypothesis is proposed.

H2: DFSK has a significant positive relationship with PFMB among career-entry final-year undergraduates at Wayamba University of Sri Lanka.

Digital financial attitude (DFAT) is a person's positive or negative orientation toward digital financial practices such as saving, borrowing responsibly, and contingency planning (Lyons & Kass-Hanna, 2021; Normawati et al., 2021). The evidence is conflicting. Dewmini et al. (2023) found no significant effect ($\beta = -.028$, $p = .745$), whereas Kalinga et al. (2024) found a significant positive effect among final-year undergraduates at another Sri Lankan university ($\beta = .175$, $p = .002$). Because a positive attitude remains an important determinant of behavior in the TPB (Normawati et al., 2021), but the empirical direction is unsettled, H3 is stated in non-directional form.

H3: DFAT has a significant relationship with PFMB among career-entry final-year undergraduates at Wayamba University of Sri Lanka.

Digital financial usage (DFU) is the actual use of digital financial services, including mobile banking, e-wallets, and online payments (Rajdev et al., 2020; Setiawan et al., 2022). Dewmini et al. (2023) found DFU to be the most influential of the four dimensions in predicting financial behavior ($\beta = .487$, $p < .001$), and Setiawan et al. (2022) concluded that digital usage positively influences saving and spending behavior. Thus, the following hypothesis is proposed.

H4: DFU has a significant positive relationship with PFMB among career-entry final-year undergraduates at Wayamba University of Sri Lanka.

The dependent variable, PFMB, refers to the practices through which individuals manage their personal finances, which in this study comprise budgeting, regular saving, spending control, and debt and bill management (Hilgert et al., 2003; Kalinga et al., 2024; Perera et al., 2025). The conceptual framework treats DFA, DFSK, DFAT, and DFU as distinct constructs, each hypothesized to relate directly to PFMB. The word "effect" in the title and objectives is used in the statistical sense of a predictor's contribution within the regression model and does not imply causation.

4. METHODS

4.1 Research Design

The study follows a positivist philosophy, which assumes an objective and measurable reality that can be studied through systematic observation and statistical analysis (Saunders et al., 2019). A deductive approach was used, building on the TPB and earlier empirical findings to develop and test four hypotheses. Primary data were collected through a structured online questionnaire administered with Google Forms, using a cross-sectional survey strategy comparable to other DFL studies (Dewmini et al., 2023; Kalinga et al., 2024; Oktaviana & Prasetya, 2026).

4.2 Population and Sampling

The target population comprised approximately 1,604 career-entry final-year undergraduates across the six faculties of Wayamba University of Sri Lanka. Krejcie and Morgan (1970) recommend a minimum sample of 310–320 for a population of this size at a 95% confidence level and a 5% margin of error. To allow for non-response and incomplete questionnaires, 350 respondents were targeted. Stratified random sampling was used because the faculties are distinct groups that are likely to differ in DFL and PFMB (Sekaran & Bougie, 2016).

Table 1. Stratified Sample Allocation and Achieved Responses by Faculty

Faculty	Population	Target	Achieved	Valid response (%)	Share of sample (%)
Business Studies and Finance	550	120	118	98.3	37.7
Applied Sciences	300	65	54	83.1	17.3
Medicine	250	55	43	78.2	13.7
Technology	200	44	39	88.6	12.5
Agriculture and Plantation Management	180	39	34	87.2	10.9
Livestock, Fisheries and Nutrition	124	27	25	92.6	8.0
Total	**1,604**	**350**	**313**	**89.4**	**100.0**

Note. Faculty populations are approximate figures from university records. Valid response (%) = achieved ÷ target.

The target number for each faculty was set by proportional allocation, $n^i = (N^i / N) \times 350$, where N^i is the faculty population and N is the total population. Within each faculty, students were selected from the official student list using a random number generator, and invitations were sent through university email lists, faculty messaging

groups, and social media, with weekly reminders. Table 1 shows the target and achieved sample for each faculty. A total of 37 questionnaires were removed because they were incomplete or inconsistent, which left 313 valid, analyzable responses (89.4% of the 350 targeted). Postgraduate, part-time, and non-final-year students, and students without personal experience of managing their own finances, were excluded.

4.3 Measures and Construct Validity

All constructs were measured on a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree), using items adapted from validated earlier instruments. DFA was measured with three items, adapted from Azeez and Akhtar (2021), Dewmini et al. (2023), and Setiawan et al. (2022), covering awareness of digital financial services, risks in digital transactions, and consumer rights. DFSK was measured with three items based on mobile banking use (Lyons & Kass-Hanna, 2021), financial terminology (Dewmini et al., 2023), and independent digital money management (Edirisinghe et al., 2017). DFAT was measured with three items, adapted from Normawati et al. (2021), Dewmini et al. (2023), and Kalinga et al. (2024), relating to saving preference, expense tracking, and financial responsibility. DFU was measured with three items, adapted from Rajdev et al. (2020), Dewmini et al. (2023), and Rahayu and Suryadi (2026), on the frequency of mobile banking, e-wallet, and online payment use. PFMB was measured with four items adapted from Hilgert et al. (2003), Kalinga et al. (2024), Perera et al. (2025), and Dewmini et al. (2023). Demographic questions covered gender, age, faculty, and monthly income or allowance. The questionnaire was pre-tested with a small group of final-year students to check clarity and wording before full deployment.

Because PFMB is multidimensional, the use of four items requires justification. Each PFMB item targets a different behavioral domain: budgeting against income and spending, regular saving, control of impulse spending, and avoidance of unnecessary debt together with timely bill payment. The four items therefore work as a compact behavioral index in which each domain is represented by one statement, and not as four interchangeable indicators of a single narrow trait. Short measures can be defensible when the construct is concrete and its domains are covered (Diamantopoulos et al., 2012), and they reduce respondent burden in online surveys. The limits of this choice are clear. A single item cannot capture a domain in depth, so the claim is one of broad coverage and not comprehensive measurement. Investing is not covered by any PFMB item, so the construct is defined in this study as budgeting, saving, spending control, and debt management, and the findings should not be generalized to investment behavior. With one item per domain, reliability within a domain cannot be assessed. These constraints are acknowledged as a primary design limitation in Section 7.3.

4.4 Data Analysis and Ethical Considerations

Data were analyzed using SPSS 23.0. Internal consistency was assessed with Cronbach's alpha, calculated separately for each of the five scales (DFA, DFSK, DFAT, DFU, and PFMB) and for the combined instrument, using .70 as the threshold for acceptable reliability (Nunnally & Bernstein, 1994; Sekaran & Bougie, 2016). Descriptive statistics profiled the sample, Pearson correlation examined bivariate relationships, and multiple linear regression tested the joint and individual contribution of the four DFL dimensions to PFMB, as specified in Equation (1).

$$PFMB = \beta_0 + \beta_1 DFA + \beta_2 DFSK + \beta_3 DFAT + \beta_4 DFU + \varepsilon (1)$$

where PFMB is personal financial management behavior, β^0 is the intercept, β^1 to β^4 are the coefficients of DFA, DFSK, DFAT, and DFU, and ε is the error term. Residual diagnostics (the histogram and normal P-P plot of standardized residuals) indicated approximately normal residuals and an acceptable linear relationship, and no correlation among predictors approached the .80–.90 range that signals multicollinearity. Hypotheses were tested at the .05 level.

Respondents were informed of the purpose of the study, participation was voluntary and anonymous, and informed consent was obtained through the online form before data collection began. No personally identifying information was collected.

5. RESULTS

5.1 Respondent Profile

Table 2. Demographic Profile of Respondents (*N* = 313)

Variable	Category	Frequency	Percent (%)
Gender	Female	187	59.7
	Male	126	40.3
Age	20–22 years	26	8.3
	23–25 years	150	47.9
	26–28 years	100	31.9
	29 years and above	37	11.8
Monthly income/allowance	Less than Rs. 10,000	50	16.0
	Rs. 10,000–20,000	91	29.1
	Rs. 20,001–30,000	92	29.4
	Rs. 30,001–50,000	49	15.7
	More than Rs. 50,000	31	9.9

Note. Percentages may not sum to 100 because of rounding.

Of the 313 respondents, 187 (59.7%) were female and 126 (40.3%) were male. The largest age group was 23–25 years (47.9%), followed by 26–28 years (31.9%), 29 years and above (11.8%), and 20–22 years (8.3%). The faculty distribution is shown in Table 1, with the Faculty of Business Studies and Finance contributing the largest share (37.7%). The most frequent monthly income or allowance band was Rs. 20,001–30,000 (29.4%), followed closely by Rs. 10,000–20,000 (29.1%). Table 2 presents the demographic profile.

5.2 Reliability

Table 3 reports Cronbach's alpha separately for each scale. The combined instrument had an alpha of .961.

Table 3. Cronbach's Alpha Reliability by Scale

Scale	Number of items	Cronbach's α
Digital Financial Awareness (DFA)	3	.812
Digital Financial Skills and Knowledge (DFSK)	3	.784
Digital Financial Attitude (DFAT)	3	.796
Digital Financial Usage (DFU)	3	.831
Personal Financial Management Behavior (PFMB)	4	.768
Combined instrument	All items	.961

Note. α = Cronbach's alpha. Source: SPSS output.

5.3 Correlation Analysis

All four DFL dimensions were positively and significantly correlated with PFMB at the .01 level ($p < .001$; Table 4). DFA had the highest correlation with PFMB ($r = .380$), followed by DFU ($r = .302$), DFAT ($r = .269$), and DFSK ($r = .263$). Correlations among the four predictors were significant but moderate, with the highest being between DFSK and DFU ($r = .422$), well below the .80–.90 range associated with multicollinearity.

Table 4. Pearson Correlation Matrix (*N* = 313)

Variable	DFA	DFSK	DFAT	DFU	PFMB
DFA	—				
DFSK	.335**	—			
DFAT	.271**	.416**	—		
DFU	.377**	.422**	.329**	—	
PFMB	.380**	.263**	.269**	.302**	—

Note. DFA = digital financial awareness; DFSK = digital financial skills and knowledge; DFAT = digital financial attitude; DFU = digital financial usage; PFMB

= personal financial management behavior. ** $p < .01$ (two-tailed). Source: SPSS output.

5.4 Multiple Regression and Hypothesis Testing

The regression model was statistically significant, $F(4, 308) = 109.464$, $p < .001$, with $R = .720$, $R^2 = .519$, adjusted $R^2 = .514$, and a standard error of the estimate of .240. Table 5 presents the standardized (β) and unstandardized (B) coefficients. DFA (β = .276, $p < .001$), DFAT (β = .125, $p = .031$), and DFU (β = .131, $p = .029$) were significant predictors, while DFSK was not (β = .064, $p = .292$). H1, H3, and H4 were therefore supported, and H2 was not supported.

Table 5. Multiple Regression Results and Hypothesis Testing

Hypothesis	Predictor	*B*	β	*t*	*p*	Decision
	Constant	1.633		4.950	< .001	
H1	DFA → PFMB	.290	.276	4.854	< .001	Supported
H2	DFSK → PFMB	.064	.064	1.057	.292	Not supported
H3	DFAT → PFMB	.130	.125	2.171	.031	Supported
H4	DFU → PFMB	.142	.131	2.199	.029	Supported

Note. Dependent variable: PFMB. R^2 = coefficient of determination (proportion of variance in PFMB explained by the four predictors) = .519; adjusted $R^2 = .514$; $F(4, 308) = 109.464$, $p < .001$. B = unstandardized coefficient; β = standardized coefficient. Source: SPSS output.

6. DISCUSSION

The results show that DFL is not a uniformly influential construct. Three of the four dimensions, namely awareness, attitude, and usage, were significant predictors of PFMB, whereas skills and knowledge were not. The discussion below treats each dimension in turn and then evaluates the study's own method. Because the data are cross-sectional, all relationships are interpreted as associations.

DFA was the strongest predictor of PFMB (β = .276), which supports H1. The direction agrees with Dewmini et al. (2023) and Prasad et al. (2018), although the coefficient found here is larger than the β = .165 reported by Dewmini et al. (2023) for management undergraduates. A possible reason is that awareness of fraud, data theft, and other digital risks has become more consequential for young adults entering the workforce during Sri Lanka's economic crisis and recovery. This explanation was not tested, and differences in samples and measures may also contribute.

DFSK was positively correlated with PFMB ($r = .263$, $p < .001$), but it was not a significant predictor once the other dimensions were controlled (β = .064, $p = .292$), so H2 was not supported. This contrasts with Dewmini et al. (2023) and Perera et al.

(2025), who identified financial skills as a strong predictor. One likely explanation is shared variance: DFSK correlates fairly strongly with DFU (r = .422) and DFAT (r = .416), so its bivariate association with PFMB may be largely absorbed by those dimensions. Students who are technically competent may still not manage their money consistently unless they also use digital tools actively and hold a positive attitude toward financial management. The skills items are also self-assessed, and confident users of digital tools may rate their skills highly regardless of their behavior, which would weaken the link with PFMB.

DFAT was a significant positive predictor of PFMB (β = .125, p = .031), which supports H3. The result agrees with Kalinga et al. (2024; β = .175, p = .002) and differs from Dewmini et al. (2023), who found no significant effect among management undergraduates from seven universities. This pattern is consistent with the view that the role of attitude depends on context, and that it may matter more at the point of career entry, when financial responsibility becomes personally salient, as the attitude component of the TPB would suggest (Ajzen, 1991). Because the studies differ in population, sampling, and measurement, why the findings diverge remains unresolved.

DFU was a significant positive predictor of PFMB (β = .131, p = .029), which supports H4 and agrees with Dewmini et al. (2023), Setiawan et al. (2022), and Rajdev et al. (2020). The result is consistent with the learning-by-doing interpretation outlined in Section 3.2. The data cannot show whether usage leads to better financial management, whether students who already manage money well adopt digital tools more readily, or whether usage transmits the influence of awareness and attitude, as a mediation account would imply. The distinction between a direct antecedent and a mediating role therefore remains open and requires longitudinal or structural-equation evidence.

Several features of the method deserve critical evaluation. Proportional stratified allocation improved faculty representation, but achieved response rates ranged from 78.2% in Medicine to 98.3% in Business Studies and Finance (Table 1), so the realized sample under-represents some faculties relative to the target. Invitations were circulated through email lists, messaging groups, and social media, which introduces the possibility of self-selection even though individuals were drawn randomly from official lists. All variables were self-reported, so social desirability may inflate the behavior scores. The five scales are short, and PFMB in particular is a four-item index that does not cover investing. Finally, the regression treats the predictors as parallel direct antecedents, which simplifies their interrelationships, so the coefficients should be read as conditional associations within one cohort.

7. IMPLICATIONS AND LIMITATIONS

7.1 Implications for Theory

The study applies the TPB to the digital financial domain in a developing economy and shows that disaggregating DFL gives a richer picture than a single composite. Awareness, attitude, and usage were each associated with PFMB, whereas skills and knowledge were necessary but not sufficient once the other dimensions were considered. The DFAT result adds evidence to the debate on attitude, consistent with Kalinga et al. (2024) and in contrast with Dewmini et al. (2023), and suggests that its effect may be more context-specific than often assumed. The study also clarifies the theoretical position of usage: DFU is treated as an experience-based antecedent in the spirit of research on past behavior (Ajzen, 2002), with mediation left as an explicit alternative. Because intention and subjective norms were not measured, the study is a partial test of the TPB and does not establish the full intention-based pathway.

7.2 Implications for Practice

Universities such as Wayamba University of Sri Lanka could include targeted digital financial education in final-year co-curricular activities, emphasizing awareness of digital financial risks and positive financial attitudes, and encouraging experiential learning with digital tools instead of theory alone. Financial institutions could design youth-oriented digital products with built-in educational modules and risk-awareness features. The Central Bank of Sri Lanka and other policymakers could adopt a usage-based, dimension-specific approach within national financial education strategy, and employers of new graduates could offer financial wellness programs to support the transition from student to employee. These recommendations follow from associations in one university and should be piloted and evaluated before wider adoption.

7.3 Limitations and Directions for Future Research

The most important design limitation concerns measurement. PFMB was measured with four items, one for each of four behavioral domains, so the scale cannot capture the full multidimensional domain of financial management behavior, and it does not measure investing at all. Future studies should use fuller validated multi-item scales for each behavioral domain, including investment, and should analyze budgeting, saving, spending control, and debt management as separate outcomes to identify where DFL matters most.

Further limitations concern design and generalizability. The study covers a single institution, so the findings may not transfer to other universities. The cross-sectional design cannot establish causal direction or capture the transition from university to work. Self-reported measures may be affected by social desirability, and recruitment through online channels may have introduced self-selection. The model leaves a substantial share of variance unexplained, and it omits other plausible influences

such as peer effects, financial self-efficacy, and locus of control, as well as the TPB constructs of intention and subjective norms. Future research could replicate the model at other universities, use longitudinal designs to follow students into employment, combine self-reports with objective financial data, test the mediating role of usage through structural equation modeling, and add qualitative interviews or focus groups to explain why skills and knowledge translate less readily into behavior than awareness, attitude, and usage.

In conclusion, digital financial literacy is associated with the financial management behavior of career-entry undergraduates, but not equally across its dimensions. Programs that build awareness, positive attitudes, and active use of digital services may serve graduating students better than those that focus on knowledge alone.

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Financial Markets and Investments

Impact of Bank Size on Liquidity Creation in Sri Lankan Listed Banks

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ABSTRACT

This study examines the association between bank size and liquidity creation in Sri Lankan listed banks. It uses a balanced panel of 12 listed private banks over 2015–2024 (120 bank-year observations). Liquidity creation is measured with the maturity-based, non-fat measure of Berger and Bouwman (2009), adapted to the maturity disclosures in Sri Lankan annual reports, in absolute terms (Rs '000) and relative to total assets. Two bank fixed-effects panel regressions with cluster-robust standard errors are estimated, with the non-performing loan ratio and the Tier 1 capital adequacy ratio as controls. Bank size, measured as the natural logarithm of total assets, has a positive and significant association with absolute liquidity creation (β = 81,703,936; $p < 0.01$). A 1% increase in total assets is associated with about Rs 813 million more liquidity creation. In contrast, size has a negative and significant association with liquidity creation per unit of assets ($\beta = -0.0512$; $p < 0.05$). Larger banks therefore create more liquidity in total but less per rupee of assets. The size coefficient is larger in 2020–2024 than in 2015–2019, but a formal equality test shows that the difference is significant only at the 10% level ($z = 1.66$; $p = 0.096$). The non-performing loan ratio is positively associated with absolute liquidity creation, while capital adequacy is not significant at the 5% level. The results suggest scale effects in the volume of liquidity creation without proportional gains in intensity. These are associations rather than causal effects, and they offer evidence for bank managers and regulators in Sri Lanka's concentrated banking system.

Keywords: Bank size; Liquidity creation; Economies of scale; Fixed-effects panel regression; Sri Lankan listed banks

JEL Classification: G21; G28; C23

1. INTRODUCTION

Banks create liquidity when they finance illiquid assets, such as long-term loans, with liquid liabilities, such as demand and savings deposits. This lets depositors hold funds they can withdraw at short notice while borrowers receive long-term finance, and it is a main reason banks exist (Bryant, 1980; Diamond & Dybvig, 1983). Berger and Bouwman (2009) made the concept measurable by weighting each balance-sheet item by its liquidity. Liquidity creation has been linked to real economic output (Berger & Sedunov, 2014) and to monetary policy transmission and bank behaviour in crises (Berger & Bouwman, 2017).

The topic is especially relevant in Sri Lanka, where capital markets are shallow and banks are the main channel from savings to investment (Levine, 1997). The banking sector is concentrated in a few large domestic banks. Between 2015 and 2024, banks operated through relative stability, the COVID-19 pandemic, the 2022 sovereign debt crisis and the early recovery, which placed different pressures on banks of different sizes. How bank size relates to liquidity creation therefore matters for bank strategy and prudential supervision.

The research problem is that theory and evidence do not give a clear prediction of how bank size relates to liquidity creation, and the existing evidence comes mostly from other settings. The research gap can be stated in four parts.

Theoretical gap can be explained where economies of scale and the "too big to fail" argument predict that larger banks create more liquidity, while relationship-lending and fragility arguments suggest that smaller banks may create more liquidity relative to their size (Berger & Bouwman, 2009). These predictions differ between liquidity in total and per unit of assets, yet few studies examine both together.

Empirical gap is there as evidence is mixed and depends on time and context. For US banks, the size relationship changed sign after the 2007–2009 crisis (Niu, 2021), and macroeconomic conditions explain more variation in liquidity creation than bank-specific factors (Duan & Niu, 2023). Studies from India, Vietnam, Indonesia and the ASEAN-5 report different patterns (Gupta & Kashiramka, 2020; Pham et al., 2021; Tran & Tran, 2025; Viverita et al., 2022). Sri Lankan studies have examined statutory liquidity and asset–liability management (Madhushani & Perera, 2022; Manel Damayanthi & Gunawardhana, 2023), but not liquidity creation as defined by Berger and Bouwman (2009).

The category-based Berger and Bouwman (2009) measure needs a loan and deposit classification that Sri Lankan annual reports do not consistently disclose, so a transparent adaptation of the maturity-based measure is needed to answer for the methodological gap.

There is also a practical gap as The Central Bank of Sri Lanka (CBSL) supervises banks of very different sizes under common rules. Evidence on whether larger banks

create more liquidity in total and per unit of assets can inform supervision and bank strategy.

This study addresses these gaps with 12 listed private banks over 2015–2024. It contributes (i) a replicable adaptation of the maturity-based measure to Sri Lankan disclosures, (ii) joint estimates for absolute and relative liquidity creation, and (iii) a formal test of whether the size coefficient differs before and after 2020. To the authors' knowledge, this is among the first studies to apply the Berger and Bouwman framework to Sri Lankan listed banks.

2. AIMS/OBJECTIVES

The main objective is to examine and quantify the association between bank size and liquidity creation in Sri Lankan listed banks, in absolute and relative terms. The sub-objectives are (i) to assess whether the evidence is consistent with economies or diseconomies of scale, (ii) to compare the relationship between 2015–2019 and the crisis and recovery period 2020–2024, and (iii) to control for asset quality (non-performing loan ratio) and capital adequacy (Tier 1 ratio). Return on assets was planned as a control but excluded (see Methods). Two hypotheses are tested:

$H0_1$: Bank size has no significant impact on liquidity creation in Sri Lankan listed banks. $H1_1$: Bank size has a significant impact on liquidity creation in Sri Lankan listed banks. H1 is tested separately for absolute liquidity creation (Model 1, H1a) and relative liquidity creation (Model 2, H1b).

$H0_2$: There are no economies of scale in liquidity creation activities of Sri Lankan listed banks. $H1_2$: There are economies of scale in liquidity creation activities of Sri Lankan listed banks. Economies of scale in volume are inferred from a positive size coefficient in Model 1, while efficiency per unit of assets is assessed from the size coefficient in Model 2.

3. THEORY

Liquidity transformation theory holds that banks issue liquid claims, hold illiquid assets and bear the resulting maturity and liquidity risk (Bryant, 1980; Diamond & Dybvig, 1983). Banks also reduce information and transaction costs between savers and firms (Levine, 1997), and they can create liquidity off the balance sheet through loan commitments (Holmstrom & Tirole, 2000). Several mechanisms link bank size to liquidity creation, with different predictions for absolute and relative liquidity creation.

Larger banks spread the fixed costs of technology, risk management and funding-market access over more assets, which lowers the cost of supplying liquidity (Pham et al., 2021). This predicts a positive size effect on absolute liquidity creation. It predicts a positive effect on relative liquidity creation only if scale also shifts the balance sheet towards illiquid assets and liquid liabilities.

Systemically important banks may expect public support, which lowers funding costs, weakens market discipline and encourages illiquid asset holdings (Casu et al., 2019). This also predicts a positive size effect, particularly under stress.

Under risk absorption, capital lets banks bear the risk of illiquid assets, so better-capitalised banks create more liquidity. Under financial fragility–crowding out, capital weakens the discipline of fragile deposit funding and crowds out deposits, so it reduces liquidity creation. Berger and Bouwman (2009) find the first effect dominant for large US banks and the second for small banks, and other evidence shows the capital–liquidity link depends on bank type and context (Distinguin et al., 2013; Horváth et al., 2013).

Larger banks may face more organisational complexity and larger regulatory liquidity buffers, and in shallow capital markets they may hold more government securities. This raises assets without raising liquidity creation in proportion, predicting a negative size effect on relative liquidity creation, while smaller banks may focus on higher-intensity relationship and retail lending (Viverita et al., 2022).

Very high liquidity creation concentrates risk on both sides of the balance sheet and can raise failure risk (Fungacova et al., 2015), and its link with stability varies with bank size and economic development (Tran & Tran, 2025).

Empirically, large US banks created about 85% of industry liquidity while being a small share of banks (Berger & Bouwman, 2009), and the size relationship changed after the 2007–2009 crisis (Niu, 2021). In Vietnam, monetary tightening reduced liquidity creation more for small banks because large banks had wider funding access (Pham et al., 2021). In India, liquidity creation was linked to bank stability (Gupta & Kashiramka, 2020). This study therefore expects a positive association between size and absolute liquidity creation, while the sign for relative liquidity creation is an empirical question.

4. METHODS

The study uses a quantitative, explanatory design with secondary panel data. The population is the licensed banks in Sri Lanka. A bank was included if it (i) was listed on the Colombo Stock Exchange, (ii) was privately owned, and (iii) published annual reports with maturity analyses of assets and liabilities, Basel III capital disclosures and asset-quality data for every year from 2015 to 2024. The two state-owned banks, Bank of Ceylon and People's Bank, were excluded because their lending is partly directed by government policy and their deposit funding is supported by the state, which makes their liquidity creation not comparable with that of private banks (Madhushani & Perera, 2022). Because state banks hold a large share of system assets, the results apply to listed private banks and should not be generalised to the whole banking system. The final sample is a balanced panel of 12 banks and 120 bank-year observations (Table 1). Data were taken from the annual reports published

on the Colombo Stock Exchange website, compiled in Excel and analysed in EViews 12.

Table 1: Sample Banks (Listed Private Banks, 2015–2024)

No.	Bank	No.	Bank
1	Commercial Bank of Ceylon PLC	7	Nations Trust Bank PLC
2	Hatton National Bank PLC	8	Pan Asia Banking Corporation PLC
3	Sampath Bank PLC	9	Amana Bank PLC
4	Seylan Bank PLC	10	Union Bank of Colombo PLC
5	National Development Bank PLC	11	HDFC Bank of Sri Lanka
6	DFCC Bank PLC	12	Sanasa Development Bank PLC

Note. Banks with average 2015–2024 total assets of Rs 500 billion or more (the CBSL threshold for domestic systemically important banks, Banking Act Direction No. 01 of 2016) are classified as large (5 banks); the other 7 are small.

Liquidity creation is measured with the maturity-based, non-fat ("mat non-fat") measure of Berger and Bouwman (2009). The category-based measure could not be used because Sri Lankan annual reports do not consistently classify loans and deposits by category, while all sample banks disclose asset and liability maturities in a maturity-analysis note. Off-balance-sheet items are excluded because they are disclosed inconsistently and are relatively small in emerging-market banks (Horváth et al., 2013). In three steps, each item in the maturity note is classified as up to one year or more than one year, weighted as in Table 2, and summed to obtain absolute liquidity creation (LC) for each bank-year:

$$LC = 0.5 \times \text{Illiquid assets} + 0.5 \times \text{Liquid liabilities} - 0.5 \times \text{Liquid assets} - 0.5 \times \text{Illiquid liabilities} - 0.5 \times \text{Equity}$$

Absolute liquidity creation is in Rs '000. Relative liquidity creation is LC divided by total assets, expressed as a fraction (0.16 means Rs 0.16 of liquidity per rupee of assets). A negative value means that the bank destroys rather than creates liquidity in that year.

Bank size is the natural logarithm of total assets (LnTA), in Rs '000. Asset quality is the ratio of non-performing loans to total loans, and capital adequacy is the ratio of Tier 1 capital to risk-weighted assets (CBSL minimum 10%). Return on assets was also collected. Both ratios are expressed as fractions before transformation and enter the models in natural logarithms (LnNPL and LnCAR). The log transformation was used because the levels of both ratios failed the panel unit-root test, while their logarithms passed it (Table 4). The logs also reduce the right skew of both ratios.

Table 2: Liquidity Classification and Weights (Maturity-Based Measure)

Balance-sheet item	Classification	Weight
Assets with residual maturity above one year (e.g., long-term loans and investments)	Illiquid assets	+0.5
Liabilities with residual maturity up to one year (e.g., demand, savings and short-term deposits)	Liquid liabilities	+0.5
Assets with residual maturity up to one year (e.g., cash, short-term loans, short-term securities)	Liquid assets	−0.5
Liability with residual maturity above one year (e.g., long-term deposits, debentures, borrowings)	Illiquid liabilities	−0.5
Total equity	Equity	−0.5

Note. Adapted from Berger and Bouwman (2009). Maturity buckets are taken from the maturity-analysis note of each annual report. Off-balance-sheet items are not included.

Two bank fixed-effects models are estimated:

$$Model\ 1:\ LC_it = \beta 0 + \beta 1\ LnTA_it + \beta 2\ LnNPL_it + \beta 3\ LnCAR_it + \mu_i + \varepsilon_it$$

$$Model\ 2:\ LCR_it = \gamma 0 + \gamma 1\ LnTA_it + \gamma 2\ LnNPL_it + \gamma 3\ LnCAR_it + \mu_i + \varepsilon_it$$

Here LC_it is absolute liquidity creation (Rs '000) of bank i in year t, LCR_it is LC divided by total assets, LnTA_it, LnNPL_it and LnCAR_it are the natural logarithms of total assets, the NPL ratio and the Tier 1 capital ratio, μ_i is a bank fixed effect capturing time-invariant differences between banks, and ε_it is the error term. The models include bank (cross-section) fixed effects only; time fixed effects are not included, so common year-specific shocks are not absorbed by the models. Because both models are level–log specifications, β1/100 approximates the change in LC (Rs '000) for a 1% increase in total assets; the exact value is β1 × ln(1.01).

After descriptive statistics and Pearson correlations, the Levin, Lin and Chu (LLC) panel unit-root test, with individual effects and one lag, was applied to each variable. Return on assets, its logarithm and its first-differenced logarithm all failed the test (Table 4), so return on assets was excluded to avoid a spurious regression, and NPL and CAR entered in logarithms. Multicollinearity was checked with variance inflation factors (VIF), and the Hausman test compared fixed and random effects. The models were estimated by least squares with bank fixed effects and White cross-section (period-cluster) standard errors, which are robust to heteroskedasticity and within-period correlation. For robustness, Model 1 was re-estimated for 2015–2019 and 2020–2024, and the difference between the two size coefficients was tested with the z-test of Paternoster et al. (1998).

5. RESULTS

Table 3 summarizes the variables. Mean absolute liquidity creation is about Rs 114.1 billion per bank-year, but the median is only about Rs 41.2 billion, so a few large banks create most of the liquidity. Values range from −Rs 92.3 billion to Rs 719.7

billion. On average a bank creates Rs 0.16 of liquidity per rupee of assets. The five large banks create about 85% of the total absolute liquidity in the sample. Compared with small banks, large banks have higher mean LnTA (20.61 versus 18.82) and ROA (1.20% versus 0.97%), lower Tier 1 capital ratios (11.92% versus 15.02%) and lower NPL ratios (4.73% versus 6.23%).

Table 3: Descriptive Statistics (N = 120)

Variable	Unit	Mean	Median	Std. dev.	Min	Max
LC	Rs '000	114,109,212	41,224,587	168,471,115	−92,297,341	719,730,474
LnTA	ln (Rs '000)	19.563	19.626	1.114	17.551	21.749
NPL ratio	fraction	0.0561	0.0448	0.0451	0.0089	0.2450
Tier 1 CAR	fraction	0.1373	0.129	0.0443	0.0782	0.3541
ROA	fraction	0.0107	0.010	0.0052	–0.003	0.032

Note: Results processed using EViews 12 Student Version Lite

LnTA is strongly correlated with absolute liquidity creation (r = 0.765) and weakly with relative liquidity creation (r = 0.288). LC has small correlations with LnNPL (r = 0.009) and LnCAR (r = −0.071). The largest correlation between explanatory variables is −0.339 (LnTA and LnCAR).

Table 4: Diagnostic Test Results

Test	Variable or model	Statistic	p-value	Decision
LLC unit root	LC; LCR; LnTA		0.0006; 0.0093; 0.0054	Stationary
LLC unit root	LnNPL; LnCAR		0.0155; 0.0257	Stationary
LLC unit root	NPL; CAR (levels)		0.1545; 0.1589	Non-stationary
LLC unit root	ROA; LnROA; D(LnROA)		0.7643; 0.4598; 0.2441	Non-stationary; excluded
VIF (centred)	LnTA; LnNPL; LnCAR; LnROA	1.228; 1.132; 1.341; 1.125		No multicollinearity
Hausman	Fixed vs random effects	$\chi^2(3) = 8.718$	0.0333	Fixed effects
Jarque–Bera	Model 1 / Model 2 residuals	322.57 / 244.94	0.000 / 0.000	Non-normal

Note. LLC = Levin, Lin and Chu test with individual effects and one lag (96 balanced observations).

Table 4 reports the diagnostic tests. All model variables are stationary at the 5% level, while NPL and CAR in levels and all forms of ROA are not. All centred VIF values are below 1.4. The Hausman test rejects random effects ($\chi^2 = 8.72$; $p = 0.033$), supporting fixed effects. The Jarque–Bera test rejects residual normality in both models, so inference relies on cluster-robust standard errors. The Durbin–Watson statistic of Model 1 (1.02) suggests possible positive serial correlation, which the period-cluster standard errors only partly address.

5.1. Model 1: Bank size and absolute liquidity creation

Table 5 reports the fixed-effects estimates. In Model 1, LnTA has a positive and significant coefficient (β1 = 81,703,936; t = 4.820; p = 0.0009). Because LC is in Rs '000 and size is in logarithms, this is the change in LC for a one-unit change in LnTA (a 172% increase in assets), about Rs 81.7 billion. For a 1% increase in total assets, the associated increase is about Rs 813 million (81,703,936 × ln 1.01 ≈ Rs '000 812,981), holding the controls and bank fixed effect constant. $H0_1$ is rejected for absolute liquidity creation (H1a). LnNPL is also positive and significant (β2 = 30,021,025; p = 0.0023): a 1% higher NPL ratio is associated with about Rs 299 million more liquidity creation. LnCAR is significant only at the 10% level (p = 0.0807). The model explains 84.5% of the variation in LC (adjusted R^2 = 0.824).

Table 5: Fixed-Effects Estimates for Absolute and Relative Liquidity Creation (N = 120)

Variable	Model 1: LC (Rs '000) Coefficient	Model 1 t-stat	Model 2: LCR (fraction) Coefficient	Model 2 t-stat
LnTA	81,703,936***	4.820	−0.0512**	−3.094
LnNPL	30,021,025***	4.203	0.0060	0.330
LnCAR	43,675,915*	1.967	−0.0025	−0.052
Constant	−1,300,000,000***	−3.544	1.1761**	3.091
Bank fixed effects	Yes		Yes	
Time fixed effects	No		No	
R^2 / Adjusted R^2	0.845 / 0.824		0.568 / 0.511	
F-statistic	40.85***		9.88***	

*Note. White cross-section (period-cluster) robust standard errors. The p-values are 0.0009, 0.0023 and 0.0807 for Model 1 and 0.0129, 0.7491 and 0.9598 for Model 2 (LnTA, LnNPL and LnCAR respectively). The Model 1 constant is reported by EViews as −1.30E+09. * p < 0.10, ** p < 0.05, *** p < 0.01.*

5.2. Model 2: Bank size and relative liquidity creation

In Model 2, LnTA has a negative and significant coefficient (γ1 = −0.0512; t = −3.094; p = 0.0129). A 1% increase in total assets is associated with a fall of about 0.0005 in the liquidity creation ratio (about 0.05 percentage points), holding the controls constant. $H0_1$ is therefore also rejected for relative liquidity creation (H1b), with a negative sign. Neither LnNPL (p = 0.749) nor LnCAR (p = 0.960) is significant, and the lower adjusted R^2 (0.511) indicates that other factors also explain liquidity creation per unit of assets.

5.3. Sub-period analysis and equality test

Table 6 re-estimates Model 1 for 2015–2019 and 2020–2024. The size coefficient is positive and significant at the 5% level in both periods: 55,682,636 (p = 0.020) before 2020 and about 132,006,433 (p = 0.038) from 2020, or about Rs 554 million and Rs

1,314 million per 1% increase in assets. The equality test gives z = 1.66 (p = 0.096), so the difference is significant only at the 10% level and the evidence of a stronger size effect after 2020 is weak. The NPL coefficient (29,003,493 before 2020, p = 0.095; 14,737,087 after, p = 0.152) is not significant at the 5% level in either period. The pre-2020 NPL and CAR values were rechecked against the EViews output, correcting transcription errors in the earlier version. With 60 observations and 12 clusters per period, these estimates are less precise than the full-sample results.

Table 6: Sub-Period Estimates for Absolute Liquidity Creation (Model 1)

Variable	2015–2019 Coefficient	2015–2019 t-stat	2020–2024 Coefficient	2020–2024 t-stat
LnTA	55,682,636**	3.723	132,006,433**	3.045
LnNPL	29,003,493*	2.178	14,737,087	1.769
LnCAR	67,347,101*	2.166	−326,829	−0.007
Constant	−750,000,000*	−2.674	−2,430,000,000*	−2.652
R^2 / Adjusted R^2	0.798 / 0.736		0.965 / 0.954	
Observations	60		60	
Equality test, LnTA (2020–2024 vs 2015–2019)	z = 1.66; p = 0.096			

*Note. Bank fixed effects and White cross-section (period-cluster) standard errors in both periods. The p-values for LnTA are 0.0204 (2015–2019) and 0.0382 (2020–2024). EViews reports the 2020–2024 LnTA coefficient as 1.32E+08; the value shown is the standard error (43,356,451) multiplied by the t-statistic. The equality test is $z = (b_2 - b_1)/\sqrt{(SE_1^2 + SE_2^2)}$ (Paternoster et al., 1998). $p < 0.10$, $p < 0.05$, ** $p < 0.01$.*

Hypothesis testing

Table 7 summarises the hypothesis decisions.

Table 7: Summary of Hypothesis Tests

Hypothesis	Evidence	Decision
H1a: Size and absolute LC	β1 = 81,703,936; p = 0.0009	$H0_1$ rejected; positive association
H1b: Size and relative LC	γ1 = −0.0512; p = 0.0129	$H0_1$ rejected; negative association
H2: Economies of scale	Positive β1 in the full sample and both sub-periods; negative γ1	$H0_2$ rejected for liquidity volume; no evidence of scale gains per unit of assets

Note. Decisions at the 5% significance level.

6. DISCUSSION

Overall, larger Sri Lankan listed banks create more liquidity in total, but less liquidity per rupee of assets.

The positive association between size and absolute liquidity creation agrees with Berger and Bouwman (2009) and with evidence that large banks keep creating

liquidity when funding tightens (Pham et al., 2021). The five large banks create about 85% of total liquidity, matching the US share reported by Berger and Bouwman (2009). Economies of scale in funding and risk management are consistent with this result, but the models do not test these channels, so they are possible explanations rather than findings. Part of the association is also mechanical, because absolute liquidity creation rises with balance-sheet size.

The negative association between size and relative liquidity creation differs from the scale advantages per unit of capital reported for large US banks (Berger & Bouwman, 2009). It is closer to evidence that smaller banks create more liquidity per unit of assets through relationship and retail lending (Viverita et al., 2022). One possible explanation is that large Sri Lankan banks hold more government securities and short-term liquid assets, partly because of regulatory liquidity requirements and the shallow capital market, which raises assets without raising liquidity creation in proportion. Asset composition was not modelled, so this remains to be tested. Together, Models 1 and 2 suggest scale effects in the volume of liquidity creation but diseconomies in its intensity.

The sub-period results extend the time-varying view of Niu (2021). In the US, the size effect changed sign after the 2007–2009 crisis, whereas in Sri Lanka it is positive both before and after 2020. The point estimate is larger in 2020–2024, but the difference is not significant at the 5% level, so the data are consistent with a stable positive size effect with weak evidence of a stronger effect during the crisis and recovery. This fits the view that macroeconomic conditions shape liquidity creation (Duan & Niu, 2023; Berger & Bouwman, 2017), but it does not show that larger banks were more resilient, because resilience was not measured.

The positive NPL coefficient is not what the credit-risk view predicts. It is significant in the full sample but not at the 5% level in either sub-period, so it should be read with caution. Possible but untested explanations are that banks with weaker loan books lend more to maintain income, that loan-classification relief during the COVID-19 and crisis period weakened the link between reported NPLs and lending, and that the log transformation hides a non-linear relationship. The weak capital effect is consistent with mixed evidence on the capital–liquidity link (Distinguin et al., 2013; Horváth et al., 2013) and may reflect limited variation in Tier 1 ratios under common Basel III minimums. In Sri Lanka, Manel Damayanthi and Gunawardhana (2023) also report an insignificant capital effect on bank liquidity, although they use a different liquidity measure.

7. IMPLICATIONS AND LIMITATIONS

Theoretically, the study shows that the maturity-based Berger and Bouwman (2009) measure can be applied to Sri Lankan disclosures, and that the size–liquidity relationship can differ in sign between total and relative liquidity creation. Theories of scale in banking should therefore distinguish the volume of liquidity creation from

its intensity. The sub-period results add Sri Lankan evidence on whether the size effect varies with economic conditions (Niu, 2021).

The practical implications are considerations rather than prescriptions, because the estimates are associations. For bank managers, asset growth is associated with more total liquidity creation, but larger banks may review whether their asset mix limits liquidity creation per rupee of assets, while smaller banks may keep a high transformation intensity through retail and relationship lending. For the CBSL, the concentration of liquidity creation in five large banks means their behaviour matters for credit supply, which supports monitoring both their total and relative liquidity creation. The positive NPL association suggests examining how asset-quality pressure and loan-classification relief interact with lending. The study does not identify an optimal bank size or test consolidation or forbearance policies.

The study has limitations. The sample of 12 listed private banks excludes state-owned and non-listed banks. The models omit time fixed effects, so common macroeconomic shocks may affect the estimates, and reverse causality between size and liquidity creation is not addressed. The measure excludes off-balance-sheet liquidity creation, and annual data limit observations, especially in the sub-periods. Residuals are non-normal and Model 1 may have serial correlation, although cluster-robust standard errors are used. Profitability is not controlled for because ROA was non-stationary.

Future research could add time fixed effects and macroeconomic controls, use instrumental-variable or dynamic panel methods, apply the category-based measure with off-balance-sheet items, use quarterly data, include state-owned and non-listed banks, and directly test channels such as asset composition, funding access and loan-classification relief.

AI DISCLOSURE

The authors used Claude (Anthropic) to assist with restructuring the manuscript, language editing, and drafting responses to reviewer comments. The authors reviewed and revised the output and take responsibility for the accuracy, originality, and final content of this manuscript.

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The Comparative Analysis of the Trading Performance of an Adapted Opening Range Breakout (AORB) Strategy across Selected Financial Assets

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ABSTRACT

Financial markets differ in liquidity, volatility, and structure, yet little is known about whether one rule-based intraday strategy performs alike across them. This study compares a single standardized Adapted Opening Range Breakout (AORB) strategy on EURUSD, Bitcoin (BTCUSD), gold (XAUUSD), and crude oil (XTIUSD) to establish whether performance is uniform or depends on the asset traded. The study follows a positivist, deductive, quantitative design based on experimental simulation. An identical Expert Advisor was backtested in MetaTrader 5 on one-minute data from January 2017 to July 2026 with initial capital of USD 10,000, giving 115 monthly observations per asset. One-way analysis of variance (ANOVA), Tukey's honestly significant difference (HSD) tests, and Kruskal–Wallis tests were used to compare four performance measures, while the Sharpe ratio and profit factor were reported descriptively. Monthly net profit ($F = 31.57$, $p < 0.001$), win rate ($F = 176.93$, $p < 0.001$), and recovery factor ($F = 13.41$, $p < 0.001$) differed significantly across assets in ANOVA. Kruskal–Wallis tests confirmed these differences and also detected one in maximum drawdown ($\chi^2 = 163.04$, $p < 0.001$) that ANOVA missed ($F = 1.38$, $p = 0.248$). XAUUSD earned the highest mean monthly net profit (USD 156.10) and an annualized Sharpe ratio of 2.31, second to BTCUSD (3.71). BTCUSD had the highest win rate (94.43%), and XTIUSD was unprofitable (USD −8.47). The findings come from historical simulation with one parameter set, ideal execution, and four instruments, so generalization requires caution. Practitioners should test asset suitability before using a common breakout rule.

Keywords: *Algorithmic Trading, Cross-Asset Comparison, Expert Advisor, Opening Range Breakout, Trading Performance*

JEL Classification: G11, G14, G15, G17

1. INTRODUCTION

Algorithmic trading executes predefined rules without discretionary intervention, and the evidence on rule-based technical trading is mixed, with profitability that is often sensitive to the market, the sample period, and transaction costs (Menkhoff & Taylor, 2007; Park & Irwin, 2007). The Opening Range Breakout (ORB) approach captures the price range formed in an initial period and trades when price breaks out of it. Prior ORB research has mostly examined exchange-traded markets such as crude oil futures, index futures, and exchange-traded funds (Holmberg et al., 2013; Tsai et al., 2019; Zarattini et al., 2024). Market microstructure theory explains how liquidity and order flow shape short-term prices (Hasbrouck, 2007; Kyle, 1985; O'Hara, 1995), and activity concentrates when major financial centers trade together (Andersen & Bollerslev, 1998; Eross et al., 2019). Because foreign exchange, cryptocurrency, and metal markets lack a common daily opening, this study adapts the ORB by using a fixed pre-session range as the reference for breakout signals.

Existing work usually studies one market and tunes parameters to it, so differences between instruments cannot be separated from differences in strategy design. Gold (XAUUSD) is a useful additional case: a precious metal with hedging and safe-haven roles in portfolios (Baur & McDermott, 2010; Erb & Harvey, 2013), yet its behavior under intraday breakout rules is seldom compared with other asset classes under identical settings.

The issue is also relevant in Sri Lanka, where the Central Bank of Sri Lanka has warned the public about unauthorized online foreign exchange platforms (Central Bank of Sri Lanka, 2019) and about the risks of cryptocurrency trading (Central Bank of Sri Lanka, 2023). Retail foreign exchange traders elsewhere have been found to lose money (Hayley & Marsh, 2016), and many rely on pre-programmed Expert Advisors (EAs) in MetaTrader 5 (MT5).

2. AIMS/OBJECTIVES

The aim is to establish whether a standardized AORB strategy produces significantly different trading performance across EURUSD, BTCUSD, XAUUSD, and XTIUSD when applied under identical conditions. Three hypotheses are tested. H1: profitability, measured by net profit and profit factor (PF), differs across the four assets. H2: risk and risk-adjusted performance, measured by maximum drawdown and the Sharpe ratio, differ across the assets. H3: consistency and recovery, measured by win rate and recovery factor, differ across the assets. PF and the Sharpe ratio are reported descriptively.

3. THEORY

The weak form of the Efficient Market Hypothesis implies that past prices contain no exploitable information (Fama, 1970). Yet simple trading-range break rules have

produced returns that are hard to reconcile with that view (Brock et al., 1992), and later reviews caution about data snooping and transaction costs (Park & Irwin, 2007). The Adaptive Markets Hypothesis reconciles these findings by proposing that efficiency varies across markets and over time (Lo, 2004), so a rule's profitability should depend on the market in which it is applied. Microstructure theory adds that participation and order flow affect short-horizon prices (Evans & Lyons, 2002), and a consolidation range followed by a surge in participation is the mechanism that breakout rules aim to exploit. Tsai et al. (2019) found that the best range definition differs across markets, implying that one specification may not suit every asset. These theories frame the interpretation; liquidity and order flow were not measured.

4. METHODS

The study is positivist, deductive, and quantitative, with experimental simulation as its strategy. an automated rule is applied to historical prices under identical conditions (Saunders et al., 2019). Four instruments were chosen purposively: EURUSD (currency), BTCUSD (cryptocurrency), XAUUSD (precious metal), and XTIUSD (energy). One-minute data were obtained through MT5 from an IC Markets server for 1 January 2017 to 31 July 2026. The unit of analysis is the asset-month, giving 115 observations per asset and 460 in total.

The EA records the high and low between 03:00 and 15:00 server time (GMT+2, or GMT+3 in daylight-saving periods), so the range closes as the London–New York overlap begins. Pending orders are placed at the range boundaries with a 20-point buffer, so a break above the high opens a long position and a break below the low opens a short position. Orders are deleted at 22:00 and open positions are closed at 22:30. One long and one short trade are allowed per day. The stop-loss equals the range width, no profit target is used, and a trailing stop starts after 100 points of profit, trails at a distance of 50 points, and moves in steps of 20 points. All parameters were identical across assets and were not optimized. Each month was tested separately from an initial deposit of USD 10,000, using every-tick modeling on real ticks, zero latency, and ideal execution; commission, swap, and slippage were not modeled..

Net profit is gross profit minus gross loss in USD, win rate is the share of profitable trades, and maximum drawdown is the largest peak-to-trough fall in account balance, reported as a decimal fraction. The recovery factor (RF) and PF are defined in Equations 1 and 2. The annualized Sharpe ratio (SR) was computed for each asset from monthly returns (monthly net profit divided by initial capital) with a zero risk-free rate (Equation 3), following Sharpe (1966). The √12 scaling assumes serially uncorrelated monthly returns (Lo, 2002).

$$RF = \frac{Net\ Profit}{Maximum\ Drawdown} \quad \text{..... (1)}$$

$$PF = \frac{Total\ Gross\ Profit}{Total\ Gross\ Loss} \quad \text{.....(2)}$$

$$SR = \frac{E[R_m]-R_f}{\sigma} \times \sqrt{12} \quad \text{..... .....(3)}$$

In Equation 3, E[Rm] is the mean monthly return, Rf is the risk-free rate, and σ is the standard deviation of monthly returns.

Differences in means were tested with one-way ANOVA, followed by Tukey's HSD test at the 5% significance level (Tukey, 1949). Because the measures are strongly skewed and Bartlett's test rejected equal variances for all four ($p < 0.001$), the rank-based Kruskal–Wallis test was also applied (Kruskal & Wallis, 1952). ANOVA tolerates moderate non-normality when group sizes are equal (Field, 2018). Data were processed in Microsoft Excel and analyzed in Stata.

5. RESULTS

Table 1 summarizes performance by asset.

Table 1. Descriptive Performance of the AORB Strategy by Asset (n = 115 Months per Asset)

Measure	BTCUSD	XAUUSD	EURUSD	XTIUSD
Net profit, mean (SD), USD	114.46 (106.75)	156.10 (233.63)	10.73 (72.53)	−8.47 (145.91)
Win rate, mean (SD)	0.9443 (0.1613)	0.8883 (0.0879)	0.7051 (0.1176)	0.4843 (0.2541)
Maximum drawdown, mean (SD)	0.0013 (0.0033)	0.0127 (0.0130)	0.0155 (0.0823)	0.0377 (0.2649)
Recovery factor, mean (SD)	58.65 (169.72)	1.56 (2.70)	0.36 (0.97)	0.15 (0.91)
Overall PF	10.05	1.98	1.08	0.60
Annualized SR	3.71	2.31	0.51	−0.20

Source: Author's analysis based on MT5 backtesting and Stata output, 2026

One-way ANOVA (Table 2) showed that mean net profit, win rate, and recovery factor differed significantly across the four assets, whereas maximum drawdown did not.

Table 2. One-Way ANOVA Results (df = 3, 456)

Measure	F	p	η^2	Significant
Net profit	31.57	< 0.001	0.172	Yes
Win rate	176.93	< 0.001	0.538	Yes
Maximum drawdown	1.38	0.248	0.009	No
Recovery factor	13.41	< 0.001	0.081	Yes

Source: Author's analysis based on MT5 backtesting and Stata output, 2026. η^2 = eta squared (effect size).

Table 3 reports the Tukey HSD comparisons. For net profit, XAUUSD and BTCUSD each exceeded EURUSD and XTIUSD but did not differ from each other (p = 0.162), and EURUSD and XTIUSD did not differ (p = 0.774). Win rate differed for every pair except XAUUSD–BTCUSD (p = 0.056). For recovery factor, only BTCUSD differed from the other three assets. No pairwise maximum drawdown difference was significant.

Table 3. Tukey HSD Mean Differences (Adjusted p-value)

Pair	Net profit	Win rate	Maximum drawdown	Recovery factor
EURUSD – BTCUSD	−103.73 (< 0.001)	−0.2392 (< 0.001)	0.0142 (0.867)	−58.29 (< 0.001)
XAUUSD – BTCUSD	41.64 (0.162)	−0.0560 (0.056)	0.0114 (0.925)	−57.08 (< 0.001)
XTIUSD – BTCUSD	−122.93 (< 0.001)	−0.4600 (< 0.001)	0.0364 (0.195)	−58.49 (< 0.001)
XAUUSD – EURUSD	145.37 (< 0.001)	0.1831 (< 0.001)	−0.0028 (0.999)	1.20 (1.000)
XTIUSD – EURUSD	−19.19 (0.774)	−0.2209 (< 0.001)	0.0222 (0.619)	−0.21 (1.000)
XTIUSD – XAUUSD	−164.57 (< 0.001)	−0.4040 (< 0.001)	0.0250 (0.522)	−1.41 (0.999)

Source: Author's Analysis Based on Mt5 Backtesting and Stata Output, 2026

Table 4 reports the Kruskal–Wallis equality-of-populations rank tests for the four measures.

Table 4. Kruskal–Wallis Equality-of-Populations Rank Test Results (df = 3)

Measure	χ^2 (unadjusted)	χ^2 (tie-adjusted)	p
Net profit	112.89	112.89	< 0.001
Win rate	303.14	304.81	< 0.001
Maximum drawdown	161.20	163.04	< 0.001
Recovery factor	205.41	205.42	< 0.001

Source: Author's analysis based on MT5 backtesting and Stata output, 2026

The Kruskal–Wallis tests rejected equality of distributions for all four measures ($p < 0.001$). Mean ranks were highest for XAUUSD in net profit (301.4) and for BTCUSD in win rate (369.1) and recovery factor (369.0), and lowest for XTIUSD on all three (156.5, 92.7, and 142.0). BTCUSD had the lowest maximum drawdown rank (95.4) and XAUUSD the highest (288.3).

6. DISCUSSION

H1 is supported by the ANOVA and Kruskal–Wallis results for net profit. XAUUSD earned the highest mean monthly profit (USD 156.10), although its profit was also the most variable (SD = USD 233.63) and did not differ significantly from that of BTCUSD. The PF ordering (10.05, 1.98, 1.08, and 0.60) points the same way, but PF was not tested statistically. Profitability that depends on the market agrees with the technical trading literature (Park & Irwin, 2007) and with the Adaptive Markets Hypothesis (Lo, 2004). The loss on crude oil contrasts with positive ORB returns reported for crude oil futures (Holmberg et al., 2013). That rule used exchange-traded futures with a defined opening, so the weak XTIUSD result may reflect rule–instrument fit rather than any inherent unsuitability of breakouts in energy markets.

A high win rate does not guarantee profit. XAUUSD averaged a monthly win rate of 88.83%, yet its average winning trade (USD 19.50) was about a quarter of its average losing trade (USD 76.31), which limits its PF to 1.98. The very high BTCUSD win rate likely reflects stop management: a trailing stop that starts after only 100 points of profit is a very small distance relative to the BTCUSD price, so most trades close with small gains. This raises the win rate and limits drawdowns regardless of the breakout's predictive power, so BTCUSD's apparent superiority is provisional until verified with realistic costs and slippage.

H2 is supported on a rank basis but not by the ANOVA. The annualized Sharpe ratio ordered the assets as BTCUSD (3.71), XAUUSD (2.31), EURUSD (0.51), and XTIUSD (−0.20), but it was not tested. Maximum drawdown did not differ in the ANOVA ($F = 1.38$, $p = 0.248$), yet the Kruskal–Wallis test detected a significant difference ($\chi^2(3) = 163.04$, $p < 0.001$), driven by the much lower drawdown ranks of BTCUSD (mean rank 95.4 against 259.6–288.3 for the other assets). Because the standard deviation of drawdown far exceeds its mean for EURUSD and XTIUSD, a few extreme months probably masked the difference in means, making the rank-based result more reliable.

H3 is supported. Win rate and recovery factor differed significantly across assets in both tests. The recovery factor result is driven by BTCUSD (mean 58.65 against 1.56 or less for the others), because its very small drawdowns shrink the denominator in Equation 1, and it should be read alongside the large standard deviation (169.72). Overall, the results are consistent with Tsai et al. (2019): settings that suit one market need not suit another, so a common AORB specification is not asset-neutral. Tukey's

test assumes equal variances, which Bartlett's test rejected, so the pairwise results should be read with caution (Field, 2018).

7. IMPLICATIONS AND LIMITATIONS

For theory, the asset-dependent results are consistent with the Adaptive Markets Hypothesis and with microstructure accounts of short-term prices, although neither was tested directly. For practice, retail traders who buy or use ready-made EAs, including those in Sri Lanka, should test a rule on each instrument before deploying it and should not treat a high win rate or PF as proof of profitability.

Several limitations apply. The results rely on historical backtesting with zero latency, ideal execution, and no commission, swap, or slippage, so they may not carry over to live trading. Each month was tested from a fresh deposit, so compounding and continuous account history are not reflected, and months without trades are recorded as zeros. BTCUSD trades at weekends while the other assets do not, and the point-based trailing-stop distances are not equivalent in relative terms across assets. The measures are skewed and heteroscedastic, and the Sharpe ratio and PF were computed once per asset without statistical testing. Only four instruments, one broker's data, and one parameter set were examined, and macroeconomic announcements and other market shocks were not modeled. Future research could add realistic costs and slippage, volatility-scaled stops, further assets and sessions, and walk-forward and live forward testing.

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The Impact of Geopolitical Conflicts on Stock Market Volatility: Evidence from the Colombo Stock Exchange

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ABSTRACT

Geopolitical conflicts are an important source of financial uncertainty. This study examines the statistical association between the global Geopolitical Risk (GPR) Index and conditional stock-market volatility in Sri Lanka. Using daily secondary data from January 2010 to June 2026, the analysis applies ARMA (2,2)-GARCH (1,1) models to the All Share Price Index (ASPI) and two purposively selected sector indices, Energy and Transportation. The dataset contains 3,876 ASPI price observations and 2,337 observations for each sector; the ASPI model reports 3,874 usable observations. The GPR and exchange-rate return are included as variance regressors. The estimated GPR coefficient is positive and statistically significant for ASPI (0.0138, $p < .001$), while estimated sector coefficients are negative. ASPI volatility persistence is approximately 0.999, and the test does not reject unity ($p = .8305$). The sector findings are exploratory, with the Transportation result limited by residual serial dependence and a data-verification concern. The results indicate conditional associations rather than causal effects. The study contributes evidence on the relationship between a global geopolitical-risk measure and daily CSE index volatility, subject to missing observations, exchange-rate mean filling, and model-diagnostic limitations.

Keywords: *Geopolitical Risk, Stock Market Volatility, ARMA-GARCH, Colombo Stock Exchange, Conditional Heteroskedasticity*

1. INTRODUCTION

Geopolitical developments can influence financial markets through uncertainty, expectations, trade disruptions, capital flows, commodity prices and perceived risk. Wars, terrorist attacks, sanctions and diplomatic tensions may affect financial assets even when a conflict occurs outside the market's home country. This is particularly relevant to frontier and emerging markets that are exposed to international trade and financial conditions. The CSE provides a meaningful setting because Sri Lanka has experienced several overlapping domestic and international shocks, including the Easter Sunday attacks in 2019, the COVID-19 period, the 2022 economic crisis and sovereign-debt default, the Russia-Ukraine conflict and renewed Middle East tensions. The domestic episodes matter because they may affect market volatility independently of the global GPR series.

Caldara and Iacoviello (2022) developed the Geopolitical Risk Index as a news-based measure of adverse geopolitical events and associated risks. The index provides a systematic alternative to examining individual conflicts. International evidence generally indicates that higher geopolitical risk is associated with greater financial-market uncertainty and stock-market volatility. (Salisu *et al.*, 2022) found significant geopolitical-risk effects on emerging-market stock-return volatility using GARCH-MIDAS, while (Bouras *et al.*, 2019) reported stronger associations with conditional volatility than average returns. (Panazan, Gheorghe and Calefariu, 2024) provide related evidence for the SAARC region.

The research problem is whether changes in geopolitical risk are statistically associated with changes in stock-market volatility in Sri Lanka after accounting for the market's own volatility dynamics and exchange-rate movements. The study's main objective is to investigate the impact of geopolitical risk on stock-market volatility in the Colombo Stock Exchange. The ASPI provides the principal overall-market analysis, while Energy and Transportation provide supplementary sectoral evidence.

Although previous studies have examined the relationship between geopolitical risk and financial market volatility, the evidence remains limited in the context of Sri Lanka and its emerging stock market. The Colombo Stock Exchange operates within an economy exposed to both global geopolitical developments and domestic political and economic disruptions. Therefore, examining the relationship between geopolitical conflicts and stock market volatility in Sri Lanka provides an opportunity to extend the existing literature. This study contributes by investigating the relationship between geopolitical risk and stock market volatility using daily market data from the Colombo Stock Exchange.

2. OBJECTIVES

The objective is to examine the association between geopolitical risk and conditional variance in ASPI returns. Energy and Transportation are supplementary, purposively selected sector-index cases. The main directional hypothesis is H1: higher geopolitical risk is positively associated with ASPI conditional variance. H0: the GPR coefficient in the ASPI conditional-variance equation is zero. Sector estimates are exploratory; the study does not formulate a causal hypothesis that geopolitical risk reduces sector volatility.

3. THEORY

The theoretical foundation combines the Efficient Market Hypothesis (EMH) and Behavioral Finance Theory. EMH, associated with (Fama, 1970), argues that publicly available information is incorporated into market prices. Geopolitical events can alter expectations about trade, growth, capital flows and risk, producing changes in returns and volatility.

Behavioral Finance Theory provides a complementary explanation by recognizing that investors do not always respond to information fully rationally. (Shiller, 2003) highlights the role of psychological factors in financial markets, while investor-sentiment research shows that uncertainty and emotion can influence pricing behavior. During geopolitical crises, fear, loss aversion, herding and uncertainty may intensify trading responses and contribute to larger price fluctuations. Thus, EMH provides an information-based explanation of how geopolitical information may be incorporated into prices, while Behavioral Finance provides a behavioral mechanism through which investor reactions may amplify and prolong volatility. The study also draws on the GARCH framework of (Bollerslev, 1986) which models time-varying conditional variance and volatility persistence.

The present study therefore treats GARCH-based conditional volatility as the principal outcome and the GPR index as the main explanatory variables.

4. METHODS

4.1 Research Design and Data

The research adopts a positivist philosophy, deductive approach and quantitative time-series design using secondary daily market data. The population consists of 289 companies listed on the CSE across 20 Global Industry Classification Standard (GICS) industries. The analytical sample uses ASPI as the overall-market index and purposively selected Energy and Transportation sector indices. The unit of analysis is the daily market observation. ASPI and GPR data cover January 2010 to June 2026, producing 3,876 ASPI observations, while each sector provides 2,337 observations from August 2016 to June 2026.

ASPI and sector-index data were obtained from CSE-related market-data sources, the GPR Index from the Caldara and Iacoviello database, and exchange-rate data from the Central Bank of Sri Lanka. ASPI daily returns were calculated as logarithmic price changes, $r_t = 100 \times [\ln(P_t) - \ln(P_{t-1})]$, where P_t is the index closing value; this is a percentage-scaled log return. The daily Geopolitical Risk Index (GPR) was obtained from the geopolitical risk database developed by Caldara and Iacoviello (2022). The GPR observations were aligned with the Colombo Stock Exchange trading dates by calendar date. The analysis uses the downloaded daily index series in its original scale. The ASPI price series contains 51 missing dates in January - February 2012. These were not replaced with unverified prices; consequently, return construction across the gap and estimation may lose observations. The raw exchange-rate sheet contains 532 missing observations corresponding to ASPI trading dates. These missing values were filled using the mean of the available daily exchange-rate returns. Mean imputation may reduce variation in the exchange-rate return series and potentially affect the estimated coefficients. An available-observation or alternative-imputation sensitivity analysis has not been completed; therefore, the results should be interpreted as conditional on the preprocessing applied.

This study focuses on geopolitical conflicts and their association with stock market volatility in Sri Lanka. Geopolitical risk is operationalized using the daily Geopolitical Risk (GPR) Index developed by Caldara and Iacoviello (2022). The index provides a systematic, news-based measure of geopolitical risks arising from adverse geopolitical events and associated threats. Therefore, the GPR Index is used as an empirical proxy to examine the volatility implications of geopolitical conflicts and related geopolitical uncertainty.

4.2 ARMA-GARCH-X Framework

The reported specification uses an ARMA (2,2) mean equation and a GARCH (1,1) conditional-variance equation. The ARMA terms capture serial dependence in returns, while the GARCH terms capture volatility clustering and persistence. The general multiplicative GARCH-X form can be expressed as $h_t = (\omega + \alpha\varepsilon^2_{t-1} + \beta h_{t-1}) \times \exp(\gamma GPR_t + \delta FX_t)$, where h_t is conditional variance, ε^2_{t-1} is the lagged squared innovation, and GPR_t and FX_t denotes the included exogenous variance regressors. The estimated GPR coefficient is therefore a parameter in the conditional-variance multiplier, not a direct percentage change in volatility. Its numerical interpretation depends on the exact transformation and scale used in estimation; accordingly, the coefficient is interpreted directionally and conditionally rather than converted into a percentage effect. AR (1) =1.144 and MA(1)=−0.898 have opposite signs and relatively similar magnitudes, which may indicate near-cancellation and motivates checking alternative ARMA orders. The ARMA (2,2) specification is retained as the originally estimated model; model-order optimality is not claimed because alternative-order AIC/BIC comparisons were not available.

Standard errors and confidence intervals are not reported in the available estimation summary, so inference is confined to the coefficient significance information supplied.

5. RESULTS

5.1 Overall Market Results

Table 1. ARMA-GARCH-X Results for ASPI Returns

Parameter	Coefficient
Constant (mean)	0.0001
AR(1)	1.144***
AR(2)	-0.223*
MA(1)	-0.898***
MA(2)	0.052
ARCH(1)	0.194***
GARCH(1)	0.805***
Exchange Rate Return	-4.213***
GPR	0.0138***
Persistence (ARCH+GARCH)	0.999
Log-likelihood	13,627.78
AIC	-27,235.57
BIC	-27,172.95
N	3,874

Source: Author's calculations based on Stata output.
Note: *** p<0.01, ** p<0.05, * p<0.10.

The reported GPR coefficient is positive and statistically significant (0.0138, p<0.001), indicating a positive conditional association with ASPI variance in the estimated specification. Exchange-rate return is negative and significant (−4.213, p<0.001). ARCH and GARCH estimates are significant; their sum is approximately 0.999. The test of persistence equal to unity gives χ^2 (1)=0.05, p=0.8305, so the null is not rejected. This is consistent with near-integrated volatility and warrants a cautious discussion of stability and slow shock decay. The dataset contains 3,876 ASPI price observations, while the model table reports N=3,874 usable estimation observations; the difference arises during return construction and model estimation and should be disclosed rather than treated as contradictory. AIC, BIC and log-likelihood refer to the complete controlled specification and do not demonstrate that GPR alone improves predictive performance. Crisis dummies and an exclusion of 2022 were not estimated, so domestic crisis confounding remains a limitation.

5.2 Sectoral Results

The Energy model reports a negative and significant GPR coefficient (-0.0029, p = 0.013), with persistence of 0.981. Residual diagnostics do not indicate significant remaining serial correlation. The Transportation model also produces a negative and

significant coefficient (-0.0147, $p < 0.001$), with persistence of 0.949. However, the standardized-residual Portmanteau test remains significant ($Q(20) = 52.65$, $p = 0.0001$), while the squared-residual test is not significant ($Q(20) = 17.73$, $p = 0.6050$). Therefore, the Transportation coefficient should be treated cautiously rather than as evidence that geopolitical risk reduces Transportation volatility. The underlying Transportation index also requires independent verification.

Table 2. ARMA GARCH-X Results for Selected Sectors

Sector	GPR coefficient	p-value	Persistence	Diagnostic observation
Energy	-0.0029	0.013	0.981	Residual diagnostics satisfactory
Transportation	-0.0147	<0.001	0.949	Standardized residual dependence remains

Source: Author's calculations based on Stata output.

5.3 Hypothesis Testing

The positive and statistically significant GPR coefficient in the ASPI conditional-variance equation provides evidence against the null hypothesis. Therefore, the alternative hypothesis, which proposes a positive association between geopolitical risk and ASPI conditional variance, is supported by the reported baseline results. The sectoral estimates are exploratory and are not used to test separate directional hypotheses.

6. DISCUSSION

The principal finding is that geopolitical risk is positively and significantly associated with overall CSE conditional volatility. This is consistent with (Salisu *et al.*, 2022), who identified significant geopolitical-risk effects on emerging-market stock volatility, and (Bouras *et al.*, 2019),who found stronger associations with conditional volatility than average returns. It is also consistent with Sri Lankan evidence from (Riyath *et al.*, 2024) and (Samarawickrama and Pallegedara, 2023), which document volatility clustering and persistence in CSE returns.

The positive ASPI coefficient indicates that geopolitical risk contains information relevant to CSE volatility after controlling for exchange-rate movements and underlying volatility dynamics. This is compatible with EMH because geopolitical information can be incorporated into prices as investors revise expectations. At the same time, the very high persistence of volatility is consistent with the possibility that investor sentiment and behavioral responses may prolong uncertainty.

The estimated ARCH-GARCH persistence of 0.999 is a central result. The formal test does not reject a sum equal to unity ($p=0.8305$), so the estimate is compatible

with near integrated volatility. The result suggests potentially slow volatility decay but also raises a stability concern; it should not be presented as definitive proof of a stable long-memory process.
The sectoral findings demonstrate that estimated geopolitical-risk associations are not uniform across market segments. The negative Energy and Transportation coefficients differ from the positive overall-market coefficient. However, the sectoral estimates should not be interpreted as evidence that geopolitical risk mechanically lowers sector volatility. In the Transportation case, significant residual serial dependence indicates that some return dynamics remain unexplained. The unresolved index-data concern further limits interpretation. The sector results are therefore supplementary evidence that motivates additional sector-specific research.

7. IMPLICATIONS, LIMITATIONS AND CONCLUSION

The findings may be considered by investors, portfolio managers and regulators as one input to market-risk monitoring. The study does not test out-of-sample forecasting improvement or establish causal effects; claims of predictive superiority are therefore avoided. The persistence estimate and its non-rejection of unity warrant caution when using the fitted model for risk decisions.

The sector findings should be used cautiously. The Energy coefficient is a conditional association, and its negative sign does not establish lower vulnerability. The Transportation result remains provisional because of residual serial dependence and the index-data concern. Practitioners should combine these estimates with independent market and sector risk assessments.

The study has several limitations. The 51 missing ASPI dates in early 2012 were not replaced by verified observations. The 532-missing exchange-rate observations corresponding to ASPI trading dates were filled using the mean of the available daily exchange-rate returns. This mean imputation may smooth variation and affect the estimates; sensitivity analysis is outstanding. The reported sample of 3,874 differs from the 3,876 index observations because returns and model estimation require usable data. The analysis uses daily index observations rather than individual firms, and only two purposively selected sector indices are examined. The Transportation index requires source verification, and its standardized residuals retain serial dependence. The model does not include explicit event dummies for the Easter 2019 attacks, COVID-19 or the 2022 economic crisis, nor does it report a model excluding 2022. Consequently, GPR may capture or be confounded by concurrent domestic shocks. Finally, global GPR does not isolate Sri Lanka-specific risk, and the study establishes conditional association rather than causality.

The study finds a positive and statistically significant association between geopolitical risk and ASPI conditional variance in the reported baseline model. Volatility persistence is estimated at 0.999 and is statistically consistent with unity

under the reported test. Selected sector estimates are negative, but they are exploratory and particularly provisional for Transportation. The contribution is a CSE daily-index analysis using a global GPR measure within an ARMA-GARCH conditional-variance framework; the conclusions remain bounded by data-preparation and model-diagnostic limitations.

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Perceived Impact of Artificial Intelligence Applications on Financial Forecasting Accuracy in Sri Lankan Commercial Banks

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ABSTRACT

Artificial Intelligence (AI) is increasingly used in banking, yet evidence on how specific AI applications relate to forecasting activities in Sri Lankan commercial banks remains limited. This study examines the perceived associations of Expert Systems (ES), Machine Learning (ML), and Robotic Process Automation (RPA) with three forecasting-related outcomes: Customer Churn Prediction, Debt Repayment Prediction, and Investment Analysis. A quantitative cross-sectional survey was conducted between 14 and 27 July 2026 using a five-point Likert-scale questionnaire adapted from Alassuli et al. (2026). Purposive and convenience sampling yielded 93 valid responses from employees of 14 licensed commercial banks who prepare, review, or use financial forecasts. Partial least squares structural equation modelling (PLS-SEM) was performed in SmartPLS 4 with 5,000 bootstrap resamples and two-tailed tests. All nine path coefficients were positive, and four were statistically significant. ML was associated with Customer Churn Prediction ($\beta = 0.471$) and Investment Analysis ($\beta = 0.421$), RPA with Debt Repayment Prediction ($\beta = 0.659$), and ES with Investment Analysis ($\beta = 0.299$), although the confidence interval for the last path marginally included zero. The results suggest that the perceived contribution of AI is task-specific rather than uniform. Because all measures are self-reported perceptions from a single source, discriminant validity was not fully established for several construct pairs, and common-method variance cannot be ruled out, the findings are interpreted as perceived associations rather than causal effects on objective forecast accuracy. Drawing on the Resource-Based View and Information Processing Theory, the study provides context-specific evidence to support task-level evaluation of AI investments in banking.

Keywords: *Artificial Intelligence; Expert Systems; Financial Forecasting; Machine Learning; Robotic Process Automation; Sri Lanka*

JEL Classification: *C53; G21; O33*

1. INTRODUCTION

Accurate forecasting underpins lending, liquidity management, investment allocation, customer retention, and risk management in commercial banking. Banks operate in information-intensive environments in which large volumes of customer, transaction, credit, and market data must be interpreted under uncertainty, and inaccurate or delayed forecasts can lead to mispriced risk and inefficient resource allocation (Wasserbacher & Spindler, 2022). Conventional statistical methods remain strong competitors (Makridakis et al., 2018), but the growing volume and complexity of banking data have encouraged the use of AI to complement them in credit scoring, customer management, risk assessment, investment services, and process automation (Herrmann & Masawi, 2022; Vuković et al., 2025).

This study focuses on three AI applications that may support forecasting through different mechanisms. Expert Systems apply codified knowledge and decision rules to structured decisions; Machine Learning derives patterns from historical data and suits complex or nonlinear problems; and RPA automates repetitive, rule-based processing such as data entry, reconciliation, and reporting, supporting forecasting indirectly by improving the timeliness and consistency of information (Lacity & Willcocks, 2016; Alassuli et al., 2026). Treating AI as a single construct may therefore conceal meaningful differences in how individual technologies relate to specific forecasting tasks.

Sri Lankan research has documented digital transformation, digital resilience, and RPA adoption in banking (Herath & Gamlath, 2024; Jayasundara & Wickramarachchi, 2024; Perera et al., 2024), but has rarely examined how specific AI applications relate to forecasting activities. International studies, meanwhile, tend to evaluate individual algorithms for isolated tasks such as credit scoring or churn prediction (Khandani et al., 2010; Lessmann et al., 2015; Coussement & Van den Poel, 2008), and their findings may not transfer to settings with different data infrastructure, skills, and regulation. This study addresses these gaps by examining nine technology–task relationships within a single framework, using the perceptions of banking employees who prepare, review, or use financial forecasts.

2. AIMS/OBJECTIVES

The primary objective is to examine the perceived associations of Expert Systems, Machine Learning, and Robotic Process Automation with three forecasting-related outcomes—Customer Churn Prediction, Debt Repayment Prediction, and Investment Analysis—among employees of Sri Lankan licensed commercial banks. The secondary objective is to assess whether these associations are uniform across tasks or task-specific. The study measures employees' perceptions of how AI supports each forecasting task; it does not measure objective forecast error, and its

findings are therefore framed as perceived associations rather than causal effects on forecasting accuracy.

3. THEORY

The study combines the Resource-Based View (RBV) and Information Processing Theory (IPT). RBV holds that performance depends on valuable resources that are effectively deployed (Barney, 1991); AI technologies create value only when combined with suitable data, infrastructure, expertise, and routines. ES, ML, and RPA represent distinct capabilities—codified knowledge, predictive analytics, and process automation—whose usefulness depends on fit with the task. IPT explains how organisations manage uncertainty by increasing information-processing capacity (Galbraith, 1973). ML may expand analytical capacity for complex, changing data; ES may improve consistency in applying structured criteria; and RPA may increase the speed and reliability of routine information flows. Together, the theories imply that associations between AI and forecasting outcomes should vary by task.

Accordingly, nine hypotheses were proposed (Figure 1). H1–H3 state that ES is positively associated with Customer Churn Prediction (CUS), Debt Repayment Prediction (DEB), and Investment Analysis (INV), respectively; H4–H6 state the same for ML; and H7–H9 state the same for RPA.

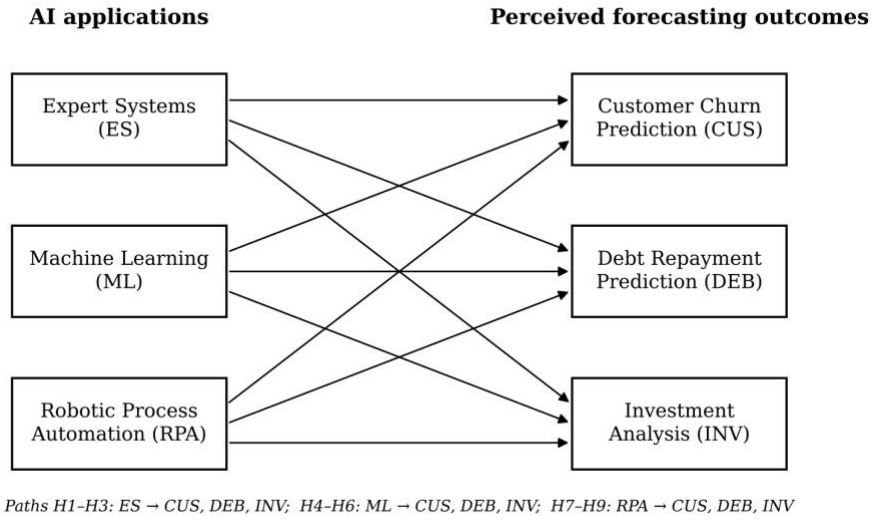

Figure 1. ***Conceptual Framework***
Source: Adapted from Alassuli et al. (2026).

4. METHODS

A positivist, deductive, quantitative cross-sectional survey design was adopted (Saunders et al., 2019). The target population comprised employees of Sri Lankan licensed commercial banks who prepare, review, analyse, or use financial forecasts

and AI-assisted financial information. Because no complete sampling frame was available, purposive and convenience sampling were combined. Invitations were distributed through LinkedIn, professional contacts, email, and direct approaches to banks, and responses were collected through Google Forms between 14 and 27 July 2026. Participation was voluntary and anonymous, and informed consent was obtained.

The final sample comprised 93 complete responses from 14 licensed commercial banks: two state-owned banks (n = 32; 34.4%), eleven domestic private banks (n = 60; 64.5%), and one foreign bank (n = 1; 1.1%). The largest contributions came from Bank of Ceylon (n = 22), Commercial Bank of Ceylon (n = 13), and People's Bank (n = 10). Respondent suitability was assessed with two screening items: involvement in preparing, reviewing, or using financial forecasts, and frequency of engagement with forecasting. Of the 93 respondents, 89 reported direct involvement; the remaining four were retained because their roles involved reviewing or using forecast-related information. Only one respondent reported engaging with forecasting rarely. The questionnaire recorded job position rather than functional department; position is therefore reported as the closest available indicator of role (Table 1).

The instrument contained 18 items, three per construct, adapted from Alassuli et al. (2026) and measured on a five-point scale (1 = strongly disagree to 5 = strongly agree); all items are listed in Appendix A. Each outcome item asks the extent to which AI systems help the respondent's bank perform a forecasting task, so the outcomes capture *perceived* forecasting performance rather than objective accuracy. Customer Churn Prediction reflects the perceived ability to anticipate which customers will leave, and Debt Repayment Prediction the perceived ability to anticipate borrowers' repayment behaviour. Investment Analysis is broader: one item refers directly to investment forecasting accuracy, while the others refer to forward-looking assessment of risks and returns and to the quality of investment decisions. This construct is therefore interpreted as perceived forecasting-related decision support for investments, not as accuracy alone.

SPSS 26 was used for screening and descriptive analysis. Kolmogorov–Smirnov and Shapiro–Wilk tests indicated non-normality for all constructs ($p < 0.001$), supporting PLS-SEM in SmartPLS 4 (Hair et al., 2022) with the path weighting scheme. The measurement model was assessed through outer loadings, Cronbach's alpha, composite reliability (ρc), average variance extracted (AVE), the Fornell–Larcker criterion, the heterotrait–monotrait ratio (HTMT; Henseler et al., 2015), and cross-loadings. The structural model was assessed through collinearity (VIF), R^2, path coefficients, and f^2. Significance was tested by bootstrapping with 5,000 resamples, two-tailed tests at $\alpha = 0.05$, and percentile 95% confidence intervals. Because all data came from a single self-report source, common-method variance was examined using full-collinearity VIFs (Kock, 2015).

Green's (1991) rule ($N \geq 50 + 8m$) gives a minimum of 74 for three predictors, but it was developed for multiple regression and does not account for the latent-variable model or the size of the effects tested. Sample adequacy was therefore also evaluated with the inverse square root method (Kock & Hadaya, 2018) and post-hoc power analysis in SmartPLS 4. With $N = 93$, the minimum path coefficient detectable at $\alpha = 0.05$ with 80% power is approximately $|\beta| = 0.258$.

5. RESULTS

5.1. Sample Profile

Table 1: Respondent Profile (N = 93)

Variable	Category	n	%
Gender	Male	46	49.5
	Female	47	50.5
Age	19–29 years	54	58.1
	30–45 years	35	37.6
	46–61 years	4	4.3
Bank ownership	State-owned (2 banks)	32	34.4
	Domestic private (11 banks)	60	64.5
	Foreign (1 bank)	1	1.1
Position	Senior Manager	5	5.4
	Manager	18	19.4
	Assistant Manager	40	43.0
	Senior Executive	10	10.8
	Executive Officer	8	8.6
	Finance Assistant	12	12.9
Work experience	Less than 5 years[a]	48	51.6
	6–10 years	21	22.6
	11–15 years	12	12.9
	Above 15 years	12	12.9
Involved in forecasting	Yes	89	95.7
	No (reviews or uses forecasts)	4	4.3

Note. [a] *The questionnaire offered "Less than 5 years" and "6–10 years"; respondents with exactly five years of experience had no exact category and most likely selected the first option. This is acknowledged as a limitation of the instrument. Source: Survey data (2026).*

5.2. Measurement Model

All 18 outer loadings exceeded 0.70 (0.775–0.897). Cronbach's alpha (0.743–0.801) and composite reliability (0.854–0.883) indicated adequate internal consistency, and all AVE values exceeded 0.50 (0.661–0.716), supporting convergent validity (Table 2).

Table 2. Reliability and Convergent Validity

Construct	Loadings	α	ρc	AVE
Expert Systems (ES)	0.786–0.826	0.743	0.854	0.661
Machine Learning (ML)	0.808–0.897	0.801	0.883	0.716
Robotic Process Automation (RPA)	0.775–0.840	0.755	0.858	0.669
Customer Churn Prediction (CUS)	0.811–0.851	0.770	0.867	0.685
Debt Repayment Prediction (DEB)	0.796–0.883	0.793	0.879	0.708
Investment Analysis (INV)	0.794–0.861	0.773	0.869	0.689

Source: SmartPLS 4 output (2026).

Discriminant validity was not fully established. Under the Fornell–Larcker criterion, the square root of the AVE for RPA (0.818) was below its correlation with DEB (0.840). The complete HTMT matrix (Table 3) shows that 11 of the 15 construct pairs exceeded the 0.90 threshold, and two pairs exceeded 1.0: RPA–DEB (1.071) and RPA–ML (1.011). Cross-loadings were more favourable, with every item loading highest on its intended construct. Inspection of item wording suggests two sources of overlap. First, all nine outcome items share the stem "AI systems help…", which may inflate correlations among the three outcomes. Second, the RPA items concern data accuracy and processing speed, while the debt-repayment items—especially monitoring repayment behaviour by tracking late payments and repayment history—describe a task that is largely automated in practice; RPA3 cross-loaded at 0.769 on DEB. The RPA, DEB, INV, and ML paths should therefore be read with caution.

Table 3. Heterotrait–Monotrait Ratio (HTMT)

Construct	CUS	DEB	ES	INV	ML
DEB	**0.933**				
ES	0.806	0.900			
INV	**0.915**	0.898	**0.957**		
ML	**0.902**	**0.911**	**0.954**	**0.967**	
RPA	0.840	**1.071**	**0.991**	**0.920**	**1.011**

Note. Values in bold exceed the 0.90 threshold (Henseler et al., 2015). Source: SmartPLS 4 output (2026).

Full-collinearity VIFs, computed from the latent-variable correlations, ranged from 2.71 to 4.76 and exceeded Kock's (2015) 3.3 threshold for DEB (4.25), ML (3.82), and RPA (4.76). Common-method variance and conceptual overlap therefore cannot be ruled out.

5.3. Structural Model

Structural VIFs ranged from 2.59 to 3.14, below the threshold of 5 (Hair et al., 2022). The model explained 53.3% of the variance in CUS (adjusted $R^2 = 0.517$), 72.1% in DEB (0.712), and 65.0% in INV (0.638); SRMR was 0.080. All nine paths were positive and four were significant (Table 4). ML was associated with CUS ($\beta = 0.471$, $t = 3.48$, $p = 0.001$) and INV ($\beta = 0.421$, $t = 3.32$, $p = 0.001$), and RPA with DEB ($\beta = 0.659$, $t = 4.35$, $p < 0.001$), each with a medium-to-large effect. ES was

associated with INV (β = 0.299, t = 2.05, p = 0.041, f^2 = 0.098), but its percentile confidence interval marginally included zero (−0.049 to 0.555); H3 is therefore regarded as only weakly supported. The paths for H1 (t = 0.81, p = 0.421), H2 (t = 0.77, p = 0.443), H5 (t = 0.99, p = 0.324), H7 (t = 1.14, p = 0.255), and H9 (t = 1.14, p = 0.254) were not significant.

Table 4. Hypothesis Testing (5,000 Bootstrap Resamples, Two-Tailed)

H	Path	β	t	p	95% CI	f^2	VIF	Decision
H1	ES → CUS	0.134	0.81	0.421	[−0.181, 0.476]	0.015	2.59	Not supported
H2	ES → DEB	0.103	0.77	0.443	[−0.155, 0.370]	0.015	2.59	Not supported
H3	ES → INV	0.299	2.05	0.041	[−0.049, 0.555]	0.098	2.59	Weakly supported
H4	ML → CUS	0.471	3.48	0.001	[0.168, 0.708]	0.155	3.06	Supported
H5	ML → DEB	0.133	0.99	0.324	[−0.122, 0.406]	0.021	3.06	Not supported
H6	ML → INV	0.421	3.32	0.001	[0.170, 0.662]	0.165	3.06	Supported
H7	RPA → CUS	0.179	1.14	0.255	[−0.152, 0.456]	0.022	3.14	Not supported
H8	RPA → DEB	0.659	4.35	<0.001	[0.361, 0.917]	0.497	3.14	Supported
H9	RPA → INV	0.156	1.14	0.254	[−0.113, 0.423]	0.022	3.14	Not supported

Note. CI = percentile confidence interval; f^2 of 0.02, 0.15, and 0.35 indicate small, medium, and large effects. Source: SmartPLS 4 output (2026).

The non-significant paths had coefficients of 0.103–0.179, below the minimum detectable effect of 0.258, and post-hoc power for these paths at α = 0.05 ranged from 0.26 to 0.53. Their non-significance may therefore partly reflect limited statistical power rather than the absence of an association.

6. DISCUSSION

The results indicate that the perceived contribution of AI differs by forecasting task. The ML associations with churn prediction and investment analysis are consistent with research showing the value of data-driven methods for identifying behavioural patterns associated with customer defection (Coussement & Van den Poel, 2008; Verbeke et al., 2012) and for modelling complex financial relationships (Fischer & Krauss, 2018). Both tasks involve many interacting and potentially nonlinear signals, where pattern recognition is most useful. The non-significant ML–debt repayment path contrasts with evidence on machine-learning credit models (Khandani et al., 2010; Lessmann et al., 2015); this may reflect the perceptual measures, differences in ML maturity across banks, the dominance of policy rules in repayment decisions, or the limited power noted above.

The RPA–debt repayment association is consistent with the process-intensive nature of repayment monitoring, which depends on timely and accurate records of payment histories, overdue balances, and reconciliations (Lacity & Willcocks, 2016; Mamede et al., 2023). However, this is also the construct pair with the most serious discriminant-validity problem (HTMT = 1.071), so the strength of the path may partly reflect overlapping perceptions of automated data processing and repayment monitoring rather than two clearly distinct constructs. The ES–investment analysis

association fits the structured, criteria-based nature of many investment decisions, but given its confidence interval it should be treated as tentative.

Theoretically, the pattern supports the RBV view that technology is valuable when matched to the task and the IPT view that a technology's usefulness depends on whether its information-processing capability fits the task's uncertainty: ML for complex pattern recognition, RPA for routine information flows, and possibly ES for structured evaluation. These interpretations concern perceived associations and should be confirmed with objective data and measures with stronger discriminant validity.

7. IMPLICATIONS AND LIMITATIONS

For practice, the findings suggest that banks should evaluate AI investments at the level of the forecasting task rather than adopting technologies because they are generally regarded as advanced. ML may merit priority for customer analytics and investment-related prediction, and RPA for repayment data and credit-monitoring processes. Relationships that were not supported should be tested in each bank's own data environment before substantial investment, and all AI tools should complement professional judgement and established governance.

Several limitations apply. First, all constructs are self-reported perceptions from a single source, so the study cannot speak to objective accuracy measures such as forecast error, realised churn, or default-prediction accuracy; full-collinearity VIFs above 3.3 indicate that common-method variance cannot be excluded. Second, discriminant validity was not established for several construct pairs, including two HTMT values above 1.0, partly because of similar item wording; future studies should refine the instrument, particularly by differentiating RPA items from debt-repayment items and varying the outcome stems. Third, the purposive and convenience sample of 93 respondents is concentrated in state-owned and a few large private banks and lacks functional-area data, which limits generalisation; the sample also has limited power for small effects. Fourth, the cross-sectional design precludes causal inference, and the work-experience categories omitted exactly five years. Future research should use larger probability-based samples, objective forecasting-performance data, longitudinal designs, and procedural remedies for common-method bias (Podsakoff et al., 2003).

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Effect of Remittances and Tourism Revenue on the Exchange Rate in Sri Lanka: Evidence from 2014 to 2024

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ABSTRACT

This study shows the relationship between remittance inflows, tourism revenue with exchange rate variation in Sri Lanka the period of 2014–2024. To show the relationship it takes 132 monthly observations from January 2014 to December 2024. The Real Effective Exchange Rate (REER) is the dependent variable. Remittances and monthly tourism foreign exchange earnings are the principal explanatory variables, while foreign direct investment (FDI), official development assistance (ODA), inflation and GDP growth are included as controls. The submitted research identifies the Central Bank of Sri Lanka (CBSL), the Sri Lanka Tourism Development Authority (SLTDA), the Department of Census and Statistics and the International Monetary Fund (IMF) as data sources. The analyses reported are correlation analysis, two ordinary least squares (OLS) specifications and Granger-causality tests at two, four and six lags. Remittances have a positive coefficient in the bivariate OLS specification (0.028; t = 6.72) and a negative coefficient after the controls are included (−0.011; t = −2.78). Tourism revenue is statistically insignificant in both reported OLS specifications. In the controlled model, FDI, ODA and inflation have negative coefficients, while GDP growth has a positive coefficient. Granger-test results indicate that remittances do not Granger-predict the REER at the tested lag lengths, while tourism predicts the REER at six lags. Because production and efficiency in tradable sectors are not considered in the study, these findings do not completely illustrate the Dutch disease theory. As consequently, the research evaluates its results as prediction correlations and exchange rate connections rather than proof of structural causal relationship.

Keywords: *Remittances, Tourism Revenue, Real Effective Exchange Rate, Dutch Disease, Sri Lanka*

1. INTRODUCTION

Foreign exchange inflows are important to Sri Lanka's external position. Worker remittances represented roughly seven to nine percent of GDP between 2014 and 2019, and tourism generated more than USD 4 billion annually before the Easter Sunday attacks of April 2019 and the COVID-19 pandemic (SLTDA, 2023). The decade also includes the currency and economic crisis of 2022.

The expected relationship is theoretically ambiguous. Balance-of-payments reasoning suggests that foreign-currency earnings support the domestic currency, whereas Dutch disease theory predicts that a large inflow raises domestic demand and the relative price of non-tradable goods, producing real appreciation (Neary&Corden, 1982). Empirical studies reflect this ambiguity. Set of evidence for remittances to real appreciation (Amuedo-Dorantes & Pozo, 2004), yet remittances also behave like counter-cyclical transfers to households rather than as an additional source of spending (R, Chami Ralpa; F, Connel ; J, 2003). For tourism, a general equilibrium model of a small island economy analyses the economy wide effects of a tourism boom within the Dutch disease framework (Nowak & Sahli, 2007), while a cross country study found no real exchange rate distortion in tourism dependent countries (Holzner, 2011).

Evidence for Sri Lanka has concentrated mainly on tourism and growth (Kurukulasooriya & Lelwala Erandathie, 2020) rather than on the exchange rate. This study contributes a single country monthly time series analysis that treats remittances and tourism earnings jointly with full time series diagnostics. Because the data contain no tradable sector output, employment or competitiveness measures, the study examines the exchange rate (spending effect) dimension of Dutch disease only. The research question is: how are remittance inflows and tourism foreign exchange earnings associated with the REER in Sri Lanka between January 2014 and December 2024, after accounting for FDI, ODA, inflation and GDP growth.

2. AIMS/OBJECTIVES

The overall objective is to examine the relationship between remittance inflows, tourism revenue and the REER in Sri Lanka from 2014 to 2024. The specific objectives are (1) to estimate the association between remittance inflows and the REER; (2) to estimate the association between tourism revenue and the REER; (3) to assess both inflows jointly, and as a combined inflow, while controlling for FDI, ODA, inflation and GDP growth; (4) to assess whether the estimated relationships are consistent with the appreciation expected from the Dutch disease spending effect, recognizing that the resource movement channel is not tested; and (5) to examine long run movement, Granger predictive relationships and stability across crisis periods.

The hypotheses are tested at the 5% level using HAC standard errors where specified. **H1:** the remittance coefficient in the REER regression differs from zero (a positive sign indicates appreciation). **H2:** the tourism earnings coefficient differs from zero. **H3:** the coefficient on the combined inflow (remittances plus tourism earnings) is positive, indicating real appreciation; the null of no appreciation is rejected only by a positive and significant coefficient. **H4:** the REER, remittances, tourism earnings, inflation and GDP growth are integrated (Johansen trace test). **H5 (exploratory):** the inflow of REER relationships differ in crisis periods (crisis dummies and interaction terms).

3. THEORY

Four exchange rate perspectives frame the analysis. Purchasing power parity links exchange rates to relative price levels and serves as a long run benchmark (Cassel, 1918). The monetary approach adds money and interest rate conditions (Frankel, 1979), the balance-of-payments approach emphasizes the supply of and demand for foreign currency from trade and capital flows (Mundell, 1963), and the asset-market approach stresses expectations and risk (Branson et al., 1977) . Together they motivate the controls. Capital and aid inflows (FDI, ODA) are expected to support the currency through the balance of payments. Higher domestic inflation is expected to raise the real exchange rate when the nominal rate is held constant and faster growth is expected to appreciate it through demand and productivity.

Dutch disease theory distinguishes a spending effect from a resource-movement effect. Higher income from a booming sector or inflow raises demand for non-tradable, increases their relative price and appreciates the real exchange rate ; labor and capital may also shift away from other tradable activities (Neary&Corden, 1982). A REER regression can speak only to the first channel.

Prior evidence yields competing expectations. For remittances, appreciation is found in a panel of 13 Latin American and Caribbean countries (Amuedo-Dorantes & Pozo, 2004), in a long run panel of less-developed countries where the relationship is small and inelastic (Hassan & Holmes, 2013), and in an estimated general equilibrium model for El Salvador that is consistent with Bayesian vector auto regression results (Pablo A. Acosta a 1, Emmanuel K.K. Lartey b 2, 2009). By contrast, remittances that respond to household hardship may dampen demand pressure (Chami et al., 2005). For tourism, theory analyses Dutch disease type effects of a tourism boom in small islands (Nowak & Sahli, 2007), but cross-country evidence shows no exchange-rate distortion among tourism dependent economies (Holzner, 2011). The gap addressed here is the lack of a joint, monthly, Sri Lanka specific test. The expectations are therefore that each inflow may be positively related to the REER if the spending effect dominates, and that the sign is an empirical question if remittances are counter cyclical or the central bank offsets inflows.

Expected relationships- Table 1 sets out the variables and the signs expected on the REER. For remittances, a positive sign is expected if recipient households spend part of the inflow on non tradable, and a zero or negative sign is plausible if remittances are counter-cyclical or are offset by policy. For tourism, a positive sign is expected if visitor spending raises non-tradable prices, but tourism earnings are volatile and exposed to travel demand shocks, so the relationship may be weaker or lagged. FDI and ODA are expected to be positive through the balance of payments, inflation positive at a given nominal rate, and GDP growth positive through demand and productivity. Because the study tests association rather than a full structural model, each coefficient is read as a conditional correlation, and a sign that differs from expectation is reported as such rather than explained after the fact.

4. METHODS

4.1. Data and variables

The study uses a quantitative single country time series design with 132 monthly observations from January 2014 to December 2024. Data were compiled from the CBSL, the SLTDA, the Department of Census and Statistics and the International Monetary Fund. The dependent variable is the REER index (base year = 100), higher values denote real appreciation, and coefficient signs are interpreted on that basis. Remittances are monthly worker remittance inflows in absolute value (LKR million) and enter all reported models in levels, not as a share of GDP. Tourism revenue is monthly tourism foreign exchange earnings (LKR million). FDI is net FDI inflows and ODA is official development assistance received (both LKR million). Inflation is the percentage change in the consumer price index, and GDP growth is the real GDP growth rate (percent). Official GDP and ODA releases are not natively monthly, so the monthly GDP growth and ODA series are derived series; the conversion procedure is not documented in the source material and is treated as a limitation. No missing data treatment or seasonal adjustment is reported, and all models use all 132 observations.

4.2. Estimation

Stationary was assessed with augmented Dickey Fuller (ADF) tests (four lags, trend) in levels and first differences, with a Phillips Perron (PP) test as a check for the REER. Four OLS models were estimated. Model 1 regresses the REER on remittances and tourism earnings. Model 2 adds the controls:

$$REER_t = \beta_0 + \beta_1 REM_t + \beta_2 TOUR_t + \beta_3 FDI_t + \beta_4 ODA_t + \beta_5 INF_t + \beta_6 GDPG_t + \varepsilon_t$$

Model 3 adds dummies for the Easter Sunday attacks (April to December 2019), the COVID-19 period (January 2020–December 2021) and the 2022 crisis. Model 4 replaces them with an aggregate crisis dummy and its interactions with remittances and tourism. Diagnostics on Model 3 comprise Breusch Pagan and White tests, Durbin Watson and Breusch Godfrey serial correlation tests, a

normality test, the Ramsey RESET test and variance inflation factors (VIF). Following the serial correlation finding, Model 3 was estimated with Newey West HAC standard errors (four lags; Newey & West, 1987). Because the series are integrated, long run relations were examined with the Johansen trace test and a vector error correction model (VECM) for the five variable system of REER, remittances, tourism, inflation and GDP growth (FDI and ODA are excluded from this system). Granger tests at two, four and six lags are read as predictive precedence, not structural causation. Supplementary models are a log log specification, a regression on the combined inflow (remittances plus tourism earnings), a specification adding the trade balance and a 36 month rolling regression.

5. RESULTS

5.1. Correlation

Table 1 shows that FDI, inflation and GDP growth do not reject a unit root in levels, while the REER, remittances and tourism earnings are stationary after first differencing. The REER is borderline (the PP test rejects at 5% but the ADF test does not), and it is treated conservatively as integrated of order one. The level regressions below are therefore read as descriptive associations, and the cointegration results are used to assess whether a stable long run relation exists. The REER is positively correlated with remittances (r = 0.622), tourism earnings (0.419), FDI (0.486) and GDP growth (0.745) and negatively with ODA (−0.651) and inflation (−0.812). Several regressors are highly correlated with one another (inflation and remittances, −0.889; GDP growth and FDI, 0.890; inflation and GDP growth, −0.881), which signals collinearity.

Table 1. Unit-Root Test Results

Variable	Level	First difference	Order of integration
REER	-	−7.822 (< 0.001)	I(1)
Remittances	-	−6.093 (< 0.001)	I(1)
Tourism earnings	-	−6.618 (< 0.001)	I(1)
FDI	−1.827 (0.692)	-	I(1)
Inflation	−1.710 (0.747)	-	I(1)
GDP growth	−1.801 (0.704)	-	I(1)
ODA	-	-	-

Note. ADF tests with four lags and a deterministic trend. p-values in parentheses.

5.2 OLS and robust estimates

Table 2 reports Models 1–4. In Model 1, remittances are positively related to the REER (0.028, t = 6.72), and tourism earnings are insignificant (0.003, t = 0.65). When the controls are added, the remittance coefficient becomes negative (−0.011,

t = −2.78, p = 0.006) and adjusted R^2 rises from 0.380 to 0.839. The reversal is consistent with confounding by inflation and GDP growth, with which remittances are strongly correlated, but the data do not identify its source. Tourism remains insignificant (−0.001, t = −0.52). None of the crisis dummies is significant (Easter p = 0.801, COVID-19 p = 0.559, 2022 crisis p = 0.328), nor are the interaction terms (p = 0.806 and 0.835).

Table 2. OLS Estimates with the REER as the Dependent Variable (Models 1–4)

Variable	Model 1	Model 2	Model 3	Model 4
Remittances	0.028 (6.72)	−0.011 (−2.78)	−0.011 (−2.80)	−0.011 (−2.69)
Tourism	0.003 (0.65)	−0.001 (−0.52)	−0.002 (−0.58)	−0.001 (−0.38)
FDI	—	−0.161 (−6.29)	−0.163 (−6.16)	−0.161 (−6.11)
ODA	—	−0.247 (−4.45)	−0.246 (−4.38)	−0.243 (−4.30)
Inflation	—	−0.691 (−6.37)	−0.670 (−6.05)	−0.696 (−6.24)
GDP growth	—	2.876 (6.59)	2.841 (6.28)	2.851 (6.25)
d_easter	—	—	0.349 (0.25)	—
d_covid	—	—	−0.936 (−0.59)	—
d_crisis	—	—	−1.614 (−0.98)	—
d_anycrisis	—	—	—	0.551 (0.19)
Remittances × crisis	—	—	—	−0.001 (−0.25)
Tourism × crisis	—	—	—	−0.001 (−0.21)
Constant	70.665	129.116	129.680	128.995
R^2	0.389	0.846	0.848	0.846
Adjusted R^2	0.380	0.839	0.836	0.835
F-statistic	41.13	114.36	75.39	74.61
Observations	132	132	132	132

Note. Coefficients with conventional t-statistics in parentheses. Monthly data, January 2014–December 2024.

Diagnostics on Model 3 show no heteroskedasticity (Breusch–Pagan p = 0.374; White p = 0.804) but positive serial correlation (Durbin–Watson = 1.378; Breusch–Godfrey p < 0.001 at lags 1–4), non-normal residuals (p = 0.010) and a RESET rejection (p = 0.026). VIFs are 11.37 for inflation and 10.01 for GDP growth (mean

5.15). Table 3 shows that Newey–West standard errors leave the conclusions unchanged: remittances remain negative and significant (p = 0.004), and tourism remains insignificant (p = 0.623). HAC errors address autocorrelation in the standard errors but not functional-form misspecification or collinearity.

Table 3. Model 3 with Newey–West HAC Standard Errors (Four Lags)

Variable	Coefficient	Newey–West SE	t-statistic	p-value
Remittances	−0.011	0.004	−2.98	0.004
Tourism	−0.002	0.004	−0.49	0.623
FDI	−0.163	0.034	−4.82	< 0.001
ODA	−0.246	0.057	−4.36	< 0.001
Inflation	−0.670	0.122	−5.51	< 0.001
GDP growth	2.841	0.578	4.92	< 0.001
d_easter	0.349	1.417	0.25	0.806
d_covid	−0.936	1.852	−0.51	0.614
d_crisis	−1.614	1.622	−1.00	0.322
Constant	129.680	6.106	21.24	< 0.001

Note. Dependent variable: REER. N = 132; model F = 91.93 (p < 0.001). P-values below 0.001 are shown as < 0.001.

5.3. Long-run and short-run dynamics

Lag-order criteria disagreed (one lag by LR and SBIC, two by HQIC, three by FPE and eleven by AIC; N = 120), so four lags were used in the Johansen test and sensitivity was checked in the Granger tests. The trace test rejects zero cointegrating relations (126.707 against a 5% critical value of 68.52) and at most one (55.629 against 47.21) but does not reject at most two (22.455 against 29.68), so H4 is supported with up to two relations; the VECM was estimated with one relation and rank two was used as a check. In the normalized vector, remittances (z = 11.45), inflation (z = 11.28) and GDP growth (z = 2.31; p = 0.021) are significant, whereas tourism is not (p = 0.350). The adjustment coefficient in the REER equation is small and insignificant (−0.033, p = 0.452), while the adjustment coefficients in the remittance (−6.295, p < 0.001) and tourism (−3.982, p = 0.003) equations are significant.

5.4. Granger tests

Table 4 shows no Granger-predictive relationship from remittances to the REER at any tested lag. Tourism predicts the REER at six lags (p = 0.015; p = 0.052 at four lags), GDP growth does so at two and four lags, inflation at six lags, and the REER predicts tourism at four lags only (p = 0.044). Tourism predicts remittances at all lags. Because 18 tests are shown, results that appear at a single lag are treated as weak evidence.

Table 4. Granger-Causality Tests (p-values)

Direction	2 lags	4 lags	6 lags
Remittances → REER	0.995	0.872	0.109
Tourism → REER	0.195	0.052	0.015
GDP growth → REER	0.016	0.007	0.173
Inflation → REER	0.546	0.428	0.013
REER → Tourism	0.161	0.044	0.356
Tourism → Remittances	< 0.001	< 0.001	< 0.001

Note. Chi-square tests within the VAR; null of no Granger causality. Bold = $p < 0.05$.

5.5. Supplementary checks

In the composite regression with controls and dummies, the combined inflow has a negative coefficient (−0.006; t = −2.35; p = 0.021; adjusted $R^2 = 0.835$), so H3 is not supported. In the log–log model, the elasticities of the REER with respect to remittances (−0.126, $p < 0.001$) and tourism (−0.065, p = 0.002) are negative, but these use conventional standard errors and the tourism result is therefore not robust to serial correlation. The 36 month rolling remittance coefficient changes sign across windows, indicating instability that the full sample dummies and interactions may not detect. A Chow type test and sub-period regressions were not usable because the sub-period estimates reverted to the full sample, so no break test result is reported.

5.6 Hypothesis summary

Table 5 relates the evidence to the hypotheses. Remittances are significantly related to the REER, but with a negative sign, so the data do not support appreciation. Tourism earnings are not significant in the linear models. The combined inflow is not associated with appreciation, a long run relation exists, and crisis effects are not detected by dummies or interactions, although the rolling estimates suggest instability.

Table 5. Summary of Hypothesis Tests

	Key evidence	Outcome
H1	Remittances: −0.011 (HAC p = 0.004)	Significant association, negative sign; appreciation not supported
H2	Tourism: −0.002 (HAC p = 0.623); significant only in log–log (not HAC-robust)	Not supported in linear models
H3	Combined inflow: −0.006 (p = 0.021)	Not supported (no appreciation)
H4	Trace test indicates two cointegrating relations	Supported
H5	Dummies p > 0.32; interactions p > 0.80; rolling coefficient unstable; no valid break test	Not detected by dummies or interactions; inconclusive

Note. Outcomes refer to the evidence in this study only and do not establish causation or test the resource-movement channel of Dutch disease.

6. DISCUSSION

The results do not show real appreciation associated with either inflow. Remittances are positively related to the REER only in the bivariate model; once inflation, GDP growth, FDI and ODA are held constant, the coefficient is negative, and the combined inflow is also negatively related to the REER. This differs from the appreciation reported in panel studies (Amuedo-Dorantes & Pozo, 2004) but is compatible with the view that remittances can act as counter cyclical household transfers (R, Chami Ralpa; F, Connel ; J, 2003). Other explanations, such as central bank intervention during parts of the period or common crisis movements in 2020–2022, are plausible but untested here. The sign of every coefficient also depends on the REER convention stated above and on the units of the series.

Tourism earnings show no significant linear association with the REER in any OLS or HAC model, and the long run coefficient is insignificant. This is consistent with cross country evidence of no systematic exchange rate distortion in tourism dependent economies (Holzner, 2011), although the theoretical literature allows for such effects (Nowak & Sahli, 2007). The significant six lag Granger result and the negative log log elasticity suggest that timing and functional form matter, but neither is strong evidence: the Granger result appears at one of three lags, and the log log standard errors are not autocorrelation robust. The REER-to-tourism result at four lags is one of 18 tests and is not interpreted as a competitiveness feedback.

The REER itself adjusts little to deviations from the long run relation, while remittances and tourism adjust significantly, and tourism Granger predicts remittances at every lag. These patterns suggest common shocks, notably in 2019–2022, which makes the individual associations hard to separate; they do not show that tourism drives remittances.

Overall, the evidence addresses only the exchange rate dimension of Dutch disease. Without measures of tradable sector output, employment or competitiveness, the study cannot say whether the resource movement channel operates. All coefficients are conditional associations in aggregate national data and should not be read as causal effects.

7. IMPLICATIONS AND LIMITATIONS

For policy, the findings suggest treating remittances and tourism earnings separately when interpreting exchange rate movements, because their estimated relationships with the REER differ across specifications and neither shows appreciation. Policymakers should not read the absence of appreciation here as an all clear for competitiveness, since tradable sector outcomes were not examined, and recommendations that go beyond observational evidence, such as specific remittance or tourism measures, require further testing. For theory, the results indicate that the spending-effect prediction does not carry over automatically to transfers that may be counter cyclical or to services exports in a managed exchange rate environment.

The limitations are material. First, Model 3 shows residual autocorrelation, non normality and a RESET rejection; HAC errors correct standard errors only, and level regressions of integrated series should be read cautiously even with cointegration. Second, collinearity is high for inflation and GDP growth. Third, the monthly GDP growth and ODA series are derived, the conversion procedure is undocumented, and remittance and tourism units need confirmation against the source series; the sign of the normalized long-run coefficients is not interpreted because it depends on the normalization convention. Fourth, lag-order criteria disagreed, the Johansen and Granger lag choices are sensitivity approach rather than criterion-based, and the rank two VECM results are not reported. Fifth, no valid structural break test is available, and the rolling regression suggests instability. Sixth, aggregate data cannot rule out endogeneity.

Future work should document each series, use native-frequency data or report the conversion method, verify the REER direction and VECM normalization, report rank-two estimates and apply formal break tests such as Bai Perron. Tradable-sector output, employment or export-competitiveness measures are needed to test the resource-movement channel, and a comparative study of Small Island and remittance-dependent economies would test generality.

AI DISCLOSURE

The authors confirm that no generative AI tools were used in the preparation, writing, editing, or revision of this manuscript. All content, analysis, interpretations, and revisions were completed by the authors, who take full responsibility for the accuracy and originality of the manuscript.

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Cardano-Based Crowdfunding for Undergraduate Final-Year Projects: Donor Adoption Analysis and System Design

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ABSTRACT

Undergraduate final-year projects need funds for hardware, software licenses, materials, and prototyping, yet small student projects rarely qualify for conventional finance. Reward-based crowdfunding is an alternative, but donors have little assurance that their money is used for the project once a campaign closes. Blockchain-based crowdfunding has been studied, but few studies link donor-side adoption evidence to the design of milestone-controlled systems. This study surveyed 169 donors in Sri Lanka, recruited through purposive and snowball sampling, and analyzed the data with partial least squares structural equation modeling (PLS-SEM), using the Unified Theory of Acceptance and Use of Technology (UTAUT) extended with perceived risk as a moderator. Effort expectancy was the only significant predictor of behavioral intention to adopt the platform, but its effect was negative ($\beta = -0.206$, $p = .011$), which is opposite to the hypothesized positive effect. Performance expectancy, social influence, and

facilitating conditions were not significant, and perceived risk moderated none of the four paths. The model explained little variance in intention ($R^2 = .131$) and had no out-of-sample predictive relevance ($Q^2predict = -0.004$). Because no UTAUT factor emerged as an adoption lever, the preliminary Cardano-based design treats milestone-controlled release of funds as a baseline accountability requirement rather than as a proven driver of giving: donations in ADA are locked by a smart contract, each tranche is released only when an authorized university verifier approves the milestone, and EDUF acknowledgment tokens are minted at 10 EDUF per ADA. The design is presented as a rationale derived from the survey and the literature, not as an evaluated system. The ledger makes contributions and releases verifiable, but milestone verification remains a trust point that the blockchain does not remove.

Keywords: *Blockchain, Cardano, Crowdfunding, Smart Contracts, UTAUT*

1. INTRODUCTION

Undergraduate final-year projects incur costs for hardware, software licenses, laboratory items, data collection, and prototype testing, and funding shortfalls lead to reduced scope, delays, and weaker learning outcomes (Brew & Mantai, 2017). Bank credit, equity finance, and institutional grants are designed for established borrowers, so early-stage, noncommercial work without collateral or a track record is rarely eligible (Ayyagari et al., 2011; World Bank, 2022). Crowdfunding raises small amounts from a large online community and has financed early-stage projects that institutional finance overlooks (Mollick, 2014). Its reward-based form suits student projects because contributions are neither repaid nor exchanged for equity (Belleflamme et al., 2014), and success depends on the quality of project information, the creator's network, and the trust that backers place in the platform (Shneor & Vik, 2020).

The main weakness of reward-based crowdfunding is the lack of transparency after funding. On centralized platforms, progress reporting is voluntary, and the use of funds is hard to verify once a campaign closes. This uncertainty raises the perceived risk of giving online and lowers participation (Cumming et al., 2020; Gefen et al., 2003). Distributed ledgers provide a tamper-resistant, independently verifiable record of transactions, and smart contracts can enforce agreed disbursement rules without relying on a single custodian (Zheng et al., 2018). Tying the release of funds to verified milestones therefore promises greater accountability, although someone must still confirm that progress has occurred in the real world.

Cardano is suited to such a design. Its proof-of-stake Ouroboros protocol (Kiayias et al., 2017) and its extended unspent transaction output (eUTXO) ledger allow scripts to validate escrow-style spending conditions and support native tokens issued under a minting policy (Chakravarty et al., 2020). Research on blockchain crowdfunding has mapped its potential and its risks (Block et al., 2021; Rejeb et al., 2025), and adoption studies show that information quality and trust shape intention to use

blockchain-based crowdfunding (Behl et al., 2024). In Sri Lanka, crowdfunding research has focused on small and medium-sized enterprises and potential entrepreneurs, for whom perceived usefulness, ease of use, trust, and perceived desirability shape intention (Deepika, 2025; Deepika et al., 2023; Fernando & Pretheeba, 2024). Nguyen et al. (2021) showed that blockchain-based social crowdfunding can create social value through transparency. However, these studies rarely examine donors, rarely consider undergraduate projects, and rarely connect adoption findings to the design of milestone-controlled systems.

This study addresses that gap. It surveys donors in Sri Lanka using an extended UTAUT model and uses the results, together with the literature, to derive requirements for a preliminary Cardano-based crowdfunding architecture for undergraduate final-year projects. The study distinguishes clearly between what the survey shows and which design choices are proposed on the basis of design reasoning.

2. AIMS/OBJECTIVES

This study aims to explain donor adoption of a blockchain-based crowdfunding platform for undergraduate final-year projects and to translate the findings into system requirements. Its objectives are to identify which factors predict donors' intention to adopt such a platform, to test whether perceived risk changes these relationships, and to derive design requirements for a milestone-controlled Cardano architecture. Three research questions (RQs) follow:

RQ1: Which factors predict donors' intention to support final-year projects through a blockchain-based crowdfunding platform?

RQ2: Does perceived risk moderate these relationships?

RQ3: How can the results inform the requirements of a Cardano-based crowdfunding architecture?

3. THEORY

The Unified Theory of Acceptance and Use of Technology (UTAUT) integrates eight earlier acceptance models into four determinants of behavioral intention: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC) (Venkatesh et al., 2003). In this study, PE is the degree to which donors believe the platform helps them support worthwhile projects effectively, EE is the ease of using the platform and its wallet, SI is the extent to which important others expect donors to use it, and FC is the availability of resources and support. The dependent variable is donors' behavioral intention to adopt the platform (BI), referred to as adoption intention. UTAUT is widely used, but a meta-analysis shows that its predictive power varies across contexts and that PE is usually its strongest predictor (Blut et al., 2022).

Perceived risk (PR) is the uncertainty that a user associates with a transaction. Featherman and Pavlou (2003) distinguish financial, privacy, and performance risk, among other facets, and show that these facets reduce the adoption of electronic services. Giving money through an unfamiliar financial technology is uncertain, so PR is a common extension in blockchain adoption research (Norbu et al., 2024; Ullah et al., 2021). When PR is high, the benefits and ease of a platform may not translate into intention to give, because donors weigh possible losses against expected value. PR is therefore modeled as a moderator of the four UTAUT paths rather than only as a direct antecedent.

In the research model (Figure 1), H1–H4 propose that PE, EE, SI, and FC positively influence BI, and H5–H8 propose that PR moderates each of these four paths. Because UTAUT was developed for users who adopt technology for their own tasks, its fit for voluntary giving is itself an open question that the study tests.

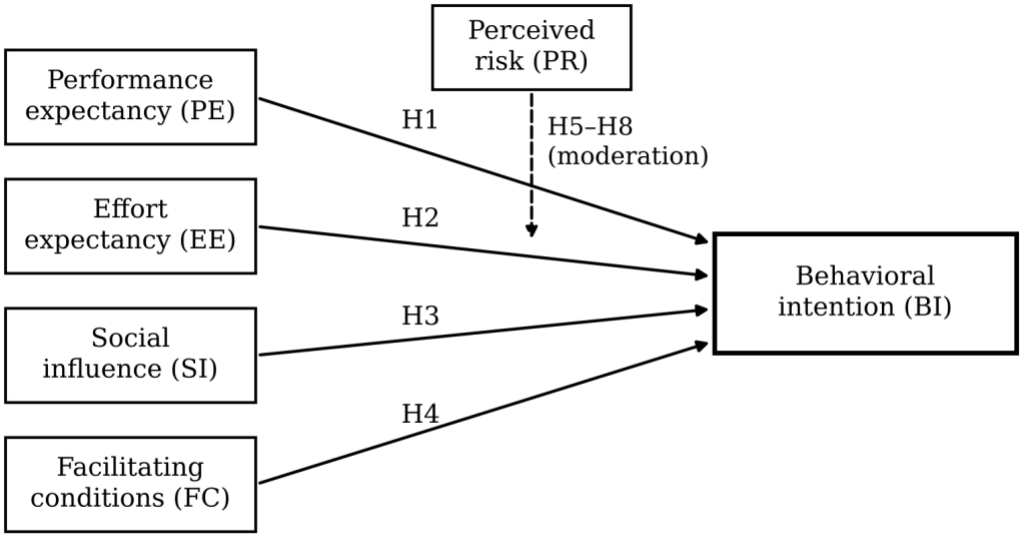

Figure 1. Research Model with Perceived Risk as a Moderator (H1–H8)

Source: Authors, based on Venkatesh et al. (2003) and Featherman and Pavlou (2003).

4. METHODS

4.1. Research Design, Sampling, and Data Collection

The study followed a pragmatist, design-oriented approach that combined an adoption survey with system design (Creswell & Creswell, 2018). The unit of analysis was the donor, because campaign success depends on donors' willingness to give. The population consisted of existing and potential donors in Sri Lanka in four groups: individual donors, university alumni, industry professionals in

technology, engineering, banking, and finance, and corporate social responsibility (CSR) representatives.

Because no register of such donors exists, purposive and snowball sampling were used. The online questionnaire was distributed through university alumni networks, LinkedIn and other professional networks, corporate CSR contacts, and personal networks, and respondents were invited to forward it to other donors. Eligibility was assessed with a screening question: only respondents who had donated to a cause in the last three years or who would consider funding a student project were retained. The four donor groups were not sampled by quota; their shares are reported in Section 5.1.

The minimum sample size was set by the part of the model with the most predictors. In the full moderation model, nine predictors point to BI: the four UTAUT constructs, PR, and the four interaction terms. A G*Power calculation for a multiple regression with nine predictors ($f^2 = 0.15$, $\alpha = .05$, power = .95) gave a minimum of 166 cases (Faul et al., 2009), which is stricter than the ten-times rule of 90 cases (Hair et al., 2019). A target of 200 responses was therefore set. Of the 200 responses received, 31 did not meet the screening criterion, leaving 169 usable cases, which is above the minimum of 166.*

4.2. Measurement Instrument

The questionnaire had three parts: a donor profile, giving behavior and interest in funding student projects, and 42 measurement items rated on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). A short explanation of blockchain-based crowdfunding preceded the items so that respondents unfamiliar with blockchain could answer meaningfully. The items were adapted to the context of a donor deciding whether to fund student projects. PE had 10 items covering perceived usefulness, job fit, and relative advantage; EE had six items covering ease of use and complexity; SI had six items covering social factors and subjective norm; FC had seven items covering compatibility and perceived behavioral control; and BI had three items (Davis, 1989; Venkatesh et al., 2003). PR had 10 items covering financial risk (for example, losing the donation if a project fails), privacy risk (misuse of personal and wallet data), and performance risk (the platform or smart contract not working as intended), adapted from Featherman and Pavlou (2003). The three complexity items in EE were reverse-coded. The instrument was pilot-tested with a small group of alumni and industry donors, and item wording was adjusted. Appendix A summarizes each construct, its sources, and the items retained.

4.3. Data Analysis

Data were screened in SPSS for missing values, straight-lining, reverse coding, outliers, and normality. Common method bias was assessed with Harman's single-factor test (Podsakoff et al., 2003). The model was estimated with PLS-SEM in SmartPLS 4, which suits predictive models with moderation and does not require multivariate normality (Hair et al., 2019). The measurement model was assessed

against these thresholds: outer loadings of at least 0.708 (with loadings between 0.40 and 0.708 retained if reliability and convergent validity were met), Cronbach's α of at least .70 (Cronbach, 1951), composite reliability (CR) of at least .70, average variance extracted (AVE) of at least .50 (Fornell & Larcker, 1981), and heterotrait–monotrait ratio (HTMT) values below .85 (Henseler et al., 2015). The structural model was assessed through inner-model variance inflation factors (VIF), path coefficients (β) with two-tailed p values and 95% bootstrap confidence intervals (CIs, reported for the significant and unstable paths) from bootstrapping with 5,000 subsamples, R^2, f^2, and out-of-sample predictive relevance using PLSpredict with 10 folds and 10 repetitions (Q^2predict; Shmueli et al., 2019). Moderation (H5–H8) was tested with the two-stage approach, in which latent variable scores from the main-effects model are used to form the interaction terms; simple-slope analysis was planned for any significant interaction.

4.4 Derivation of Design Requirements

Design requirements were derived from three sources: donor trust problems reported in the literature, the donor concerns represented in the questionnaire items (for example, wallet set-up effort within EE and loss of funds within PR), and the survey results. Each concern was mapped to a requirement and then to an architectural response (Table 3). Where the related survey factor was not significant, the requirement was retained only if the literature supported it, and the table states this. The mapping is a design rationale; the effect of each response on adoption was not tested.

5. RESULTS

5.1 Sample Profile and Data Screening

Of the 200 responses, 31 respondents had not donated to a cause in the last three years and would not consider funding a student project, so they were excluded. The 169 usable responses had no missing values and no straight-lining patterns, and no further cases were removed. After reverse coding, item skewness ranged from −0.53 to −0.20 and excess kurtosis from −0.85 to 0.03, all within ±1. The first unrotated factor explained 12.17% of the variance, well below 50%, so common method variance is unlikely to bias the results.

Of the 169 respondents, 32.5% were alumni, 30.2% individual donors, 19.5% CSR representatives, and 17.8% industry professionals. More than half (53.8%) had donated to a cause in the last three years, and 46.2% had used a crowdfunding platform. Most respondents (53.3%) were not familiar or only slightly familiar with blockchain technology. When asked whether they would support a final-year project, 43.8% of the 169 respondents answered yes, 40.2% answered maybe. The most common affordable contribution was less than LKR 5,000 (30.2%), and 31.4% of respondents said they required no reward.

5.2 Measurement Model

With all 42 items included, PE, EE, SI, FC, and PR did not reach an AVE of .50. Items with loadings below 0.40 were removed first, and the remaining items with the lowest loadings were then removed one at a time, with the model re-estimated each time, until every construct reached an AVE of .50. Of the 42 items, 28 were retained (Table 1; Appendix A). Retained outer loadings ranged from 0.506 to 0.999, and 12 loadings between 0.40 and 0.708 were retained because their constructs met the reliability and convergent validity criteria. Cronbach's α ranged from .757 to .830, CR from .778 to .867, and AVE from .509 to .686. The highest HTMT value was .268 (EE–BI), and the Fornell–Larcker criterion was met.

Two features of the measurement model need explanation. First, the SI composite is dominated by a single item with a loading of 0.999, and the CR of SI is lower than its α. After item deletion, SI is therefore effectively measured by one indicator, which limits its interpretation and explains why the SI path was unstable across bootstrap samples. Second, the low maximum HTMT does not indicate a measurement error; it reflects the weak correlations among the constructs, which are consistent with the low explanatory power of the structural model. Item deletion also reduced the content coverage of PE, SI, and PR, so these constructs represent narrower versions of their original definitions.

Table 1. Reliability, Validity, and Descriptive Statistics

Construct	Items	α	CR	AVE	Mean	SD
Performance expectancy (PE)	5/10	.779	.835	.515	3.24	0.72
Effort expectancy (EE)	5/6	.757	.838	.509	3.19	0.70
Social influence (SI)	3/6	.806	.778	.557	3.17	0.82
Facilitating conditions (FC)	6/7	.830	.862	.512	3.20	0.76
Perceived risk (PR)	6/10	.827	.862	.512	3.26	0.72
Behavioral intention (BI)	3/3	.784	.867	.686	3.22	0.78

Note. N = 169. Items = retained/original. Mean and SD are for the unweighted mean of the retained items on a 1–5 scale. α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted. Source: Authors' survey data.

5.3. Structural Model

Inner VIF values ranged from 1.007 to 1.072 for the main effects and did not exceed 1.135 with the interaction terms, so collinearity was not a concern. The full model explained 13.1% of the variance in BI ($R^2 = .131$, adjusted $R^2 = .082$), and the main-effects-only model explained 10.8%. Q^2predict for BI was −0.004, indicating no out-of-sample predictive relevance (Table 2).

PE ($\beta = -0.099$, $p = .271$), SI ($\beta = 0.179$, $p = .264$), and FC ($\beta = 0.119$, $p = .327$) had no significant effect on BI, so H1, H3, and H4 were not supported. EE had a significant effect in the direction opposite to the hypothesis ($\beta = -0.206$, $p = .011$, 95% CI [−0.358, −0.054], $f^2 = 0.045$, a small effect). Because H2 predicted a positive

effect, H2 was not supported. PR had no direct effect on BI (β = 0.026, p = .836), and none of the four interaction terms was significant (all p > .18), so H5–H8 were not supported and no simple-slope analysis was needed. The SI estimate was unstable (95% CI [−0.291, 0.330]) because it rests on a single item. As the data are cross-sectional, the paths represent associations rather than causal effects.

Table 2. Structural Model Results (Bootstrapping, 5,000 Subsamples)

H	Path	β	t	p	f^2	Result
H1	PE → BI	−0.099	1.105	.271	0.011	Not supported
H2	EE → BI	−0.206	2.579	.011	0.045	Not supported (opposite direction)
H3	SI → BI	0.179	1.122	.264	0.033	Not supported
H4	FC → BI	0.119	0.983	.327	0.015	Not supported
–	PR → BI	0.026	0.207	.836	0.001	–
H5	PR × PE → BI	−0.005	0.056	.955	0.000	Not supported
H6	PR × EE → BI	0.038	0.408	.684	0.002	Not supported
H7	PR × SI → BI	0.015	0.166	.869	0.000	Not supported
H8	PR × FC → BI	−0.148	1.318	.189	0.025	Not supported

Note. R^2(BI) = .131, adjusted R^2 = .082, Q^2predict = −0.004. Two-tailed tests. Confidence intervals for the significant EE path and the unstable SI path are reported in the text. Not supported = the hypothesis was not supported. Opposite direction = the effect was significant (p < .05) but negative, whereas the hypothesis predicted a positive effect. Source: Authors' analysis in SmartPLS 4.

5.4 Preliminary System Design

Table 3 maps donor concerns to requirements and architectural responses, with milestone-controlled release as the core requirement. The design has four layers. A presentation layer provides dashboards for students, donors, verifiers, and administrators. Donors sign transactions in a browser wallet that follows the Cardano CIP-30 wallet standard, so private keys are never entered on the platform. An application layer manages campaigns, milestones, contributions, and verification and builds blockchain transactions. An off-chain database stores user, campaign, and milestone records. Only financial events are recorded on-chain: contributions, releases, the ADA held at the escrow validator's script address, and the minting of EDUF, the platform's acknowledgment token.

In the fund-control lifecycle (Figure 2 and Algorithm 1), a donor connects a wallet and contributes A ADA, the native currency of Cardano. In the same transaction, the ADA is locked at the escrow validator's script address and the minting policy issues 10A EDUF to the donor, so EDUF cannot be issued unless the corresponding ADA is locked. When a student submits evidence for a milestone and the authorized university verifier approves it, the validator releases only that milestone's allocation to the student's address, and the funds for later milestones stay locked.

The verifier is a staff member appointed by the student's faculty, whose wallet key is registered to the campaign; approval is a signed transaction, so every decision is

recorded and attributable. If the verifier rejects the evidence, the student may resubmit, and the design specifies that a disputed rejection is referred to a second faculty reviewer. If a project is abandoned or misses its final milestone deadline, the unreleased ADA is returned to donors in proportion to their contributions. The rate of 10 EDUF per ADA is a fixed, easily understood ratio; EDUF serves only as a record of acknowledgment, has no claimed monetary value, return, or tradability, and is not an incentive to invest. Because ADA prices change, each contribution and allocation is shown in LKR at the time of contribution, and donors are told before giving that the LKR value of locked ADA may change before release.

Implementation status should be read precisely. The campaign, donation, and milestone workflows were implemented off-chain in a full-stack web prototype (React, TypeScript, Tailwind CSS, TanStack Start, and MongoDB), and test transactions were submitted on the Cardano Preprod test network. The escrow validator, the minting policy, the dispute route, and the refund rule are specified at the architectural level only. No usability, security, cost, or performance evaluation is reported, so the architecture is a preliminary design rather than an evaluated solution.

Table 3. Derivation of Design Requirements

Donor concern	Survey evidence	Requirement	Architectural response
Opacity after funding	Literature (Cumming et al., 2020)	Verifiable financial record	Contributions and releases as on-chain transactions
No control over use of funds	Literature (Gefen et al., 2003)	Conditional custody	Escrow validator holds ADA
Loss if a project fails (PR)	PR → BI and moderation NS; retained from literature	Staged disbursement and refund rule	Milestone allocations; unreleased ADA returned pro rata
Wallet set-up effort (EE, FC)	EE significant but negative; FC NS; 53.3% low blockchain familiarity	Lower entry barrier	Guided wallet connection; service layer builds transactions
Personal data exposure (PR)	PR NS; retained from literature (Finck, 2018)	Minimal on-chain data	Only financial events on-chain
ADA price movement (PR)	PR NS; retained as disclosure	Value visibility	Amounts shown in Sri Lankan rupees (LKR) with a volatility notice
Recognition of contributors	31.4% required no reward	Transparent acknowledgment	10 EDUF minted per ADA, as acknowledgment only
Wrong or disputed approval	Literature (Caldarelli, 2020)	Accountable verification	Registered verifier key; second reviewer for disputes

Note. PR = perceived risk; EE = effort expectancy; FC = facilitating conditions; NS = the related survey path was not significant. Source: Authors.

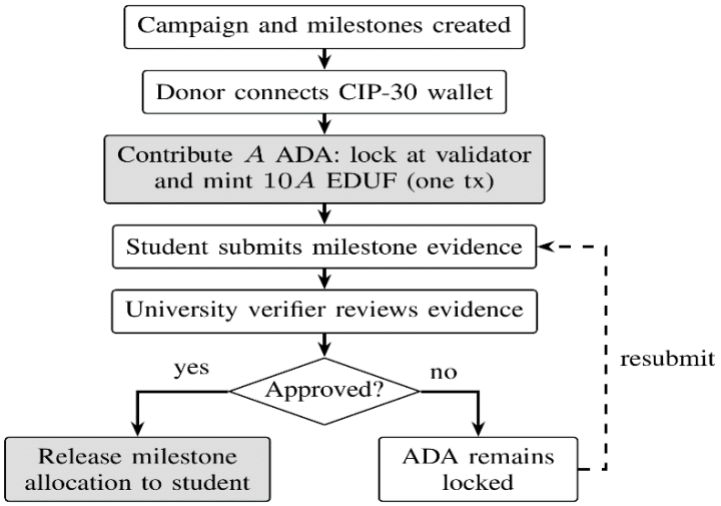

Figure 2. Milestone-Controlled Fund Release (Shaded Steps Are On-Chain Transactions)

Source: Authors.

Algorithm 1. Milestone-Controlled Fund Release (Architectural Pseudocode)

```
Require: campaign C with milestones M1…Mk, allocations a1…ak, registered verifier V
  1: on contribution of A ADA by donor D do
        2: lock A at the escrow script of C; mint 10A EDUF to D (one transaction)
  3: end on
  4: on submission of evidence for milestone Mi do
        5: if V approves Mi (signed transaction) then
              6: release ai to the student address (on-chain transaction)
        7: else retain ai under the escrow script; allow resubmission or referral to a second
        reviewer
        8: end if
  9: end on
  10: on abandonment or a missed final deadline do
       11: return unreleased ADA to donors in proportion to their contributions
  12: end on
```

Source: Authors.

6. DISCUSSION

The extended UTAUT model received little support in this donor context. PE, SI, and FC were not related to BI, and the model explained only 13.1% of the variance in intention and had no out-of-sample predictive relevance. This is far below the explanatory power typically reported in UTAUT research (Blut et al., 2022; Venkatesh et al., 2003). In particular, PE, which meta-analytic evidence identifies as the strongest UTAUT predictor (Blut et al., 2022), was not significant. One interpretation is that donors do not evaluate a giving platform in the utilitarian terms that users apply to technology they use for their own tasks. The nonsignificant SI

path is consistent with the voluntary nature of giving, because in the original UTAUT study social influence mattered mainly when use was mandatory (Venkatesh et al., 2003).

The only significant path, from EE, was negative: donors who found the platform easier to use reported slightly lower intention. This finding should be treated as tentative rather than as evidence that ease of use deters giving. The effect is small, it is one of nine tests, and the model as a whole has no predictive relevance, so the result may not replicate. A possible explanation is that respondents who found the platform easy had more experience with digital finance and were more critical of new blockchain services, but the study did not test this. Unlike blockchain payment research in which risk shapes intention (Norbu et al., 2025), PR neither moderated any path nor affected intention directly. Respondents evaluated a described platform rather than a working one, which may have made its risks less concrete.

The methods also limit what can be concluded. The UTAUT constructs combine sub-dimensions from different models, and item deletion narrowed PE, SI, and PR, so the nonsignificant paths may partly reflect measurement rather than the absence of a relationship. Compared with Sri Lankan crowdfunding studies, which found that usefulness, ease of use, and trust predicted intention among entrepreneurs and SMEs (Deepika et al., 2023; Fernando & Pretheeba, 2024), the present results suggest that donors may respond to different motives, such as altruism, trust in the institution, or ties to the university, which UTAUT does not capture.

Because no predictor was significant in the hypothesized direction, the survey does not provide an empirical ranking of the design requirements, and its implications for design are limited. Guided wallet set-up remains relevant because more than half of the respondents had little familiarity with blockchain; the negative EE path shows only that ease of use alone will not motivate giving. Milestone-based release, university verification, and on-chain transaction links remain baseline accountability measures supported by the literature rather than proven adoption levers. Finally, because 31.4% of respondents required no reward, EDUF is better positioned as an acknowledgment than as a principal incentive.

7. IMPLICATIONS AND LIMITATIONS

For theory, the results suggest that UTAUT alone does not explain donors' intention to give through a blockchain platform. Future models should include donor-specific constructs such as altruism, trust in the verifying institution, and attachment to the university. For practice, conditional escrow, verified milestones, and public financial records offer a design response to donors' accountability concerns, and universities considering such a platform would need to define the verifier's role, workload, and accountability. However, on-chain records cannot verify real-world progress. Inaccurate evidence or a dishonest verifier would still lead to release, so the design is not fully decentralized. Self-custody makes wallet compromise a donor risk, and

ADA volatility changes the real value of escrowed funds, which the LKR display makes visible but does not remove.

The study has several limitations. Non-probability sampling limits generalization to all donors in Sri Lanka or elsewhere. The measures were self-reported at one point in time and captured intention rather than actual donations. Item deletion narrowed construct coverage, and SI rests largely on one item. At the system level, the correctness, security, transaction costs, latency, and usability of the design remain to be evaluated, and the regulatory treatment of ADA and EDUF was outside the scope of the study. Future research should implement and test the validator and minting policy on the Preprod test network, measure cost, latency, and usability, observe actual giving, replicate the survey with donor-specific constructs, and examine verifier governance.

8. CONCLUSION

This study surveyed 169 donors in Sri Lanka and used the results to derive requirements for a Cardano-based crowdfunding architecture for undergraduate final-year projects. For RQ1, none of the four UTAUT constructs positively predicted donors' intention; EE was negatively related to intention, and the model had low explanatory power and no predictive relevance. For RQ2, perceived risk did not moderate any relationship. For RQ3, because the survey did not identify an adoption lever, the design draws on the literature and treats milestone-controlled release, verified university approval, minimal on-chain data, LKR value display, and EDUF acknowledgment as baseline requirements. The survey findings and the proposed architecture are therefore different kinds of contribution: the first is empirical evidence about donors, and the second is a preliminary design that still requires technical and user evaluation.

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