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The Impact of Climate-Related Reporting on the Financial Performance of Aotearoa New Zealand Companies

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Abstract

Effective 1 January 2023, Aotearoa New Zealand has implemented mandatory climate-related reporting requirements, aligning with global developments in climate-change regulatory frameworks. Changing from voluntary reporting to mandatory reporting may incur financial consequences for Aotearoa businesses. Therefore, this study aims to analyse the impact of climate-related reporting requirements on the financial performance of Aotearoa businesses during the voluntary reporting period and post-implementation periods of mandatory reporting. Twenty-six listed companies were selected for the study as sample companies based on the regulatory guidelines of the New Zealand External Reporting Board (XRB). By reviewing five years of annual reports of sample companies, return on equity (ROE) and return on assets (ROA) data was collected as financial performance measures. For the same period, the climate reporting score was measured based on the climate reporting checklist published by KPMG New Zealand. Two regression analyses were conducted using the panel data collected to achieve research objectives. The analysis provided mixed results. Only one element of climate-related reporting, metrics and targets, has a significant positive impact on ROA. All other climate reporting variables, such as governance, risk management, consistency and comparatives, have no significant relationship with either ROE or ROA in both the voluntary reporting period and the post-implementation periods of mandatory reporting. The study provides recent evidence from Aotearoa on the impact of climate reporting on company performance, comparing pre- and post-mandatory periods.

Keywords

Climate-related reporting
Aotearoa New Zealand
Financial performance

1. Introduction

The cumulative impact of extreme climate events presents a serious threat to economic development globally, with losses of USD 143 billion annually and projected to hit USD 178 trillion by 2070 if no measures are implemented (Dietz et al., 2016; Sari, 2024). However, increasing efforts towards developing a net-zero economy could reduce the losses to USD 43 trillion. To recognise this opportunity, governments around the world are passing on regulatory frameworks to respond to the effects of climate change. Leading countries, such as the United Kingdom, Japan, Switzerland and Singapore, have imposed climate-related reporting requirements (Jones et al., 2023). Aotearoa has become one of the world's first countries to transform its voluntary reporting to mandatory climate-related reporting within financial reports, effective from 1 January 2023, for large publicly listed companies. Insurers, banks, non-bank deposit takers and investment managers support Aotearoa's overall ambition to reach net-zero emissions by 2050 (Bui et al., 2021; Lindsay, 2023).

The transition from voluntary to mandatory climate reporting imposes cost implications for businesses in the short and long term (Kowsana & Muraleethran, 2021). Given the economic significance of big companies, regulatory requirements must be balanced with financial feasibility by business executives, investors and policymakers. It is in the interest of not just the businesses that have to do so but also the wider business community in Aotearoa to understand the impact of climate reporting on financial performance.

The mandatory climate reporting regime applies to major financial institutions, including banks, insurance providers, fund managers, and listed companies with a market standardisation of more than $60 million (External Reporting Board, 2024). To support this transition, Aotearoa introduced the Aotearoa New Zealand Climate Standards, which aim to encourage consideration of climate risks in business, investment, lending and insurance activities, to improve transparency and accountability of reporting entities, and transition towards a low-emission, sustainable economy based on well-informed investment choices (Ministry of Business, Innovation and Employment, 2023). Additionally, this policy development, led by the External Reporting Board, reflects growing national recognition of climate risk as a financial risk. Furthermore, the Financial Markets Authority (2022) identifies growing expectations of decision-useful, high-quality climate reporting by key sectors. These developments highlight the necessity to examine the effect of climate-related disclosures on firm financial performance in the unique regulatory and environmental context of Aotearoa.

Historically, Aotearoa firms have adhered to global patterns in reporting about environmental, social and governance (ESG) measures and corporate social responsibility (CSR), according to voluntary sustainability reporting guidelines (Hsiao et al., 2022). Firstly, previous studies examining the impact of sustainability reporting on accounting performance were restricted to voluntary reporting information. At the same time, climate-related disclosure was not mandated, which limited comparability between companies' performance and identifying the real impact before and after mandatory reporting regimes (Umar et al., 2021; Carvajal & Nadeem, 2022). Secondly, the research lacked sector-level analysis, particularly in key industries such as the financial, industrial and materials sectors. Thirdly, while some of the research analysed ESG disclosure in financial organisations (Yu, 2023), little effort was made to examine the impact of climate-related reporting on specific industries within Aotearoa.

In summary, despite Aotearoa's reporting requirement for climate-related matters, its impact on the financial performance of companies remains unknown. Though the rules aim to enhance transparency and ensure more sustainable business, there is a lack of empirical evidence to indicate whether they lead to improved financial performance. This study examines the relationship between financial performance and climate reporting.

This study was conducted to answer two major research questions, as follows:

1. What is the impact of climate-related reporting on the financial performance of Aotearoa businesses?
2. Is there any significant financial-performance change in the mandatory reporting period compared to the voluntary climate-related reporting period?

Understanding climate-related reporting is essential to business managers, investors, policymakers and government institutions (Atasel et al., 2020). Through the analysis of climate disclosures and financial performance, this study provides insights into market opinions regarding climate reporting, its influence on investment choices, and its influence on business value. The implications could lead investors to focus on green companies, ultimately making sustainability a strategic corporate imperative. Further, Aotearoa's move towards mandatory climate reporting has required a fundamental overhaul of the corporate reporting systems (Dey et al., 2023). Our study offers empirical evidence on how companies have reacted to the new mandates regarding financial performance and firm conduct. The findings of this study can help regulators evaluate the effectiveness of current mandatory climate reporting requirements.

The examination of the relationship between climate disclosures and financial performance provides insight into whether such regulations are attaining their respective goals. This, in effect, can inform policy making and consideration in the future, and highlights any further reform or adjustment that may be needed to improve reporting quality, consistency and relevance.

Considering increasing international attention to climate risks, studies in this field are highly pertinent. While there is limited Aotearoa literature on climate reporting in the financial, industrial and materials sectors, this study contributes to the emerging body of literature by providing sector-level results and issuing a call for more research into the integration of climate reporting with sustainable business practices.

The paper is organised as follows: In section two, the literature review describes international climate reporting history and Aotearoa's progress in climate reporting, followed by methodology, with the study design, data collection and analysis strategy in section three. The results and discussion in section four present analytical findings, and finally, the conclusion summarises key findings, study limitations and potential future research avenues.

2. Literature Review

2.1 Evolution of global climate-related reporting and the Aotearoa context

Climate reporting has roots in mid-20th-century CSR concepts and has grown significantly over the past 40 years (Helmold et al., 2022; Maroun, 2020). In the 1990s, the Global Reporting Initiative standardised environmental reporting, and more recent efforts have been the European Union's Nonfinancial Reporting Directive and United Nations Sustainable Development Goals (Dinu et al., 2023; Ferranti, 2018; Rimmel, 2020).

Projections of 1.0°C–1.5°C by the year 2050 for global warming may be conservative, with the existing trend in carbon emissions suggesting such levels could be achieved by 2033 or 2035 (Diffenbaugh & Barnes, 2022). Aotearoa, economically vulnerable to climate change due to its agriculture-driven economy, has committed to reducing greenhouse gas (GHG) emissions by 30% by 2030 and achieving net-zero emissions by 2050 through the COP21 Paris Agreement (Kimura et al., 2023). To realise these goals, the government is launching strict climate reporting requirements, and businesses, particularly in agriculture, are adopting technologies to reduce environmental impacts (Lawrence et al., 2022). However, Aotearoa's per capita GHG emissions rank among the highest globally, as a result of its agriculture and animal production industries (Campbell-Hunt et al., 2015). Aotearoa's Emissions Trading Scheme (ETS), introduced in 2008, has also come under criticism as not leaving sufficient room for low-carbon behaviour change and investments, and for diluting Aotearoa's role as a responsible climate-governing country of the world (Campbell-Hunt et al., 2015; Wang, 2019).

With global pressure and COP21 interactions, Aotearoa and fellow members of the Asia–Pacific region are aligning business processes with climate regulations. Companies include climate adaptation strategies in financial reporting to transparently communicate climate risk and financial performance information to stakeholders (Abhayawansa & Adams, 2022). However, climate-related reporting so far is occasionally inconsistent, and there is poor integration of climate-related risks into financial reports, together with minimal cross-referencing between non-financial and financial reports (Рожнова & Efimova, 2020). This highlights the need for standardisation of climate-risk disclosures to better reflect the interconnectivity of climate change and business opportunities.

Early voluntary reporting was non-standardised, and comparability was difficult (Simon & Mkumbuzi, 2024). Across the globe, the shift to mandatory climate reporting is on the rise due to the lack of standardisation in voluntary practices. Thus, governments and stock exchanges are increasingly demanding green reporting to address environmental concerns (Chen et al., 2024). Aotearoa has also acted, being one of the earliest countries to establish mandatory climate reporting requirements, which commenced on 1 January 2023. This move mirrors the growing importance of transparent, consistent reporting in addressing climate challenges and aligning financial and non-financial disclosures, where the impact on the company's performance is yet to be discovered.

2.2 Financial consequences of adapting to climate-change reporting

2.2.1. Findings with a positive relationship

Sustainability reporting has evolved a lot, and there have been numerous studies all over the world on the connection between CSR, ESG, sustainability and climate-change reporting (Drempetic et al., 2020). Empirical studies consistently indicate a positive relationship between reporting practices and financial performance, with companies adopting strong, transparent reporting tending to deliver improved financial outcomes (Evans & Peiris, 2010). Climate-change adaptation comes at a cost, either in terms of capital investment or periodic maintenance, to the profitability of an enterprise. Financial performance, a key indicator of business effectiveness, is measured using ratios such as return on equity (ROE) and return on assets (ROA) (Venanzi, 2012).

ESG reporting, focusing on environmental, social and governance practices, is another critical factor, as is an earlier generation of climate reporting. Companies with improved ESG ratings and clear reporting have a greater tendency to achieve improved financial performance (Raghavan, 2022). Pioneering research by Eccles et al. (2014) tracked US firms over 18 years and found that the companies that integrated ESG factors into their strategies outperformed comparable firms in both stock market returns and profitability. These firms demonstrated enhanced risk-management and resilience against market volatility. An extensive survey by Friede et al. (2015) of over 2200 studies revealed that nearly 90% of them found a favorable or neutral relationship between profitability and ESG reporting. Clark et al. (2015) found that 88% of firms with strong sustainability practices achieved positive operating results, and 80% achieved long-term financial success. Margolis and Walsh (2003) also noted a statistically significant positive relationship between sustainability reporting and financial performance, attributed to enhanced operational effectiveness, innovation and value creation.

As the newest reporting framework, climate-disclosure-related studies reveal that firms that disclose climate information, such as greenhouse gas emissions and energy efficiency, experience lower capital costs and perform better than competitors in market performance (Matsumura et al., 2014; Khan et al., 2022). Also, disclosures of climate threats and opportunities engage investors and contribute to the financial success of entities (Kaklauskaite & Streimikiene, 2024). Transparent climate disclosures are being considered more of a competitive advantage, of value to all stakeholders.

Several studies provide empirical evidence of the positive relationship between environmental disclosure and firm performance. Voluntary disclosures of climate change are positively related to board effectiveness (Ben-Amar & Mcilkenny, 2014) and employee stock ownership (Abdelnour et al., 2023), suggesting that improved governance structures result in increased transparency. Additionally, mandatory and voluntary disclosures on the environment have a positive relationship with financial performance in heavy-polluting Chinese companies (Wu & Li, 2022). A study of US-listed companies provides evidence of a positive link between ESG performance and quality of financial disclosure (Ferdous et al., 2024). In addition, voluntary disclosure indexes are positively associated with proxies for firm performance (Hamrouni et al., 2015), and greater disclosure rankings are associated with improved stock returns, firm value and subsequent financial performance measures (Jiao, 2011).

Generally, although some studies show a positive relationship between climate reporting disclosures and firm performance, the evidence is not entirely consistent. Factors such as board performance, employee ownership and local economic growth can influence this relationship (Abdelnour et al., 2023; Ben-Amar & Mcilkenny, 2014; Wu & Li, 2022). The differing results establish the nature of the issue and the need to continue conducting studies to fully grasp the dynamic between climate disclosure and firm performance in different industries and geographical areas.

Overall, the literature reflects a strong positive relationship between financial performance and every form of green reporting, including CSR, ESG, sustainability reporting and climate reporting. The practices enhance market and operating performance, leading firms to adopt holistic and transparent reporting methods.

2.2.2. *Findings with a negative relationship*

While the majority of studies find a positive relationship between financial performance and CSR, ESG, sustainability reporting and climate reporting, others find a negative relationship, primarily due to the cost of implementing sustainability programmes (Buallay et al., 2021). For instance, CSR activities may divert resources from core business operations, increasing costs and reducing profitability.

ESG reporting, while much praised, is also criticised for its cost. Duque-Grisales and Aguilera-Caracuel (2019) contend that the expenses associated with conducting ESG activities, including the deployment of green technologies and enhancing employee working conditions, can put financial performance under stress, particularly in the short term. Wang et al. (2016) also indicate that excessive costs of ESG compliance may lead to suboptimal financial performance and lower market returns, because companies are not able to balance profitability and ESG goals.

Sustainability initiatives, though positive in the long term, tend to require heavy initial technology investment and change in operations, which negatively affect short-term financial performance (Nugrahani & Artanto, 2022). Jacobs et al. (2010) found that companies with lofty goals of sustainability normally experience short-run financial losses due to the expenses incurred.

Similarly, Lioui and Sharma (2012) also assert that excessive investment in sustainability initiatives may result in reduced share prices, due to the fact that investors may perceive these as a diversion of resources from profit-generating activities.

Climate reporting also brings with it the financial challenge that companies must spend considerable amounts to address climate risk-management and emission reduction. Kartadjumena and Rodgers observe that investments are made to deliver long-term social non-monetary outcomes rather than immediate monetary return (2019). Griffin and Sun (2013) found that companies that disclose climate-related risks underperform within the market, as investors view them as risky, particularly in carbon-intensive activities that require a lot of emissions-management investment.

In summary, the negative link between green reporting and financial performance is primarily sustained by the very high expenses in embracing sustainability culture, particularly in the short term. Those expenses can cause decreased profitability as well as investors' demand for their shares, even though greater profits may arise in the future than short-run financial hardships.

2.2.3. *Findings with no relationship*

Different studies have examined the relationship between financial performance and green reporting – i.e., CSR, ESG, sustainability and climate-change reporting – and found that there is no specific positive or negative relationship (Buallay et al., 2021). The studies show that while green reporting is more prominent in modern business, its impact on financial performance is neutral.

ESG reporting has also shown a neutral relationship with financial performance. Almeyda et al. (2006) also argue that the impact of ESG reporting varies by industry, whereas upfront costs can offset anticipated long-term benefits. Margolis and Walsh (2003) reviewed 127 studies and found weak or no correlation, attributing this to the long-term period of sustainability returns. Nelling and Webb (2009) agree, noting that sustainability reporting enhances reputation and stakeholder confidence but has no significant short- or medium-term financial impacts. Also, a study conducted in Australia reported no material correlation or significant association between environmental performance and the extent of environmental disclosure (Sutantoputra et al., 2012). This suggests that the relationship between climate reporting and firm performance is not consistent across markets and settings.

Climate reporting, or carbon emissions and climate risk-management as a topic, also does not exhibit a material connection with profitability in some cases. Munjal and Sharma (2019) found no direct relationship in the Indian public banking sector, because climate-risk reporting works more out of compliance than driving profitability. Murray et al. (2006) state that expenditure on climate risk-management pays long-term benefits and, therefore, there is no net effect on finance.

In short, while green reporting improves reputation and stakeholder trust, its economic effect is commonly neutral, as short-term expenses counterbalance long-term gains. Industry-specific, regulatory and long-term implications of sustainability and climate actions impact this neutrality.

According to the literature analysis, different outcomes have been reported on the relationship between various forms of green reporting and the financial performance of businesses. Much literature highlights long-term positive outcomes. Thus, we developed the hypothesis that there is a positive association between financial performance and the extent of ESG disclosures, whereas some other researchers argue for a negative relationship in the short term. There were instances of reported neutral relations, which balanced out the long-term benefits with immediate cost-sustainability initiatives.

2.3. Findings on post-regulation-period impact

Regulatory shifts such as CSR, ESG, sustainability reporting and climate-related reporting have transformed from voluntary to mandatory. In India, the Companies Act 2013 mandates that businesses meet specific financial thresholds to spend 2% of their net income on CSR (Sharma & Aggarwal, 2022). Similarly, the EU's Non-Financial Reporting Directive (NFRD) in 2014 required large companies to report on environmental and social policies. Companies that strategically integrated NFRD requirements saw improved financial performance, risk management and stakeholder relationships, while those treating them as mere compliance did not (Hummel & Schlick, 2016).

The EU's Sustainable Finance Disclosure Regulation (SFDR) in 2019 impacted financial markets by differentiating compliant investment funds, attracting investor attention, though not all firms experienced positive financial outcomes (Birindelli et al., 2023). The Corporate Sustainability Reporting Directive (CSRD) in 2021 further standardised sustainability disclosures, leading to operational efficiencies and increased investor interest in compliant firms (KPMG, 2020).

Similarly, climate-related reporting also evolved with the Task Force on Climate-Related Financial Disclosures (TCFD) framework in 2015, shifting from inconsistent voluntary disclosures to standardised reporting. Post-TCFD, firms in the Indian energy sector demonstrated improved financial performance linked to climate disclosures (Maji & Kalita, 2022).

In conclusion, the financial impact of green reporting regulations provides mixed results and varies by industry, adaptation costs and strategic integration. Firms aligning regulations with long-term goals often achieve better financial outcomes, while those treating compliance as a standalone requirement may not see significant benefits (Eccles & Krzus, 2017).

3. Methodology

3.1. Variable measurements, sample and data collection

Data related to measuring the financial performance of businesses and climate reporting is collected from all financial and investment companies listed in the financial sector as of 5 August 2024, as well as companies with a market capitalisation exceeding $60 million and listed in the industrial, materials and energy sectors of the NZXS mainboard of the New Zealand Stock Exchange (NZX) as of 5 August 2024. A total of 26 listed companies, including all nine financial sector companies, were considered as sample companies. These entities that are required by the climate-related disclosures legislation to produce climate statements are known as climate reporting entities (CREs) (External Reporting Board, 2024). Apart from the financial sector, other companies in the sample were involved in aviation, manufacturing, transport, energy supply, freight handling and material supply. Therefore, the sample selected appropriately represents Aotearoa businesses that actively contribute to the economy.

According to the climate standard published by the External Report Board of New Zealand, entities should adhere to numerous climate-reporting requirements, which can be categorised as governance, strategy, risk management, metrics and targets, consistency comparatives, and others (KPMG, 2023). Using KPMG's *Climate disclosures checklist*, a criteria-based (governance, strategy, risk management, metrics and targets, consistency comparatives, and others) scoring system was used to measure the level of climate reporting in businesses (KPMG, 2023). Climate disclosure scores were analysed using a content analysis framework based on the KPMG (2023) ESG reporting framework. A 5-point Likert scale was used, where:

1 = no disclosure
2 = minimal disclosure (general statements)
3 = moderate disclosure (some quantitative information or specific reference)
4 = detailed disclosure (metrics, targets and performance)
5 = integrated disclosure (strategy, governance, metrics and assurance)

Annual reports and sustainability reports of companies for the five-year period from 2018 to 2024 were read. Two independent researchers performed the exercise of coding. After initial scoring, the discrepancies were debated and solved. Inter-coder reliability was assessed, and an agreement was achieved, indicating high agreement in the scoring. The process helps to mitigate subjectivity and improve the robustness of the analysis, and enhances the measurability of research content and the reliability of the research outcome by reducing bias (Adeleke et al., 2024). The level of adherence to climate reporting requirements was measured collectively for all categories as one independent variable and each category individually as more independent variables, making a total of seven independent variables. However, due to the requirement of consistent application for several companies' annual report evaluation, the KPMG checklist (KPMG, 2023) was simplified with very specific and important information in climate reporting (see Appendix 1).

In this research, financial performance information such as return on equity (ROE) and return on assets (ROA) was used to measure business performance. ROE shows profit generation from shareholders' equity, while ROA reflects asset utilisation efficiency, indicating better asset management, making it a critical comparative measure (Chakkravarthy et al., 2024; Panigrahi & Vachhani, 2021). Both ratios offer insights into profitability and operational effectiveness. The ultimate sample consisted of 26 publicly traded companies in Aotearoa that made climate-related disclosures continuously over the five years to 2024. Financial performance indicators (ROE and ROA) and climate disclosure scores were obtained from annual reports, sustainability reports and publicly available ESG databases such as Refinitiv Eikon. In total, the dataset consisted of 130 firm-year observations (26 companies × 5 years). As of September 2024, annual reports for 2023/24 had been published by some companies, while others had only published reports up to 2022/23. Where necessary, the most recent five years of data available for each company were utilised to give consistency to the panel.

For a deeper understanding of the variables and related data, including the sources that were collected, these are summarised in Table 1.

Table 1. Variable definition and measurement.

Variable type	Variable name	Code	Definition/ Explanation	Data source	Reference
Independent variables	Governance	GOV	Under the governance section of climate reporting, businesses must disclose how the board and management have structured themselves to oversee climate-related issues. This includes how roles and responsibilities are assigned to manage climate risk and opportunities. The simplest way of handling this is by appointing a committee to oversee climate-related risks and opportunities. Accordingly, seven sub-disclosure elements were evaluated under this section.	Annual reports of sample companies were the key data sources. Additionally, the NZX website was also used.	KPMG, 2023.
	Strategy	STR	This disclosure requires businesses to explain their climate-related risks and opportunities and how they are adopted into the overall strategic-planning process of the business. Moreover, how management assesses potential climate impacts and how to adopt and mitigate the impact through scenario analysis needs to be disclosed. Accordingly, six sub-disclosure elements were evaluated under this section.		
	Risk management	RSK	Under this disclosure, businesses need to outline the process of identifying, assessing, and managing climate risks and opportunities. Moreover, organisations are required to disclose short-, medium- and long-term risk assessments and the frequency of revisiting these assessments to update the changes. Accordingly, two sub-disclosure elements were evaluated under this section.		
	Metrics and targets	MNT	Organisations are required to quantify and disclose climate impacts from their business operations, and how business targeting controls and minimises the impact to improve climate performance. Under this, organisations may disclose their level of greenhouse gas emissions, energy consumption, water usage and other applicable factors on climate risk. Moreover, organisations must set clear long- and short-term targets to minimise these impacts. Accordingly, three sub-disclosure elements were evaluated under this section.		
	Consistency and comparatives	CNC	Businesses are required to present climate-related disclosures consistently over the reporting periods. Comparative information should be provided in order to get analytical information. When material changes occur in the current period, comparative information should be presented for the past reporting periods. Accordingly, three sub-disclosure elements were evaluated under this section.		
	Other	OTR	Here, businesses are required to report on methods and assumptions used; any data estimation uncertainties, statements of fair presentation, and compliance need to be disclosed. Accordingly, six sub-disclosure elements were evaluated under this section.		

Variable type	Variable name	Code	Definition/ Explanation	Data source	Reference
	Total climate reporting score	TLS	This is the addition of weighted average scores of all sub-disclosure elements of climate-related reporting. To decide the total climate reporting score, weights were allocated as 30% for governance, 25% for strategy, 10% for risk management, 15% for metrics and targets, 10% for consistency and restatement of comparatives, and 15% for other factors were allocated to decide overall climate score.		
Control variables	Total assets in NZD millions	TAM	This was used as a control variable to manage firm size, which significantly affects the dependent variables. This is a typical numeric measure of a business and its operating capacity. Total asset value was taken in millions from financial position reports of all sample companies at every financial year-end.	Annual report information on sample companies	
	Total assets log	TAL	The natural log value of total asset value at every financial year end was taken as a control variable in order to ensure the control variables were also in a similar value range with dependent and independent variables.		
	Firm age	AGE	Number of years for the business from the initial establishment. However, to ensure consistency, the date listed on NZX was considered as the start date. The number of years from the listing date to every financial year's end date was calculated.		
	Market capitalisation in NZD millions	MCM	This is another control variable that provides an idea of market performance and firm size, which has a significant impact on financial performance. Market capitalisation value was taken in millions from NZX's records at every financial year-end date. When data was not available on the exact closing date, most closed dates were considered before the financial year's end.		
	Market capitalisation log	MCL	The natural log value of market capitalisation at every financial year end was taken as a control variable to ensure the control variables were also in a similar value range with dependent and independent variables.		
	Board size	BDZ	In the governance of climate-related reporting, the board is a critical factor that has a significant impact on non-financial reporting, such as CSR, ESG, sustainability and climate reporting. Every financial year, the actual board size was taken for all sample companies.		
Dependent variable	Return on equity	ROE	This refers to the return earned for equity shareholders by the business. This was calculated by dividing the profit earned by the total equity value in the financial position report every financial year.	Financial reports of sample companies were published in their annual reports.	Nithin, 2023.
	Return on assets	ROA	This refers to the efficiency of the profit generated by businesses from their overall assets base. ROA was calculated by the profit generated before interest and tax divided by the company's total assets in the financial position report at every financial year.		

Source: Authors' own creation.

As mentioned in Table 1, there were a number of different sub-disclosure elements for each independent variable (GOV, STR, RSK, MNT, CNC, OTR), except for the total climate reporting score (TLS). The evaluation score was marked for each sub-disclosure element as how much out of the full score of 5 allocated for each sub-disclosure element. By adding all the sub-disclosure element scores, the overall score was stated as a percentage for the particular independent variable (Berg et al., 2022). Appendix 1 shows all evaluation criteria for each independent variable and how climate scores were calculated. Annual reports for each financial year of all sample companies were individually evaluated to get complete climate-score data.

3.2. Data analysis techniques

Our study involved panel data for different entities, different time periods and different industries. Therefore, for a better understanding of the data and trends, descriptive analyses were conducted under three categories as follows.

- Descriptive statistics for all variables: Under this, descriptive statistics were run for all the variables as a pool of data without factoring in entity, industry or period (financial year).
- Descriptive statistics for industry-wise: Financial performance data and climate reporting data may have industry-specific trends and characteristics. Therefore, analysing descriptive statistics for all the variables by factoring in the industry can provide valuable insights into such industry-specific trends and characteristics.
- Descriptive statistics for year by year: This analysis was important to identify time trends and characteristics of all variables. More specifically, this analysis might provide valuable insights into the pre- and post- impacts of mandatory climate reporting requirements on financial performance.

In order to find solutions for the two objectives of this research, two different regression analysis methods were used.

Analysis 1 – Climate reporting impact analysis:
This analysis focused on resolving objective one of this study: to understand the impact of climate-related reporting on the financial performance of Aotearoa businesses in the period of 2018–24, a regression analysis was conducted by factoring in the industry and year. Since the total climate reporting score (TLS) was calculated by adding the individual climate scores of all sub-climate reporting variables (GOV, STR, RSK, MNT, CNC, OTR), TLS was multicollinear with them. In addition to that, there were two dependent variables (ROE and ROA) that needed to be checked separately for the relationship with the independent variables. Therefore, the following four regression equations were built:

$$\mathrm{ROE} = \alpha_0 + \beta_1\mathrm{GOV} + \beta_2\mathrm{STR} + \beta_3\mathrm{RSK} + \beta_4\mathrm{MNT} + \beta_5\mathrm{CNC} + \beta_6\mathrm{OTR} + \beta_7\mathrm{TAM} + \beta_8\mathrm{TAL} + \beta_9\mathrm{AGE} + \beta_{10}\mathrm{MCM} + \beta_{11}\mathrm{MCL} + \beta_{12}\mathrm{BDZ} + \text{factor (Year)} + \text{factor (Industry)} + \epsilon \quad (1)$$

$$\mathrm{ROE} = \alpha_0 + \beta_1\mathrm{TLS} + \beta_2\mathrm{TAM} + \beta_3\mathrm{TAL} + \beta_4\mathrm{AGE} + \beta_5\mathrm{MCM} + \beta_6\mathrm{MCL} + \beta_7\mathrm{BDZ} + \text{factor (Year)} + \text{factor (Industry)} + \epsilon \quad (2)$$

$$\mathrm{ROA} = \alpha_0 + \beta_1\mathrm{GOV} + \beta_2\mathrm{STR} + \beta_3\mathrm{RSK} + \beta_4\mathrm{MNT} + \beta_5\mathrm{CNC} + \beta_6\mathrm{OTR} + \beta_7\mathrm{TAM} + \beta_8\mathrm{TAL} + \beta_9\mathrm{AGE} + \beta_{10}\mathrm{MCM} + \beta_{11}\mathrm{MCL} + \beta_{12}\mathrm{BDZ} + \text{factor (Year)} + \text{factor (Industry)} + \epsilon \quad (3)$$

$$\mathrm{ROA} = \alpha_0 + \beta_1\mathrm{TLS} + \beta_2\mathrm{TAM} + \beta_3\mathrm{TAL} + \beta_4\mathrm{AGE} + \beta_5\mathrm{MCM} + \beta_6\mathrm{MCL} + \beta_7\mathrm{BDZ} + \text{factor (Year)} + \text{factor (Industry)} + \epsilon \quad (4)$$

These four regression equations were used to examine research objective one. In order to perform a more robust analysis of the relationship between climate report requirements and company performance, it is recommended to use regression models controlling for industry and time (Kargin & Alp, 2023). Further, it is important to consider and control other influencing factors on the company's performance, such as company size and age (York, 2018). Therefore, company size (assets value and market capitalisation), company age, and board size were added as control variables. To test multicollinearity among explanatory variables, we computed Pearson correlation coefficients and variance inflation factors (VIFs). As expected, total assets in their absolute values (TAM) and the logarithmic value (TAL) correlated highly ($r > 0.90$). We resolved the redundancy and potential multicollinearity issue by retaining TAL alone in the models. The log-transformed variable is commonly used to adjust for firm size and reduce the impact of skewness of distribution (Gujarati & Porter, 2009).

Analysis 2 – Post-regulation impact analysis:
This analysis examines whether there is any significant financial performance change in businesses in Aotearoa in the post-implementation period of the mandatory climate reporting requirement. Since mandatory climate regulation has been implemented effectively from 1 January 2023, the financial years of 2023 and 2024 are considered as post-implementation periods and other years as pre-implementation periods of the mandatory climate reporting requirement (External Reporting Board, 2024). For the purpose of grouping financial year periods as pre- and post-periods, dummy variables needed to be introduced as pre-periods as zero and post-periods as one (Yulianto & Suryaningrum, 2019). Accordingly, a post-implementation regression analysis was also separately run to determine if the association between climate-related disclosure and financial performance altered after adopting the External Reporting Board's Climate-related Disclosure Framework. This sub-sample consisted of 52 firm-year observations from 26 companies spanning the period of 2023–24. The goal was to isolate the prospective regulatory influence and evaluate the model's robustness in a new disclosure environment.

The following regression models were used to solve objective two of the study. The conceptual model for analysis two is shown in Figure 1. The following regression equations were built to check for changes in financial performance in the post-implementation period of the mandatory climate reporting requirement:

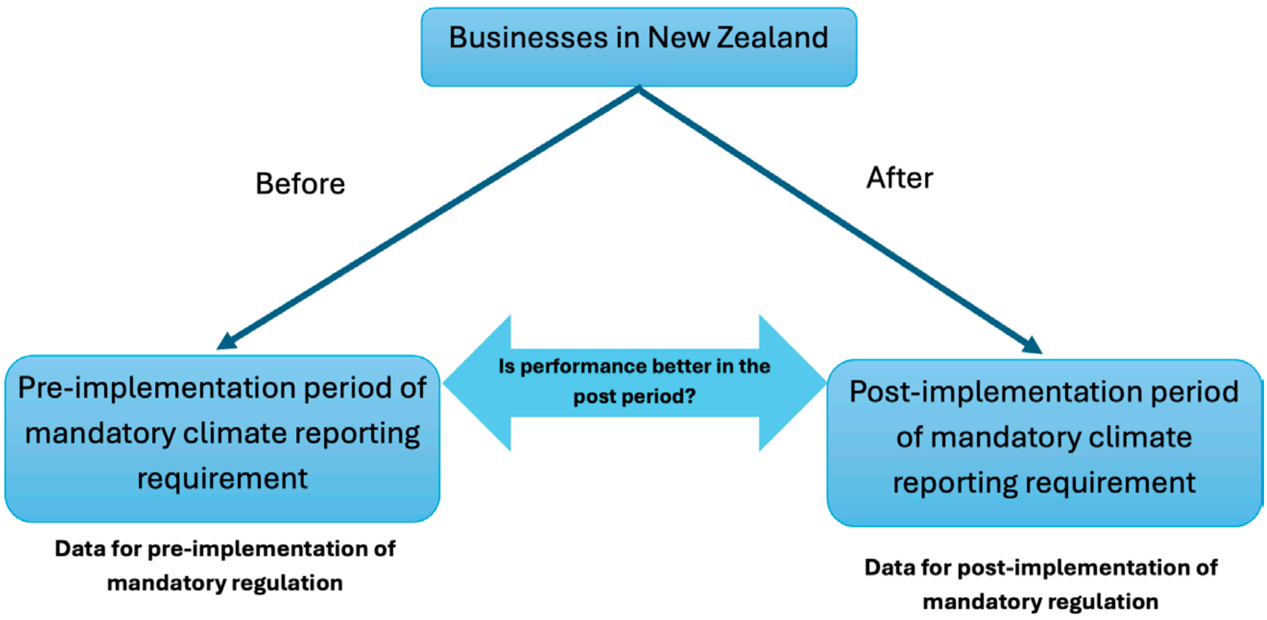
$$ROE = \alpha_0 + \beta_1 Post\_Implementation + \beta_2 GOV + \beta_3 STR + \beta_4 RSK + \beta_5 MNT + \beta_6 CNC + \beta_7 OTR + \beta_8 TAM + \beta_9 TAL + \beta_{10} AGE + \beta_{11} MCM + \beta_{12} MCL + \beta_{13} BDZ + \text{factor (Year)} + \text{factor (Industry)} + \epsilon \quad (5)$$

$$ROE = \alpha_0 + \beta_1 Post\_Implementation + \beta_2 TLS + \beta_3 TAM + \beta_4 TAL + \beta_5 AGE + \beta_6 MCM + \beta_7 MCL + \beta_8 BDZ + \text{factor (Year)} + \text{factor (Industry)} + \epsilon \quad (6)$$

$$ROA = \alpha_0 + \beta_1 Post\_Implementation + \beta_2 GOV + \beta_3 STR + \beta_4 RSK + \beta_5 MNT + \beta_6 CNC + \beta_7 OTR + \beta_8 TAM + \beta_9 TAL + \beta_{10} AGE + \beta_{11} MCM + \beta_{12} MCL + \beta_{13} BDZ + \text{factor (Year)} + \text{factor (Industry)} + \epsilon \quad (7)$$

$$ROA = \alpha_0 + \beta_1 Post\_Implementation + \beta_2 TLS + \beta_3 TAM + \beta_4 TAL + \beta_5 AGE + \beta_6 MCM + \beta_7 MCL + \beta_8 BDZ + \text{factor (Year)} + \text{factor (Industry)} + \epsilon \quad (8)$$

Figure 1. Conceptual model for pre- and post-implementation analysis.



Source: Authors' own creation.

4. Analytical Results, Findings and Discussion

4.1. Descriptive analysis

4.1.1. Descriptive statistics: All variables pooled

As Table 2 depicts, the mean ROE of -0.01 suggests minimal losses by firms between 2018 and 2024, while the median ROE of 0.08 suggests low profitability. Contrary to Cahan et al. (2016), who found that strong ESG practices equate to good financial performance, the huge losses by RTO Ltd and other firms in 2020–21 (the worst time of the Covid-19 impact) lowered the mean. The high standard deviation (0.48) indicates extreme variation in ROE. Similarly, the mean ROA is -0.07, and the median is 0.04, indicating that most firms have positive returns, but some extreme losses pull down the mean. The high spread (standard deviation 0.78) and negative skewness (-0.06) confirm mixed financial performance, particularly post-pandemic, as supported by Białkowski and Sławik (2022).

The mean total climate reporting score (TLS) is 0.57, with a median of 0.58, reflecting varied climate reporting. Despite mandatory climate requirements, discrepancies exist (KPMG NZ, 2022). Variations in firm size in terms of total assets and market capitalisation necessitated log transformation for examination. Board sizes range between three and seven, with a mean of seven directors, in accordance with Deloitte NZ (2021), which advocates for board diversity to enable effective ESG governance.

Table 2. Descriptive statistics.

Variable name	Code	Mean	Median	Standard deviation	Min	Max	Skewness
Dependent variables							
Return on equity	ROE	-0.01	0.08	0.48	-4.09	0.73	-5.81
Return on assets	ROA	-0.07	0.04	0.78	-6.06	0.38	-7.06
Independent variables							
Governance	GOV	0.60	0.63	0.18	0.26	0.97	-0.03
Strategy	STR	0.56	0.57	0.18	0.17	0.93	-0.26
Risk management	RSK	0.59	0.60	0.20	0.20	0.90	-0.32
Metrics and targets	MNT	0.52	0.53	0.19	0.07	0.87	-0.40
Consistency and restatement of comparatives	CNC	0.53	0.47	0.18	0.13	0.93	0.07
Other	OTR	0.56	0.57	0.17	0.27	0.87	-0.17
Overall climate reporting score	TLS	0.57	0.58	0.17	0.22	0.91	-0.25
Control variables							
Total assets in NZD millions	TAM	46,922.17	628.01	188,490.27	0.03	1,029,774.00	4.54
Total assets log	TAL	20.43	20.26	3.18	10.18	27.66	-0.55
Entity age	AGE	24.79	23.00	12.49	0.00	61.00	0.83
Market capitalisation in NZD millions	MCM	8,192.60	538.94	22,653.25	1.05	112,724.70	3.29
Market capitalisation log	MCL	20.26	20.11	2.54	13.87	25.45	-0.27
Board size	BDZ	7.04	7.00	1.79	3.00	13.00	0.89

Source: Authors' own creation.

4.1.2. *Descriptive statistics industry-wise*[1]

Financial performance across sectors is generally varied. Profitability for the financial sector is weak, with a negative average ROE and ROA of -0.14 and -0.31, respectively, and high variability in data according to KPMG (2023) findings on pressure from the economic downturn. The industrial sector has the best performance, with a positive mean and median ROE and ROA, followed by deteriorating performance from the energy sector due to volatile global prices (Meade et al., 2017). The materials sector shows moderate performance with narrow margins. Financial data in the industrial sector is skewed positively, while other sectors, especially the financial sector, have high negative skewness.

Climate scores are most significant in the industrial sector (mean 0.62, median 0.63), as greater financial performance enables greater climate investment (Deloitte NZ, 2021). The finance and energy sectors have lower scores, but all industries score better. Data spread is great for the industrial sector, with the materials sector being normally distributed. The sector with the highest value of assets (mean NZD 128,103.60M) is from large firms such as Westpac and ANZ, although

1. A descriptive statistics table for all variables industry-wise is not provided due to its size.

median values suggest smaller firms lag (Reserve Bank of New Zealand, 2022). The energy sector has the oldest age for companies (mean 59), according to the Ministry of Business, Innovation and Employment (2018). Board size is five to seven directors, except for the energy sector, which is seven to nine (Financial Markets Authority, 2018).

4.1.3. *Descriptive statistics for all variables, year by year*[2]

The descriptive statistics indicate the various financial performances of firms from 2018–24. The period of Covid-19 (2020–21) indicated huge losses in firms such as Air New Zealand and RTO Limited, with a negative mean ROE (-0.05 and -0.15). Being AI Limited's huge loss in 2023 resulted in a negative mean ROA (-0.18), while losses by RTO Limited, Being AI Limited and ArborGen Holdings Limited resulted in a negative mean ROE (-0.1) in 2024. ROE data was positively skewed only in 2019, while ROA was positively skewed in 2019 and 2020. Financial performance as a whole was not consistent, with negative outcomes being more common following the pandemic (Białkowski & Sławik, 2022).

Climate scores improved significantly in 2023–24, with both mean and median being higher than 0.72, against 0.41 and 0.43 in 2019. ESG reporting by Aotearoa's top companies increased from 69% in 2017 to 74% in 2020 (Prichard et al., 2020). Asset values and market capitalisation showed variability, with gradual declines due to loss-making firms. Both were strongly positively skewed, aligning with Puri's (2022) findings on NZX-listed firms' market performance. Board sizes ranged from three to 13 directors, averaging six to eight, highlighting a need for improved diversity (Institute of Directors, 2024).

4.2. Regression results, findings and discussion

4.2.1. *Climate reporting impact analysis*

Table 3 shows the regression analysis results, which indicate that climate reporting items (GOV, STR, RSK, MNT, CNC and OTR) are not statistically significantly related to ROE. Similarly, the composite climate reporting metric (TLS) is not statistically related to ROE. The coefficient suggests a negative relationship between ROE and climate reporting. This is consistent with Chen et al. (2022), who did not establish a significant relationship between ESG performance and financial outcomes. However, companies undertaking social performance programmes such as employees' wellbeing and community participation demonstrated long-term financial performance. There was a positive relationship between climate risk-management and ROA.

In the case of ROA, regression analysis suggests that none of the climate reporting factors are significant except for metrics and targets (MNT), which has a positive significant coefficient. A rise of 1% in MNT is linked with an increase of 2.3% in ROA. The model has a moderate fit (Multiple R-squared: 0.39; Adjusted R-squared: 0.28). While some climate reporting factors (GOV, STR, CNC) have a negative association with ROA, there are others (RSK, MNT, OTR) that have a positive correlation. Regression analysis also confirms that TLS does not significantly affect ROA, with the model having a moderate fit (Multiple R-squared: 0.36; Adjusted R-squared: 0.27). Iriyadi and Antonio (2021) found a U-shaped relationship between climate-change disclosures and financial performance, where initial disclosure requirements reduced ROA but improved it in the long term. They recommend mandatory climate disclosure regulations for better risk-management and reporting quality. Supporting the same argument, descriptive statistics also show no strong trend in ROE or ROA for 2018 and 2019. Regression results also verify that financial performance does not have any strong relation with climate reporting, except that the MNT factor positively

2. A descriptive statistics table for all variables year by year is not provided due to its size.

impacts ROA. Greenhouse gas management, energy and water management result in better ROA. For example, a European study by Secinaro et al. (2020) found that corporate environmental activities, particularly carbon reduction, positively impact financial performance. Good environmental policies help firms reduce risks and costs, leading to improved profitability. Firms with high environmental performance also attain high ROE and ROI. These findings highlight the importance of integrating sustainability practices into business strategies to enhance long-term financial stability.

Table 3. Regression results for Equations 1, 2, 3 and 4.

	Eq. 1		**Eq. 2**		**Eq. 3**		**Eq. 4**	
	Coefficient	**p-value**	**Coefficient**	**p-value**	**Coefficient**	**p-value**	**Coefficient**	**p-value**
Constant	-3.26	0.00***	-2.78	0.00***	-2.36	0.02*	-2.61	0.01**
GOV	1.39	0.11			-0.21	0.88		
STR	-1.43	0.13			-0.96	0.51		
RSK	0.57	0.36			0.27	0.78		
MNT	-0.89	0.19			2.30	0.03*		
CNC	0.25	0.69			-0.73	0.46		
OTR	-0.34	0.68			0.31	0.81		
TLS			-0.41	0.39			1.18	0.11
TAM	0.00	0.79	0.00	0.76	0.00	0.36	0.00	0.28
TAL	-0.18	0.00***	-0.16	0.00**	0.28	0.00***	0.30	0.00***
AGE	0.00	0.99	0.00	0.93	0.00	0.68	0.00	0.86
MCM	0.00	0.12	0.00	0.24	0.00	0.45	0.00	0.39
MCL	0.31	0.00***	0.28	0.00***	-0.18	0.08	-0.19	0.06
BDZ	0.08	0.02*	0.07	0.03*	-0.02	0.71	-0.04	0.49
Adjusted R = 0.3499			0.2016		0.2783		0.2745	

(Sig. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1)
Source: Authors' own creation.

4.2.2. *Post-regulation impact analysis*

Regression results in Table 4 (Eq. 5) show that climate reporting items (GOV, STR, RSK, MNT, CNC, OTR) are not related to ROE during the post-implementation period of mandatory climate reporting. Coefficients capture mixed associations: GOV, RSK and CNC are positively related to ROE, while STR, MNT and OTR are negatively related. These blended clusters suggest that the impact of some climate reporting factors on profitability can be complex and context dependent. This contrasts with Bendersky and Burks (2019), who speculate that ESG practices are generally beneficial to long-term profitability by reducing costs, enhancing efficiency and avoiding climate risk.

Table 4. Regression results for post-regulation (Equations 5, 6, 7 and 8).

	Eq. 5		Eq. 6		Eq. 7		Eq. 8	
	Coefficient	**p-value**	**Coefficient**	**p-value**	**Coefficient**	**p-value**	**Coefficient**	**p-value**
Constant	-3.26	0.00***	-2.78	0.00***	-2.36	0.02*	-2.61	0.01**
Post_impl.	0.01	0.97	0.11	0.68	-0.31	0.48	-0.45	0.29
GOV	1.39	0.11			-0.21	0.88		
STR	-1.43	0.13			-0.96	0.51		
RSK	0.57	0.36			0.27	0.78		
MNT	-0.89	0.19			2.30	0.03*		
CNC	0.25	0.69			-0.73	0.46		
OTR	-0.34	0.68			0.31	0.81		
TLS			-0.41	0.39			1.18	0.11
TAM	0.00	0.79	0.00	0.76	0.00	0.36	0.00	0.28
TAL	-0.18	0.00***	-0.16	0.00**	0.28	0.00***	0.30	0.00***
AGE	0.00	0.99	0.00	0.93	0.00	0.68	0.00	0.86
MCM	0.00	0.12	0.00	0.24	0.00	0.45	0.00	0.39
MCL	0.31	0.00***	0.28	0.00***	-0.18	0.08 .	-0.19	0.06 .
BDZ	0.08	0.02*	0.07	0.03*	-0.02	0.71	-0.04	0.49
Adjusted R2 = 0.3544			0.2177		0.2691		0.2644	

(Sig. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1)
Source: Authors' own creation.

Regression results in Table 4 (Equation 6) do not show a statistical relationship between ROE and total climate-related reporting score (TLS) during the post-climate-reporting mandate period. However, a negative coefficient means a negative correlation. On the other hand, Naeem and Çankaya (2022) found that ESG performance was positively related to ROE in Europe, while they documented a negative correlation between ESG and ROA. Equation 7 in Table 4 reveals that none of the climate reporting items (GOV, STR, RSK, CNC, OTR) have a significant relationship with ROA, except for metrics and targets (MNT), which is statistically positively correlated with ROA. Equation 8 also confirms no significant relationship between ROA and TLS.

Overall, requirements for climate reporting have no significant impact on financial performance apart from MNT, which positively impacts ROA. Giannopoulos et al. (2022) also found comparable mixed results among Norwegian-listed firms, with a negative relationship between ROA and ESG but a positive one between ESG and firm value (Tobin's Q). These findings suggest ESG's financial impact varies by measure, with potential short-run negative impacts but long-run benefits.

5. Summary and Conclusion

The study examines the impact of mandatory and voluntary climate reporting on the financial performance of Aotearoa companies. Using ROE and ROA as financial performance metrics and climate reporting scores as explanatory variables, the study examined the effects from 2018 to 2024 and post-implementation impacts. The findings show no significant relationship between climate-related disclosure and financial performance, apart from the metrics and targets (MNT) dimension, which has a positive association with ROA. This aligns with the previous literature (e.g., Brammer et al., 2006; Murray et al., 2006; Nelling & Webb, 2009) that contends that sustainability efforts do not yield short-term benefits but can improve financial performance over the long term. The comparison after the implementation of mandatory reporting also finds no significant impact on financial performance, except for the positive association of MNT with ROA. The results provide valuable insights for policymakers to enhance climate regulations and promote investments in climate adaptation initiatives.

The findings suggest that climate reporting can have a significant role in shaping markets' perception and investment decisions. Firms with more transparent and comprehensive climate reporting will be seen favourably by investors, as these reports reflect future-oriented risk management, regulatory readiness, and value-based regulators' thinking in the long run. This is in line with stakeholder theory and signalling theory, which hold that discretionary disclosure can reduce information asymmetry and maximise stakeholder trust. Therefore, investors can consider climate transparency as an indication of sound governance and lower risk-exposure in the future, which in turn might be reflected in enhanced financial performance and firm valuation (Krüger, 2015; Lins et al., 2017). Therefore, as a supplement to the regulatory or moral imperative, climate reporting would be a strategic tool to raise funds and stay competitive in more sustainability-focused markets.

Overall, the data indicates that mandated climate reporting has no impact on Aotearoa's financial performance. First, this could be due to market efficiency, because investors could have priced in the climate risks even before the mandate, and the majority of the companies might already have ESG strategies in place. Thus, additional reporting might not be required. Additionally, investors may prefer financial metrics over sustainability reports; thus, the compliance costs may be low, and there is no identifiable financial cost. Secondly, the short-term impact on finances could be limited, as the benefits of climate reporting, such as improved risk-management and reputation, would be more valued in the long term than in the short term. However, further research is needed to discuss and investigate these behavioural aspects more.

Future researchers should be mindful of some research constraints. First, five years is a comparatively short time for evaluating environmental programmes, and the actual impact might be observed in the longer term (Mardones, 2019). Climate reporting in Aotearoa has been voluntary prior to 2023, which limits data quality and availability. Therefore, its full implications must be seen over longer periods. Future research must account for longer post-enforcement time periods to establish financial performance changes. Industry-level studies with longer datasets can provide more meaningful conclusions regarding the effects of climate reporting. Second, shortcomings in financial performance metrics such as ROE and ROA might be unable to capture the long-term benefits of climate reporting (Nithin, 2023). Incorporating a broader set of performance indicators that can capture both financial and non-financial impacts of climate reporting will be helpful for future researchers to mitigate this problem. Additionally, investor perception and preference studies regarding climate reporting in the Aotearoa setting would be interesting and useful, offering helpful insights to investors with a sustainability agenda.

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Appendix 1. Climate Reporting Evaluating Scorecard

Climate reporting evaluation scorecard (KPMG NZ, 2023)

	For:	Year:		
	Reporting criteria	**Score 1–5**	**Score %**	**Weight %**
01	**Governance**			
01.1	Identity of the governance body responsible for oversight of climate-related risks and opportunities.			
01.2	Description of the governance body's oversight of climate-related risks and opportunities.			
01.3	Processes and frequency by which the governance body is informed about climate-related risks and opportunities.			
01.4	Skills and competencies available to provide oversight of climate-related risks and opportunities.			
01.5	Consideration of climate-related risks and opportunities in strategy development and oversight.			
01.6	Oversight of metrics and targets for managing climate-related risks and opportunities.			
01.7	Management's role in assessing and managing climate-related risks and opportunities.			
	Total governance	**0** **Out of 35**	**0.0%**	**30.0%**
02	**Strategy**			
02.1	Description of current climate-related impacts (physical and transition impacts).			
02.2	Financial impacts of physical and transition impacts.			
02.3	Description of scenario analysis undertaken.			
02.4	Description of climate-related risks and opportunities identified over short, medium, and long term.			
02.5	Anticipated impacts of climate-related risks and opportunities.			
02.6	Positioning as the global and domestic economy transitions towards a low-emissions, climate-resilient future.			
	Total strategy	**0** **Out of 30**	**0.0%**	**25.0%**

03	**Risk management**			
03.1	Processes for identifying and assessing climate-related risks (transition and physical risks).			
03.2	Integration of climate-related risks into overall risk management processes.			
	Total risk management	**0** **Out of 10**	**0.0%**	**10.0%**
04	**Metrics and targets**			
04.1	Disclosure of relevant metrics (GHG emissions, GHG emissions intensity, etc.).			
04.2	Disclosure of transition risks, physical risks and climate-related opportunities.			
04.3	Internal emissions price and remuneration linked to climate-related risks and opportunities.			
	Total metrics and targets	**0** **Out of 15**	**0.0%**	**15.0%**
	Consistency and restatement of comparatives			
05.1	Consistency in reporting climate-related information over time.			
05.2	Disclosure of restatements of previous disclosures, if any.			
05.3	Explanation for restatements and their impact.			
	Total consistency and restatement of comparatives	**0** **Out of 15**	**0.0%**	**10.0%**
	Other			
06.1	Description of methods and assumptions used in climate-related disclosures.			
06.2	Discussion on data and estimation uncertainties.			
06.3	Statement of compliance with relevant reporting standards (e.g., TCFD, GRI).			
06.4	Alignment with industry best practices and guidelines.			
06.5	Fair and balanced presentation of climate-related risks and opportunities.			
06.6	Avoidance of misleading or biased information.			
	Total other	**0** **Out of 30**	**0.0%**	**10.0%**
Total climate reporting score				**0.0%**

Transformational Leadership and Employee Retention among HR Professionals in the Telecommunication Sector: The Mediating Role of Burnout and Emotional Exhaustion

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Transformational Leadership and Employee Retention among HR Professionals in the Telecommunication Sector: The Mediating Role of Burnout and Emotional Exhaustion

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Abstract

Transformational leaders are often associated with positive outcomes at work, such as increased employee retention and motivation. However, this efficacy is also vital in stressful situations, such as those in the telecommunications sector, where the emotional state of the worker and their ability to respond to the escalating workload are crucial. This research study examines the relationship between transformational leadership and employee retention among senior HR professionals in telecommunication organisations in Islamabad, with a special focus on the mediating effects of burnout and emotional exhaustion. The study is cross-sectional and quantitative, and the data was calculated on the basis of a structured survey, which was administered through a questionnaire to 215 senior HR professionals. The research proposes that organisations cannot stop at discrete explanations of pressure, but must turn to global cultural issues related to overburdened workloads and the latest trend of 'always-on' culture. Leadership development plus structural change has to be encouraged to foster a sense of psychological sustainability and long-term participation.

Keywords

Transformational leadership
Employee burnout
Emotional exhaustion
Employee retention
Telecommunication industry
Leadership theory

1. Introduction

1.1. Study background

Pakistan's telecommunication sector is a dynamic industry in which technological change is rapid and market competition is very stiff, which puts the workforce under great pressure and makes it very difficult to enable alignment between leadership practices and employee sustainability. According to the Pakistan Telecommunication Authority (2023), telecommunication companies are facing a growing challenge in retaining experienced employees, particularly in strategic positions. Since employee retention plays a vital role in determining the effectiveness of organisations, leadership practices have become an area of interest. Transformational leadership, which has been associated with motivating people through vision, personal attention and intellectual stimulation, has resulted in increased employee satisfaction and commitment (Bass & Riggio, 2006). It may be considered highly crucial in forming a good working culture, especially during periods of change. However, recent research suggests that the impact of transformational leadership could vary according to circumstances (Rudolph et al., 2022). Even though there has been research on the issue of transformational leadership, aspects such as the exhausting, emotionally demanding character of the leadership have not been analysed to a high degree among senior human resource (HR) professionals.

Many prevailing studies focus on the effects of leadership on workers as a whole, overlooking those individuals who directly experience and implement policies. The study focuses on senior HR professionals working in telecommunication firms, a segment that is not often mentioned in retention studies. The professional perspective offered by these professionals enables them to provide an exclusive view of the relationship between leadership style and workforce sustainability. The research will give more of an overview of the role played by transformational leadership in retention in high-demand organisations, since burnout and emotional exhaustion are deliberated as potential mediators of this relationship.

1.2. Research objectives

The objectives of the study are as follows:

- To discover the association between transformational leadership and employee retention.
- To analyse whether burnout plays a mediating role in the relationship between transformational leadership and employee retention.
- To investigate whether emotional exhaustion functions as a mediator between transformational leadership and employee retention.
- To provide practical insights for telecommunication firms on crafting leadership policies that balance performance prospects with employee wellbeing to increase retention.

1.3. Research questions

- **RQ1:** Does transformational leadership affect employee retention among senior HR professionals in the telecommunication sector?
- **RQ2:** Does employee burnout mediate the association between transformational leadership and employee retention?
- **RQ3:** Does emotional exhaustion mediate the relationship between transformational leadership and employee retention?

- **RQ4:** Do organisational factors such as workload and leadership expectations contribute to employee burnout and emotional exhaustion?
- **RQ5:** Do leadership strategies concentrated on employee wellbeing improve retention outcomes in the telecommunication sector?

1.4. Research significance

This paper adds to the growing literature on transformational leadership by focusing on how this leadership style prevents employee turnover in the telecommunication industry. The study focused on senior HR staff, a group that is frequently involved in learning and mastering leadership practices. Their view is of great benefit in understanding how leadership can promote employee dedication and retention. The importance of these research findings to telecommunication organisations, with the purpose of improving stability in the workforce, cannot be overemphasised. When organisations are aware of what encourages retention, including the leadership styles and experiences of the staff members, their HR strategies can be improved. The investigation also offers advice on the set-up of leadership-development programmes, which can contribute to long-term employee-engagement strategies.

2. Literature Review

2.1. Theoretical foundation

The study is grounded in the leader–member exchange (LMX) theory, which suggests that leaders establish one-on-one relationships with followers, depending on the levels of trust, respect and responsibility exchanged between them (Graen & Uhl-Bien, 1995). LMX theory has been found to play a vital part in improving organisational results under modern workplace conditions. According to a recent study by Bennouna et al. (2024), the transformational approach to leadership styles, which helps motivate and inspire employees, sheds light on their issues and is likely to lead to an increase in quality LMX relationship development. Such exchanges lower the risk of burnout and fatigue brought forth by emotions by building on relationships, trust and employee appreciation. Such a transformation of leadership behaviours assists not only in terms of performance outcomes but also in emotional resilience and staff retention. Therefore, it can be concluded that in the LMX framework, transformational leadership not only enhances performance but also leads to a reduced level of emotional strain and increased employee retention in the predominantly challenging area of telecommunications. In the telecommunication industry, where individuals working in the HR department tend to experience heavy workloads, fast technological shifts and unrelenting demands on performance, the quality of the leader–member relationship is paramount.

LMX relationships of high quality are also capable of relieving the emotional burden that is dominant in this fast-paced industry. Transformational leaders who work within an LMX model can not only work to improve the wellbeing of an individual but can also work to improve the stability of an organisation by enhancing retention, Because different emotional resources are maintained, this theoretical school of thought guides the research questions to organise the study to understand how the transformational leadership behaviour has a mediating effect on burnout and emotional exhaustion, which ultimately affect employee retention among HR professionals in the telecommunication industry.

2.2. Transformational leadership

The positive effects of transformational leadership on employee motivation, satisfaction and commitment are well known. Transformational leadership is based on four main behaviours: idealised influence, inspirational motivation, intellectual stimulation and individualised consideration (Shukri & Noor, 2024). Through these, leaders can match individual goals with the organisation's purpose (Gupta, 2025). As stated by Agazu et al. (2025), notably, transformational leadership also has a moral and ethical aspect, where leaders behave in an honourable way and they raise followers. Through shared values, such behaviours are directly related to positive employee behaviour, the rise in job satisfaction, a greater sense of organisational commitment, and lower turnover intention. Transformational leadership is most significant in situations of high stress such as telecommunication, where change and the necessity of having to execute it is ever-accelerating. Leadership is crucial in such environments to ensure stability, motivation and retention of employees (Waseem et al. 2025).

2.3. Transformational leadership and employee retention

Transformational leadership has received much attention in organisational behaviour and HR management because of its profound impact on employee retention (Febrian et al., 2023), inspiring, motivating and fostering employee commitment. Because retaining top talent is increasingly challenging, scholars have extensively studied the relationship between transformational leadership and employee retention (Umair et al., 2024). Leaders with the aforementioned attributes of idealised influence, inspirational motivation, intellectual stimulation and individualised consideration (Shukri & Noor, 2024) develop an atmosphere in which trust, motivation and engagement are experienced by employees. Idealised influence refers to a situation in which leaders act as role models and are able to display the right kind of conduct to win the respect and admiration of the employees (Gachira & Ntara, 2024). According to Oyewobi (2024), transformational leadership is known to produce a strong surge of job satisfaction, which in turn can boost organisational commitment and lower turnover intentions. If employees feel their leaders are supportive and inspirational, they are likely to stay longer in the organisation. Transformational leaders also create an environment in which an employee feels motivated and encouraged at work (Bakker et al., 2023). Transformational leaders were also discovered to be a moral and ethics-based source of integrity and common values (Alwali & Alwali, 2025). Transformational leaders have also contributed towards job satisfaction, creating affective commitment, which reduces turnover intentions (Choi et al., 2025). Through high-quality leader–member exchanges, transformational leadership strengthens employee trust and loyalty, which is especially important in the telecommunication sector (Hasib et al., 2020). In the light of LMX theory, transformational leadership has qualities of generating only high-quality relationships between leaders and subordinates, where subordinates receive social and emotional support, which eliminates burnout probabilities and emotional exhaustion (Sharif et al., 2024).

2.4. Burnout, transformational leadership and employee retention

Burnout is a mental condition caused when people are exposed to persistent job stress, and can be described as emotional exhaustion, cynicism and the lack of personal effectiveness (Channawar, 2023). This has adversely impacted individual and organisational performance, resulting in lower job satisfaction, productivity and commitment, and higher absenteeism and turnover intentions (Jogi et al., 2025). Some of the factors that usually lead to burnout include high workload, low control of the work, and insufficiency of a supervisor or teammates (Nápoles, 2022). Transformational leadership is important in avoiding burnout, given that it creates trust-based, emotionally supportive relationships, which are at the core of the theory of LMX. Positive traits and continuous interaction between a leader and members of their organisation, which connote candid communication, personal recognition and emotional stability, help to shield employees from the negative effects of stress load and psychological pressure (Payne, 2024). Once the transformational leaders express their concern about the workers by involving them in the two-dimensional decision-making process, the risk of emotional exhaustion is minimised (Cheng et al., 2023). A worker is more likely to show commitment to the organisation when they are appreciated and are given opportunities to be involved in decision-making processes. Despite this, employees generally strive to prevent burnout. Thus, high-quality LMX can help raise the wellbeing and retention of employees because transformational leaders are strong (Petrilli et al., 2024).

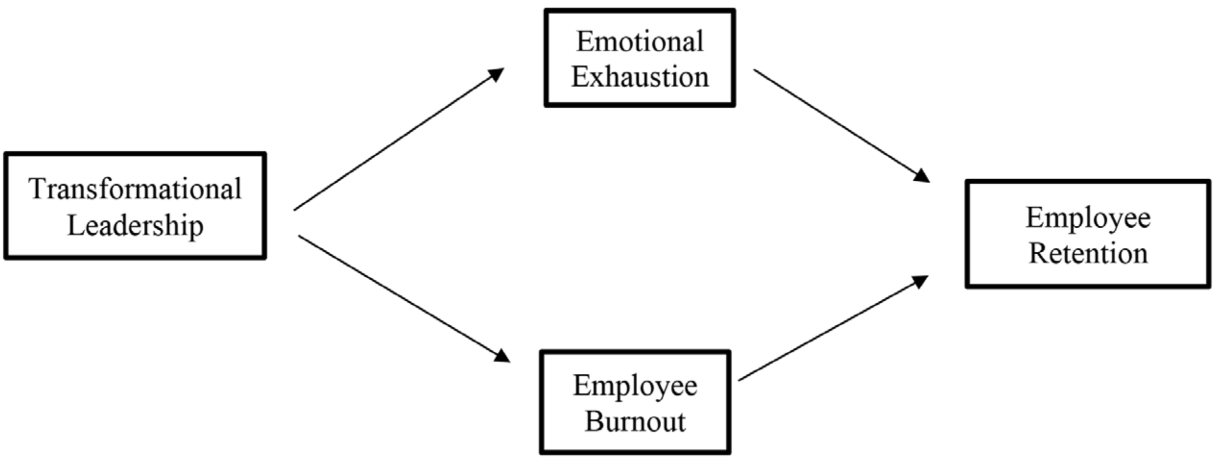
2.5. Emotional exhaustion, transformational leadership and employee retention

Transformational leadership, involving visionary leadership, individualised consideration, intellectual stimulation and inspirational motivation, has been generally acknowledged to enhance employees' levels of engagement, job satisfaction and retention (Khan et al., 2022). Emotional exhaustion is the depletion of emotions and the psyche, which occurs under the influence of intensive interpersonal and organisational stress (Ahmed et al., 2024). Emotional exhaustion compromises the working activity of personnel and causes retreat, impairment of welfare and the emergence of a desire to leave the workplace (Shinde, 2025).

Transformational leadership can help avoid emotional exhaustion through the creation of confidence, emotional support and a sense of purpose (Geremias et al., 2024). Transformational leaders can improve employees' morale, as they make them feel a valued and integral part of the firm (Shatila et al., 2024). Premru et al. (2023) believe that high-quality leader–member relationships (that is, relationships that are based on equality and care) can be viewed as an emotional asset protecting against fatigue. In a case where such healthy exchanges exist, the emotional load is minimised, meaning employees are more likely to stay. Conversely, emotional exhaustion mediates the influence of transformational leadership on retention, especially in high-pressure sectors, including telecommunication.

2.6. Theoretical framework

Based on the literature review, the following is the proposed theoretical framework.



2.7. Hypotheses

- **H1:** Transformational leadership is positively associated with employee retention.
- **H2:** Transformational leadership is negatively associated with employee burnout.
- **H3:** Transformational leadership is negatively associated with emotional exhaustion.
- **H4:** Employee burnout is negatively associated with employee retention.
- **H5:** Emotional exhaustion is negatively associated with employee retention.
- **H6:** Employee burnout mediates the relationship between transformational leadership and employee retention.
- **H7:** Emotional exhaustion mediates the relationship between transformational leadership and employee retention.

3. Research Methodology

3.1. Research design

3.1.1. Research philosophy

The study assimilates the positivist research philosophy. This is a school of thought that considers that knowledge follows scientific observation and reasoning. The approach stresses facts that can be verified and follows a logical approach to create information (Karupiah, 2022). Positivism emphasises hypothesis testing, quantifiable observations and statistical analysis (Irshaidat, 2022).

3.1.2. Research approach

This study embraced a deductive research approach, which involves formulating hypotheses based on established theories and testing them. Theories are tested using deductive reasoning, which goes from the general to the specific (Casula et al., 2021). Deduction is usually used by positivists, and is appropriate for research that uses robust past frameworks and either validates or refutes recognised notions (Mbanaso et al., 2023).

3.1.3. Research methodology

The research adopted a quantitative methodology. Quantitative research allows researchers to test hypotheses, measure variable relationships, and generalise findings across populations (Mulisa, 2022). For this purpose, structured questionnaires were used to collect data from the target population. Pilot testing was carried out with a sample size of at least 30 respondents to assess the transparency, consistency and reliability of the instruments (In, 2017). Moreover, the data collected by these questionnaires was further analysed through SPSS software.

3.1.4. Research strategy

A survey-based research strategy was applied to enable efficient data collection from the large sample in a limited time-frame. The survey was carried out using systematic questionnaires, which give the researchers the power to collect and interpret numerical data by asking a series of predetermined questions of the subjects or respondents (Kittur, 2023).

3.1.5. Time horizon

This research was carried out under certain time and budget constraints, so a cross-sectional time horizon approach was used. This approach captured the current views and experiences of employees at a single point in time, making it possible to identify connections among the variables (Wang & Cheng, 2020).

3.2. Sampling design

3.2.1. Target population

The data was collected from senior HR professionals (HR managers, consultants and specialists) employed in telecommunication companies operating in Islamabad. They were selected on the basis that they are carriers and bearers of leadership practices. Their strategic positioning and participation in HR operations, plus intimate contact with leadership systems, provide incisive perspectives on transformational leadership, and its impact on emotional outcomes and employee sustainability.

3.2.2. Unit of analysis

The unit of analysis is individual senior HR professionals. This decision corresponds to the focus of the study, which dwells on the role of examining the leadership behaviour and emotional results at the individual level.

3.2.3. Sample size

The sample was 215 senior HR professionals. This is according to the recommendations of Guilford (1954) that a sample size of 200+ is sufficient and acceptable to make a statistical analysis of a survey. To achieve diversity in the firms used and to reduce the possibility of institutional bias, the sample was drawn from the five major telecommunication service providers in Islamabad.

3.2.4. Sampling technique

The simple random sampling process was employed to offer every member of the target population (senior HR professionals) an equivalent probability of selection. Such a probability-based measure strengthens the objectivity and generalisability of the results in the stated HR domain.

3.3. Measurement of variables

Data was collected using a structured, self-administered questionnaire with closed-ended questions developed on already-established scales. The study measured all variables on a structured scale with items that used a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree) as a response scale. Transformational leadership was the independent variable, as measured by the Multifactor Leadership Questionnaire (MLQ) created by Bass and Avolio (1996), and comprised of the following dimensions: idealised influence, inspirational motivation, intellectual stimulation and individualised consideration. Employee retention as a dependent variable was achieved on a modified scale as stated by Tian et al. (2020), where emphasis was on intention to remain, job satisfaction and job commitment. Burnout and emotional exhaustion proved to be reliable; the reliability of all of the measurements was checked by using an initial pilot study.

4. Data Analysis and Interpretation

The survey was conducted among 215 senior HR personnel employed in various established telecommunication organisations across Islamabad. This selection of the sample was especially made around the senior HR professionals, as they also have a very specific and unique role in the leadership processes within an organisation. This has already been mentioned earlier in the methodology section to ensure transparency, as well as to guarantee that any other concerns that might arise regarding the possibility of misrepresenting participants are sufficiently covered.

4.1. Descriptive analysis

4.1.1. Gender demographics

Table 1. Gender demographics of the survey respondents.

Gender	Frequency (n)	Percentage (%)	Mean	SD
Male	133	61.9%	1.38	0.49
Female	82	38.1%		
Total	**215**	**100%**		

Source: Authors' own creation.

Out of 215 respondents, a majority (62%) of respondents were male and 38% were female. The gender mix sheds light on the fact that female employees are dominated by their male counterparts in the pool of senior HR professionals in the telecommunication industry of Islamabad, Pakistan. The male dominance is further defined in the mean gender value of 1.38. However, having 38% female representation shows that there is an ongoing effort to make the top leadership accommodating as far as gender diversity is concerned.

4.1.2. Age-group distribution

Table 2. Age-group distribution of the survey respondents.

Age Group	Frequency (n)	Percentage (%)	Mean	SD
18–30 years	50	23.3%	2.18	1.01
31–40 years	97	45.1%		
41–50 years	58	27.0%		
51+ years	10	4.7%		
Total	**215**	**100%**		

Source: Authors' own creation.

The age distribution of respondents indicates that the majority of the senior HR professionals are aged 31–40 years (45.1%) and 41–50 years (27%). In particular, the age group of 31–40 years comprises 97 respondents (45.1%), and the age group of 41–50 years comprises 58 respondents (27%). The standard deviation of 1.01 and the mean age-group value of 2.18 indicate that there is a concentration in these two middle categories. Such distribution demonstrates a well-developed and experienced HR staff, which conforms to the character of HR senior positions, as they often involve a significant amount of experience and organisational wisdom. The sample consisted of only 23.3% of respondents 18–30 years of age, and 4.7% of repsondents aged 51 years and older.

4.1.3. *Years of experience*

Table 3. Years of experience of the survey respondents.

Years of Experience	Frequency (n)	Percentage (%)	Mean	SD
1–5 years	50	23.3%	2.14	1.04
6–10 years	97	45.1%		
11–15 years	50	23.3%		
16+ years	18	8.4%		
Total	**215**	**100%**		

Source: Authors' own creation.

Distribution reveals that almost half of the respondents are mid-career professionals with 6–10 years of experience. This serves as a sign of a workforce that is most likely subject to diversity of leadership styles, and might offer implications about the impact working with transformational leadership styles has on retention.

4.1.4. *Educational level*

Table 4. Educational level of survey respondents.

Educational Level	Frequency (n)	Percentage (%)	Mean	SD
Bachelor's degree	65	30.2%	1.49	0.62
Master's degree	145	67.4%		
Doctorate	5	2.3%		
Total	**215**	**100%**		

Source: Authors' own creation.

The sample reveals high education levels, with 67% of the respondents holding a master's degree, which could suggest the workforce has been well educated and trained with analytical skills to work out critical leadership practices. This would align with the specialised knowledge requirements of the telecommunication sector. The proportion of respondents holding a bachelor's degree is 30%, while 2% hold a doctorate; hence, the sample is very well qualified. The mean of 1.49 suggests a strong educational foundation among respondents.

4.1.5. *Organisational role*

Table 5. Survey respondents' roles within their organisations.

Organisational Role	Frequency (n)	Percentage (%)
HR Managers	85	39.5%
HR Specialists	60	27.9%
Senior HR Executives	45	20.9%
HR Consultants/Advisors	25	11.6%
Total	**215**	**100%**

Source: Authors' own creation.

The distribution of roles in the organisations indicates that the sample is mainly composed of HR managers (39.50%), followed by HR specialists (27.9%), senior HR executives (20.9%) and HR consultants/advisors (11.60%). Such a tendency towards the input of senior HR professionals is an indication of the particularity of the study, which attempts to explore the issue of transformational leadership and employee retention using the perspectives of individuals who are no strangers to these issues, undertaking the central task of leadership formulation, implementation, and designing items of HR policy.

4.2. Correlation analysis

The variables used in this study were subject to correlation analysis. Apart from the mean, correlation analysis was used to find the extent of the relationship between two variables. The correlation coefficient is usually given as r, which varies between -1 and +1: between -1 and 0 implies a negative correlation, between 0 and +1 implies a positive correlation, and r = 0 implies no correlation at all.

Table 6. Correlation matrix.

Variables	1	2	3	4
1. Transformational leadership	1.00			
2. Employee burnout	-0.45**	1.00		
3. Emotional exhaustion	-0.40**	0.75**	1.00	
4. Employee retention	0.68**	-0.50**	-0.60**	1.00

** Denotes statistical significance at p < 0.01
Source: Authors' own creation.

Correlation analysis revealed that the respondents (senior HR professionals working in large telecommunication firms in Islamabad) provided statistically significant correlations between the variables of the study. Respondent opinions demonstrated a close positive correlation between how transformational leadership was perceived, i.e., there was close positive correlation between perceived transformational leadership and employee retention intentions ($r = 0.68, p < 0.01$), such that in the sample of cases, the higher the rating of transformational leadership behaviours, the higher the self-reported intentions to stay with the organisation. Transformational leadership showed moderate negative correlations towards employee burnout ($r = -0.45, p < 0.01$) and emotional exhaustion ($r = -0.40, p < 0.01$), meaning that the higher the professionals rated the behaviours of transformational leadership, the lower their markings were towards burnout and emotional exhaustion. Furthermore, employee burnout and emotional exhaustion, as perceived by the respondents, was generally negatively correlated with employee retention intentions ($r = -0.50, p < 0.01$ and $r = -0.60, p < 0.01$, respectively); thus, it can be surmised that increased stress in the workplace may be related to low chances of retaining the employee in the company. The theoretical expectations in the perception of the relationship between burnout and emotional exhaustion ($r = 0.75, p < 0.01$) were also confirmed by a strong positive correlation.

4.3. Regression analysis results

Regression analysis was used to determine the predictors of employee retention in the context of transformational leadership, burnout and emotional exhaustion.

Table 7. Multiple regression analysis on employee retention.

Predictor	B	β	T	p
(Constant)	2.10	—	4.20	.000
Transformational leadership	0.45	0.38	6.21	.000
Employee burnout	-0.32	-0.26	-4.25	.000
Emotional exhaustion	-0.40	-0.35	-5.15	.000

Source: Authors' own creation.

The model was found to be statistically significant, since $R^2 = 0.72$ denotes that the collective influences of transformational leadership, employee burnout and emotional exhaustion could describe the variance targeted at the intended employee retention attributes of at least 72% within this sample. More precisely, perceived transformational leadership is positively linked to employee retention intentions (0.38, $p < 0.01$), which implies that the greater the rating of the transformational leadership behaviours, the greater the stated intentions to remain. Conversely, negative relationships were found between employee burnout (0.26, $p < 0.01$) and emotional exhaustion (0.35, $p < 0.01$) and retention intentions; i.e., both burnout and emotional exhaustion were associated with higher intentions to leave the organisation.

4.4. Reliability analysis results

Table 8. Reliability analysis of key variables.

Variable	Cronbach's Alpha (α)
Transformational leadership	0.87
Employee burnout	0.82
Emotional exhaustion	0.85
Employee retention	0.79

Source: Authors' own creation.

The reliability analysis showed that all the measurement scales used in this research had a high internal consistency, with Cronbach's Alpha ranging between 0.79 and 0.87. Of these, the transformational leadership scale had the greatest reliability coefficient (alpha = 0.87), showing good consistency of answers given by senior HR professionals. The employee burnout scale scored 0.82 reliability, but emotional exhaustion showed the highest reliability, 0.85. A Cronbach's Alpha score of 0.79 was achieved by the employee retention scale, though this still falls within the acceptable range of research studies. These findings affirm the consistency of the measures used in this research and their ability to reliably assess the perceptions of participants concerning leadership practices, employee wellbeing and retention intentions in the organisational setting.

4.5. Mediation analysis results

It was found in the mediated analysis that burnout is a moderately influential mediator in the association between transformational leadership and employee retention intentions, as is emotional exhaustion. The mediated effects of burnout and emotional exhaustion were also statistically significant, as the confidence intervals did not reach the value of zero. This indicates that transformational leadership is indirectly, as well as directly, related to employee retention intentions through negative correlation with burnout and emotional exhaustion. These results serve to explain how any of the mediators individually contribute to the correlation between transformational leadership and retention intentions among the respondents of a senior HR professionals sample.

Table 9. Mediation analysis.

Path	Coefficient	SE	95% CI (Lower)	95% CI (Upper)
Direct effect (c′)	0.45	0.08	0.32	0.58
Leadership → Burnout (a_1)	-0.45	0.10	-0.65	-0.25
Burnout → Retention (b_1)	-0.35	0.09	-0.53	-0.17
Indirect effect via burnout ($a_1 b_1$)	-0.16	0.06	-0.28	-0.07
Leadership → Emotional exhaustion (a_1)	-0.40	0.09	-0.58	-0.22
Emotional exhaustion → Retention (b_1)	-0.30	0.08	-0.46	-0.14
Indirect effect via emotional exhaustion	-0.12	0.05	-0.22	-0.05

Source: Authors' own creation.

5. Discussion

The study under consideration examined the relationship between transformational leadership and employee burnout, emotional exhaustion and employee retention in the intentions of senior HR professionals of large and well-established telecommunication organisations in Islamabad. The study aimed to find out both the direct effects and the indirect effects of transformational leadership on retention intentions, where the mediating factors were burnout and emotional exhaustion. The results indicate a positive relationship between transformational leadership and employee retention intentions. This implies that when the senior HR professionals view their organisational leaders as being transformational by exhibiting such behaviours as articulate vision and individualised consideration, or are intellectually stimulating, they indicate a high desire to stay in the organisation. Additionally, transformational leadership is characterised not only by negative relations to employee burnout and emotional exhaustion; positive leadership behaviours can also help preserve employee wellbeing. Burnout and emotional exhaustion showed a large negative correlation with retention intentions, which were their effects on the cumulative intentions of employees to leave the organisation. This means that transformational leadership does not have a direct impact on retention intentions, but it may indirectly make a positive impact through the welfare of personnel. Burnout and emotional exhaustion had significant negative correlations with retention intentions, representing their cumulative impact on employees' intentions to leave the organisation. These findings match the available body of literature, but can make a particular contribution to the area of discussion because they focus on senior HR representatives in the telecommunication sector, which is typically lacking in the general literature on leadership.

Notably, these specifics of the sample character have to be taken into account when interpreting the results of the current study. Senior HR professionals tend to have more of a role to play when it comes to the application of leadership strategies and policies. Their experience is thus to some extent the most pertinent, but not to the extent of the staff in general working in the operation. The latter will be able to develop a more positive view of transformational leadership because of their access to the schemes of leadership and decision-making patterns. The research, hence, takes into consideration views held by a highly active and powerful part of the labour force and not necessarily the whole range of every organisational level. These results have more than a few practical implications. Transformational leadership needs to be encouraged in this process of retention of talent in telecommunication companies. Although the leadership development may already be implemented in many large companies, it is also important to ensure that the levels of burnout and emotional exhaustion decrease through leadership behaviours. Some of the practices that are important include facilitating a healthy work–life balance, provision of manageable workloads, facilitation of feedback and support structures, and development of employee wellness programmes. These strategies should not only be channelled to operational employees but also to the top HR professionals, whose work has specific pressures, because their roles are very important regarding policy formulations and management of change in organisations. One should also mention the role of organisational culture. This paper affirms that the performance of leadership is not a factor that can be individually distinguished in the general cultural setting in which it is administered. These findings again state the fact that the performance of leadership is not an individual attribute of a person, but also lies in the heart of the organisational culture. Even the best transformational leadership practice in high-stress industries, such as telecommunication, where constant connectivity and working excessive hours is the norm, will make burnout worse unless combined with organisational cultural change that promotes recovery and rest, work–life flexibility and psychological safety. Companies need to make sure that a positive leadership practice is supported by systems that deter the overworking and stress-creating habits such as the demand for constant connectedness.

The combined efforts towards improvement of a leadership intervention targeting improved retention become even more effective when the organisational culture is targeted comprehensively, rather than just a leader's behaviour. Lastly, limitations of the study are its being cross-sectional, meaning that one cannot draw any causal conclusions based on the study. The relationships that are observed are the result of associations of a perception, and not the intention of retention but the actual behaviour of turnover. Longitudinal designs should be taken into account in the future so it can be observed whether there is any change over time, or not, to determine the outcomes of perceived transformational leadership. The study can also be extended to other categories of employees in telecommunication organisations, to give a better picture of how leadership influences retention at various levels of the organisation. Overall, this study contains evidence that transformational leadership is positively associated with retention intentions among senior HR professionals working in large telecommunication companies, both directly and indirectly; namely, through the correlation with less burnout and emotional exhaustion. These results further highlight the significance of leadership quality in retaining quality HR professionals, as long as organisations can incorporate leadership development with wide-scale cultural and wellbeing practices.

6. Limitations

Although the study has also gathered some positive data on the relationship between transformational leadership and burnout, and other factors such as emotional exhaustion and retention intentions of workers, there are also a number of limitations that need to be taken into account. To start with, the sample included only the senior HR officers of well-established and big telecommunication companies based in Islamabad. Though this sample was selected purposely based on their strategic importance in both leadership and retention processes, their opinions may not necessarily reflect those of the operational employees or other areas within the telecommunication industry. Second, self-reported data can be subject to abuse, such as social desirability bias and response bias, since individuals can respond more positively with regard to leadership or may report fewer negative experiences in the workplace. A cross-sectional research design was applied, which paints a picture of the current perceptions. It does not allow characterising causal relations or defining the change of retention behaviour with time. And, lastly, although the participants were recruited within several telecommunication companies, neither number nor size of participating organisations were described, which can decrease the transparency and generalisability.

7. Future Research Directions

Future studies must consider addressing the above-presented limitations, and could increase the sample population by involving telecommunication company employees with various functional specialisations and hierarchies. This would help to increase researchers' understanding of the impact of transformational leadership on employee retention in the broader workforce. A longitudinal study that would monitor the consequences of leadership practice, burnout and emotional exhaustion on the real employee retention levels, and also some rigorous methodological precautions, is highly recommended. The organisations should also include objective indicators of burnout, e.g., physiological stress measures or 360-degree feedback by supervisors and peers, making data more reliable and free of sampling bias. Lastly, future research could examine possible moderators such as organisational culture, size of firms or generational variation, to help understand how such variables influence the effect of leadership on employee retention within high-stress industries such as the telecommunication industry.

Ethics Approval and Declarations

This study was conducted as an independent examination and has no formal affiliation to any academic or medical institution. The data was collected via personal and professional networks. All participants were fully informed of the purpose of the study and their confidentiality was ensured during the research. The authors also state that there are no conflicts of interest with regard to the study.

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The Purchase Intention of Green Personal-Care Products: An Artificial Neural Networks Approach

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Abstract

This study explores the use of deep learning (DL) to predict consumer purchase intentions for green personal-care products. Using primary data collected from 110 consumers via online questionnaires, the study applies artificial neural networks (ANNs) to analyse purchasing behaviour, diverging from traditional statistical methods. Through a rigorous optimisation process, the ANN model achieves outstanding performance, with 90% Accuracy, 100% Recall, and F1 and Precision scores of 95%. These results outperform other machine learning models tested, including random forest, support vector machine (SVM), gradient boosting, XGBoost and decision tree, highlighting the ANN's superior ability to handle complex, non-linear relationships within small datasets. This study demonstrates that deep learning models are highly adaptable to business requirements in the green personal-care sector, whether in traditional retail or online settings, and can be applied effectively to forecast consumer trends regardless of whether the datasets are complex or relatively simple.

Keywords

Purchase intention
Green product
Deep learning
Artificial neural network

1. Introduction

The demand for green personal-care products is rising in Aotearoa New Zealand, with one in ten consumers shifting their spending for environmental reasons (Taunton, 2024). Products featuring non-toxic ingredients and biodegradable or recyclable packaging are also gaining traction due to increasing awareness of allergies and skin sensitivities linked to harsh chemicals (Biswas & Roy, 2015). Aotearoa New Zealand's personal-care market reached USD 1.53 billion in 2024 and is projected to grow at a CAGR of 5.5% through 2028, outpacing Australia (Statista, 2024). This growth is driven by an increasing preference for sustainability, prompting companies to integrate biodegradable components, eco-conscious packaging and green marketing campaigns into their business strategies. As product safety and environmental friendliness become core brand values, businesses are leveraging these trends to gain a competitive advantage (Choudhury et al., 2024; Coriolis Research, 2022).

However, as personal-care companies adapt to increasing demand for green products in Tāmaki Makaurau Auckland, understanding and predicting green purchase intentions is crucial. Consumer behaviour is shaped by a mix of attitudinal, behavioural, and demographic factors. Traditional predictive methods struggle to capture these non-linear, multifaceted relationships. Therefore, advanced tools such as deep learning (DL) are needed to develop robust, data-driven models for more precise forecasting. This study adopts artificial neural networks (ANNs), a DL method, to fill that gap. Predictive models, including machine learning (ML) and DL approaches, are increasingly being used to assess consumer intentions, segment markets and support strategic business decisions (Choudhury et al., 2024; Witek & Kuźniar, 2021). Such models not only forecast future sales, but also help identify key consumer segments, thereby enhancing marketing efficiency (Atienza et al., 2022).

A variety of analytical techniques have been used in similar contexts. ML methods such as decision trees (DTs), random forest (RF), XGBoost and support vector machines (SVMs) have gained popularity for their ability to handle non-linear variable interactions and produce classification-based predictions (Choudhury et al., 2024). More recently, DL models such as ANNs and recurrent neural networks (RNNs) have demonstrated even higher accuracy and learning capabilities in predicting purchase behaviour, particularly in the green product space (Prashar et al., 2016). Previous research has identified multiple factors that influence green purchase intention. These include environmental attitudes, behavioural motivations, and demographic characteristics such as age, gender and education level (Lasuin & Ng, 2014). This study incorporates these variables to build a comprehensive predictive model tailored to green personal-care consumption.

Using primary data from consumers, this study tested ANN algorithms to classify purchase intentions. Following model optimisation, the ANN model achieved an Accuracy of 90%, Recall of 100%, and both F1 and Precision scores of 95%. These results significantly outperformed traditional ML models – including random forest, SVM, gradient boosting, XGBoost and decision tree – demonstrating the ANN's superior capability in learning patterns and generalising effectively to new data. While ML models are prone to overfitting, ANN showed robustness by minimising sensitivity to noise and maintaining consistent performance across training and test datasets.

This research offers practical value for Aotearoa's personal-care sector. By pinpointing key drivers of purchase intention, businesses can optimise product positioning, personalise outreach and allocate resources more effectively. Additionally, this study contributes to the business analytics field by showcasing the application of neural networks in consumer behaviour prediction. The methodology offers a framework for analysing non-linear relationships in complex datasets and highlights how ANN can elevate forecasting capabilities in the consumer packaged goods (CPG) sector. Ultimately, the findings support the use of AI-powered tools in strategic decision-making and market innovation.

2. Literature Review

This section reviews prior research relevant to this study. Section 2.1 outlines the theoretical basis for purchase intentions and the importance of predicting green purchase intentions. Section 2.2 presents machine learning techniques used for purchase prediction. Section 2.3 examines attitudinal, behavioural and demographic influences on green personal-care purchase intention.

2.1. Theoretical background

The theory of reasoned action (TRA), developed by Fishbein and Ajzen (1975), has been widely adopted to explain behavioural intention. It states that people's intentions are the strongest predictors of their behaviour, and defines intention as a person's readiness to act, shaped by attitudes toward behaviour and perceived social norms. The key determinants of intention are attitudes toward behaviour and subjective norms, which also reflect perceived social pressure from family, friends and society (Fishbein & Ajzen, 1975). TRA is particularly effective in explaining deliberate, non-routine consumer decisions, and has been extensively applied in marketing and consumer behaviour research, particularly in understanding purchase intentions (Ha & Janda, 2012).

Purchase intention reflects a consumer's likelihood or plan to buy a product (Albayrak et al., 2013) and is a strong predictor of actual behaviour (Chen & Yang, 2020). Green purchase intention (GPI) refers to the willingness to choose eco-friendly products over conventional alternatives, signifying concern for environmental impact while maintaining quality expectations (Sabeen et al., 2022).

Biswas and Roy (2015) define green products as those produced with non-toxic materials and eco-friendly packaging. The rise in environmental crises and consumer advocacy for sustainability has shifted consumer behaviour. Individuals increasingly prefer products with non-toxic, safe ingredients and recyclable packaging, driving the awareness and demand for green personal-care products (Kim & Seock, 2009; Biswas & Roy, 2015). Understanding purchase intentions enables companies to tailor marketing strategies, segment audiences and gain a competitive edge. In the green personal-care market, this insight helps identify key decision drivers – such as environmental awareness, ethical sourcing and product performance and supports targeted communication and long-term customer loyalty (Atienza et al., 2022; Choudhury et al., 2024).

2.2. Predictive models for prediction of purchase intention

2.2.1. Machine learning models

Prediction models for purchase intention typically fall into statistical or ML categories. While statistical models such as linear and logistic regression rely on assumptions such as linearity and no multicollinearity, they often fail to capture the complexity of real-world behavioural data, which is seen to be complex, non-linear and influenced by latent factors (Chen et al., 2021). ML algorithms address these limitations by transforming unstructured behavioural data into predictive models without relying on assumptions of linearity (Zhou et al., 2019).

Classification-based ML techniques, such as SVM, DT, RF and gradient boosting (including XGBoost), are widely used to predict binary outcomes such as purchase or no purchase (Larose & Larose, 2014). ML has proven effective in predicting consumer purchase decisions. Choudhury et al. (2024) applied six ML algorithms, including RF and XGBoost, to a dataset of 310 respondents and 12 variables related to green purchasing. All models achieved over 75% accuracy, with

RF producing the highest AUC (0.84). Feature importance plots highlighted the most influential predictors of green purchase intention.

2.2.2. *Deep learning*

DL models, or neural networks, are computational systems that mimic human neural biology by using multiple simple processors to learn relationships between variables and simulate neural processes through multiple layers of interconnected nodes (Prashar et al., 2016). These models use backpropagation and hidden layers to detect complex patterns in non-linear, high-dimensional data (Prashar et al., 2016; Vora & Bhatia, 2023). Their robustness against noise and adaptability make them ideal for classification problems in consumer prediction (Larose & Larose, 2014). Neural networks, such as ANN, consist of input, hidden and output layers, with activation functions such as ReLU and tanh determining neuron outputs (Bigarella, 2024). Optimisation techniques such as stochastic gradient descent (SGD) and Adam adjust weights to minimise error. Key parameters such as batch size, learning rate and number of epochs significantly impact performance and require fine tuning (Kalliola et al., 2021). While some studies favour ReLU for efficiency, others find that performance varies by dataset and problem type. For example, Bigarella (2024) found both tanh and ReLU to be effective under different conditions. Hence, model performance and optimisation are achieved by configuring the above parameters.

Different types of neural networks offer different, unique strengths in predictive modelling. RNNs have been extensively used for sequential data processing, making them ideal in prediction tasks involving sequential or time-dependent data due to their ability to retain historical context (Nayebi et al., 2022). Deep neural networks (DNNs), with their inherent multiple hidden layers, are capable of learning deep abstract representations; hence, they are effective in handling complex, high-dimensional datasets where shallow models fail to capture underlying structures, such as human decision-making (Fintz et al., 2022). DNNs use multiple fully connected layers, thereby enhancing their learning capability (Chaudhuri et al., 2021).

Various DL architectures serve unique functions. RNNs process sequential data and are effective in retaining historical context, making them suitable for time-series prediction tasks (Nayebi et al., 2022). DNNs, with multiple hidden layers, capture abstract relationships in complex datasets, such as decision-making behaviour (Fintz et al., 2022; Chaudhuri et al., 2021). Convolutional neural networks (CNNs), typically used for image and spatial data, are also applied to high-dimensional datasets in scientific contexts, such as chemical analysis (Peleato, 2022). ANNs, with a feedforward architecture and no backward connections, are well suited for static classification tasks. Chaudhuri et al (2021) reported 89% accuracy using DNNs for behavioural prediction. Similarly, Kumar et al. (2022) achieved 93.5% accuracy with ANNs on internet purchase intention, and Prashar et al. (2015) reached 96% accuracy in an impulse-purchase prediction model involving 24 variables. These results underscore the reliability of ANNs when carefully optimised.

2.3. Key influencing factors of green personal-care purchase intention

2.3.1. *Perceptions and attitudinal factors*

The theory of reasoned action (Fishbein & Ajzen, 1975) identifies attitudes as a key factor influencing purchase intention. Research highlights environmental consciousness as a significant predictor of green consumption. Environmental consciousness reflects a consumer's emotional engagement with environmental issues and willingness to act (Lasuin & Ng, 2014). Studies confirm that heightened environmental consciousness positively impacts green purchasing behaviour (Qomariah & Prabawani, 2020; Vinoth, 2023). Another crucial factor is environmental knowledge, which refers to a consumer's awareness of ecological and sustainability issues (Qomariah &

Prabawani, 2020; Choudhury et al., 2024). Consumers with high environmental knowledge often exhibit strong pro-environmental attitudes, increasing their likelihood of purchasing eco-friendly products (Mostafa, 2009). Choudhury et al. (2024) incorporated this variable into machine learning models to predict purchase intention.

Product and brand-related factors also influence green purchasing. Brand image plays a crucial role in shaping consumer perceptions (Tsarenko et al., 2013) and purchase decisions (Swaminathan et al., 2020). Many companies invest in green marketing to enhance their brand's perception of sustainability (Samarasinghe, 2012). A green brand-image formed through sustainability initiatives fosters positive associations with green products and increases purchase intention (Chen & Yang, 2020). Studies confirm that a strong green brand-image significantly impacts consumer buying behaviour (Wu & Chen, 2014), making it a vital predictor in purchase intention models.

Green self-image, or self-identity, also drives green purchasing. It represents how individuals perceive themselves as being environmentally responsible (Van der Werff et al., 2013). Choudhury et al. (2024) found green self-image to be the strongest predictor of green purchase intention in India and integrated it into ML models. Consumers align purchases with personal values and seek social recognition, as seen in Malaysian university students (Lasuin & Ng, 2014). Egoistic values also positively impact green purchase intention (Atienza et al., 2022). Therefore, green self-image is a critical factor influencing eco-friendly purchasing decisions.

2.3.2. *Behavioural factors*

Social influences play a significant role in shaping purchase intentions. Solomon et al. (2006) describe peer influence as a key factor, where opinions of others impact purchasing decisions. Choudhury et al. (2024) emphasise that social consciousness in green purchasing creates peer pressure, leading to feelings of guilt when individuals fail to conform. Studies support this notion, with Larsson and Arif Khan (2012) finding that Swedish consumers buy organic food to engage in socially acceptable behaviours. Similarly, Öhman (2011) highlights Sherman's (1980) findings that consumers tend to over-indulge in green purchases due to social responsibility and adherence. However, not all studies confirm the impact of social pressure. A study among Jakarta university students found that social influence ranked as the second-lowest factor affecting green purchase intentions (Irawan & Darmayanti, 2012).

Price sensitivity is another crucial factor in green purchasing. Price significantly influences purchasing decisions and consumer satisfaction (Herrmann et al., 2007). As green products are often more expensive than conventional ones (Witek & Kuźniar, 2021), price acts as a deterrent to purchase. Consumers tend to prioritise financial advantages over eco-friendliness (Kim & Seock, 2009). However, some studies suggest that consumers who highly value environmental benefits are willing to pay a premium, reducing price sensitivity (Moslehpour et al., 2021). Their research confirms the significant impact of price sensitivity on green purchase intentions, highlighting the importance of understanding consumer price perceptions when marketing eco-friendly products.

2.3.3. *Demographic factors*

The impact of demographic factors on green personal-care product purchases varies across studies. Some research suggests that women show stronger environmental concerns and a higher affinity for green products (Chekima et al., 2016). A study in Hong Kong found that female adolescents had greater environmental awareness, positively influencing their green purchase intentions (Lee, 2008). However, research in Malaysia reported no significant gender effect (Chen & Chai, 2010). Some scholars argue that gender differences are not universal, as men with greater environmental knowledge may also engage in green purchasing (Diamantopoulos et al., 2003).

Age also plays a role in purchase intention. A Malaysian study found that younger consumers make simpler purchasing decisions, whereas older consumers take a more cautious approach (Che In & Ahmad, 2018). Fisher et al. (2012) found that individuals over 55 were among the most frequent green product users in the United States. However, other studies suggest that younger consumers are more responsive to eco-friendly products (Chan, 2001).

Education level influences green purchasing behaviour. Highly educated consumers tend to buy more green products due to increased awareness of environmental issues (Che In & Ahmad, 2018). Fisher et al. (2012) and Chan (2001) confirm that higher education correlates with eco-friendly behaviours. However, Yin et al. (2010) found only a marginal impact in China, as educated consumers prioritised personal needs over environmental concerns.

This study developed a prediction model using artificial neural networks (ANNs) to classify green personal-care product purchase intentions. It incorporated factors such as environmental knowledge, green brand image, green self-image, social influence, price sensitivity, age, gender and education level.

3. Research Methodology

3.1. Data collection and sampling

The study entailed primary data collection and obtained full ethical approvals from Unitec's Research Ethics Committee, and thus has adhered to ethical standards by ensuring informed consent, avoiding harm, protecting privacy and preventing deception. For example, researchers provided a statement to participants that declared: "*Your responses will be anonymous, and the responses of this survey will be used only for the purpose stated* ...". In addition, participants were fully informed about the research purpose and their voluntary participation, with the option to review questions beforehand and withdraw at any time. The questionnaire administered online posed no risk of emotional stress or cultural insensitivity, and no personal information was collected. Data confidentiality was strictly maintained.

The target population was current and potential users of personal-care products, which included members of all genders above the age of 18 years and residing in Tāmaki Makaurau Auckland. Purposive sampling was used and included the following segments to reduce sample bias:

- Male, female, transgender and non-binary
- Age group above 18 years
- Working and non-working
- Education qualifications: high school qualifications, certificates and diplomas, bachelor's degrees, and postgraduate qualifications

Purposive sampling was used in this study to ensure representation across key consumer segments relevant to personal-care product usage (e.g., oral care, haircare, skincare, cosmetics, etc.). The questionnaire responses were regularly reviewed to purposively select individuals who brought in diverse experiences not yet captured. A similar approach was taken to ensure diversity in education levels, as prior research (Che In & Ahmad, 2018; Fisher et al., 2012; Chan, 2001) has shown that education influences green purchasing behaviour. This ensured a well-rounded sample reflective of Aotearoa New Zealand consumers, helping to reduce selection bias and enabling validation through feature importance analysis in the predictive model.

Since the target population is unknown, this study used Wibisono's (2003) formula to calculate the sample size.

$$N = \left(\frac{\frac{Z\alpha}{2} .\sigma}{e} \right)^2$$

$$N = \left(\frac{1.96 .0.25}{0.05} \right)^2$$

$$N = 96.04$$

Where,

N = sample size

$\frac{Z\alpha}{2}$ = confidence level (95%)

σ = standard deviation (0.25)

E = error rate

To determine an appropriate sample size for this study, Wibisono's (2003) formula was employed, given its wide application in applied business research involving model development and validation. This approach ensures statistical adequacy and data representativeness, both of which are essential for building reliable deep learning models capable of generalisation and avoiding overfitting. Wibisono's method is particularly suited to research contexts where multiple independent variables, such as demographic and psychographic factors, are analysed. It supports the practical execution of predictive modelling while maintaining academic rigour, enabling the development of models that are both robust and generalisable across diverse consumer segments.

The minimum sample size was 96, as per the above formula. The data collection instrument was a structured questionnaire incorporating question items in Table 1. Additional questions were included as control questions. Since the sample included both current and potential users, the questionnaire included questions for both segments about the use of environmentally friendly products. The questionnaire was administered online through Google Forms.

3.1.1 *Operationalisation of factors*

Factors including Environmental Knowledge, Green Brand Image, Green Self-Image, Social Influence, Price Sensitivity and Purchase Intention each incorporated several questions. While two questions were included for Green Brand Image, three questions each were included for Environmental Knowledge, Green Self-Image, Social Influence, Price Sensitivity and Purchase Intention. These questions were fine-tuned and structured separately in the questionnaire to suit current and potential users of environmentally friendly personal care products.

A 5-point Likert scale was used to obtain responses for each of these sub-questions. One question was used to collect responses for each of the demographic factors: Age, Gender and Education Level. The operationalisation of the nine factors is depicted in Table 1.

Table 1. Operationalisation of factors.

Factors	Questions	Reference	Question No.
Environmental Knowledge	• I am aware of the general environmental problems. • I understand what environmental protection is about. • I understand the primary causes of global warming.	Moslehpour et al., 2021.	E1 E2 E3
Green Self-Image	• I think of myself as a socially responsible consumer. • I think of myself as an environmentally conscious consumer. • I think of myself as someone who is concerned about social issues.	Hustvedt & Dickson, 2009.	SF1 SF2 SF3
Green Brand Image	• I think/will think of brands that care about the environment when purchasing environmentally friendly personal-care products. • I think/will think of brands that are trustworthy, environmentally friendly personal-care products.	Agmeka et al., 2019. Rahmi et al., 2017.	B1, B3 B2, B4
Social Influence	• I learn so much about environmentally friendly products from friends and relatives. • I learn so much about environmental issues from friends and relatives. • I consider/will consider the opinions of friends, relatives and peers when buying eco-friendly products.	Mei et al., 2012.	SC1 SC2 SC3, SC4
Price Sensitivity	• When I buy environmentally friendly products, I compare/will compare prices with ordinary products. • I remember/will remember the prices of environmentally friendly products that I use. • I check/will check my budget before buying environmentally friendly personal-care products.	Moslehpour et al., 2021.	P1, P4 P2, P5 P3, P6
Purchase Intention	• Over the next month, I am likely to purchase any environmentally friendly personal care products. • Over the next month, I will consider switching to other brands for ecological reasons. • Over the next month, I plan to switch to an environmentally friendly version of products I purchase now.	Chan, 2001. Che In, 2018.	PC1 PC2 PC3
Age	What is your age?		3
Gender	• Male • Female • Other		4

Education Level	• Highest level of education • High school • Certificate/Diploma • Bachelor's degree • Postgraduate certificate/diploma • Master's degree • PhD	5

Note: The table above presents the factors, corresponding survey questions, and their references. Each factor represents a key construct related to green consumer behaviour, with associated questions designed to measure respondents' attitudes and intentions.
Source: Authors' own creation.

3.2. Data analysis

3.2.1. Reliability and validity of data

The reliability and validity of variables used in this study were measured using Cronbach's alpha and composite reliability for internal consistency and average variance extracted (AVE) for convergent validity. The discriminant validity was used to measure how strongly the constructs of purchase intention are related. These metrics were computed using SmartPLS structural equation modelling and tested against recommended thresholds (0.7 for reliability, 0.5 for AVE) (Hair et al., 2019). If the computed values of some constructs fell below these thresholds, this study removed those constructs in accordance with literature guidelines (Sarstedt et al., 2022). The final validated results are presented in Tables 2 and 3 after adjustments.

Table 2. The reliability and convergent validity assessment

Variables	Cronbach's Alpha	Composite Reliability	AVE
Green Brand Image	0.983	0.992	0.983
Environmental Knowledge	0.764	0.863	0.678
Price Sensitivity	0.935	0.969	0.939
Purchase Intention	0.879	0.925	0.804
Green Self-Image	0.829	0.898	0.748
Social Influence	0.878	0.942	0.891

Source: Authors' own creation.

As depicted in Table 2, all the values of Cronbach's alpha and composite reliability for the variables were greater than the minimum value of 0.7 recommended (Hair et al., 2019). Similarly, the AVE values for all variables were above the recommended minimum value of 0.5 (Hair et al., 2019). Hence, the variables' internal consistency, reliability and convergent validity were confirmed.

To test the discriminant validity of the variables, the indicator loadings were compared with the cross-loadings. Table 3 represents the results of this comparison.

Table 3. Discriminant validity assessment.

	Green Brand Image	Environmental Knowledge	Price Sensitivity	Purchase Intention	Social Influence	Green Self-Image
B1	0.992	0.342	0.941	0.521	0.344	0.389
B2	0.991	0.342	0.925	0.479	0.334	0.404
E1	0.252	0.822	0.195	0.222	0.181	0.368
E2	0.199	0.811	0.208	0.271	0.241	0.429
E3	0.387	0.836	0.390	0.293	0.272	0.532
P1	0.933	0.342	0.967	0.465	0.327	0.364
P2	0.892	0.300	0.971	0.502	0.406	0.341
PC1	0.543	0.298	0.547	0.880	0.376	0.433
PC2	0.361	0.299	0.375	0.912	0.366	0.411
PC3	0.431	0.268	0.399	0.898	0.401	0.386
SC1	0.391	0.218	0.421	0.385	0.939	0.400
SC2	0.260	0.319	0.300	0.417	0.948	0.426
SF1	0.351	0.515	0.316	0.392	0.370	0.890
SF2	0.402	0.422	0.372	0.436	0.400	0.915
SF3	0.274	0.493	0.243	0.358	0.366	0.783

Source: Authors' own creation.

3.2.2. *Data processing*

Following data collection via Google Forms, responses were exported to Excel, converted to CSV format and analysed. Since the Google Form design ensures complete responses, no missing values existed.

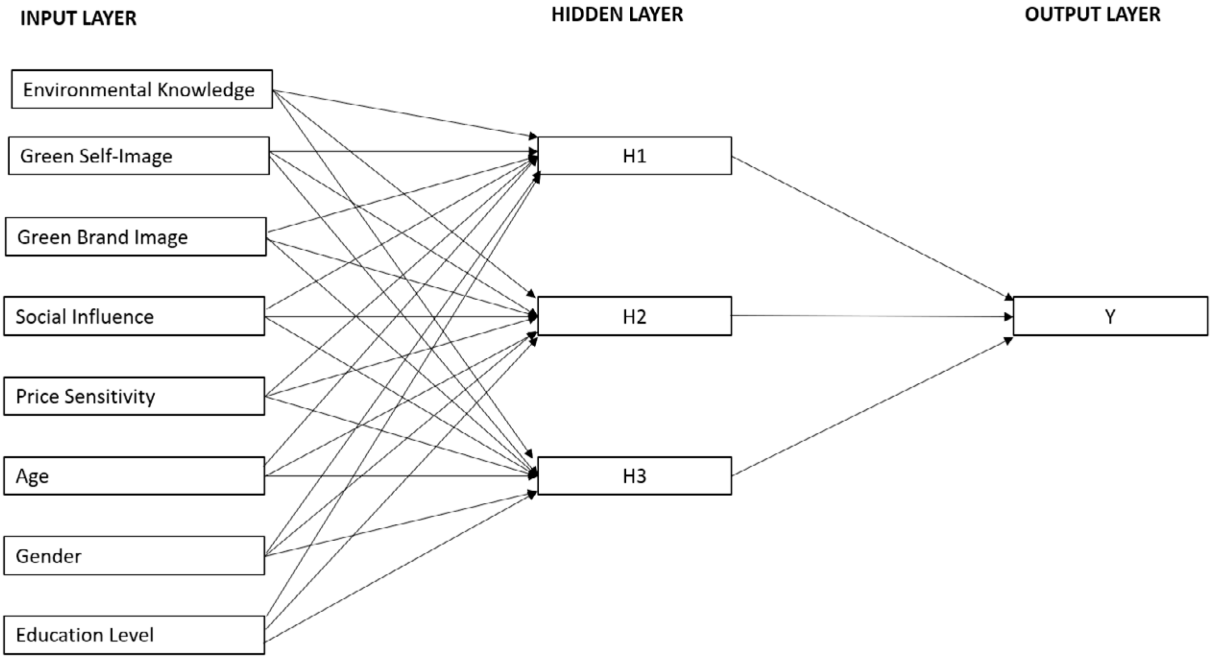
Data transformation involved aggregating mean scores of sub-questions for each of the eight independent variables. Categorical variables such as Gender and Education Level were converted into dummy variables using one-hot encoding. Following Choudhury et al. (2024), Purchase Intention was binarised (scores >2.5 = 1). Python software was used for data preprocessing.

3.2.3. *The prediction model*

This study employed ANN for classification-based prediction, as ANN effectively handles non-linear relationships and non-normal distributions (Leong et al., 2019). It is particularly suited for predicting purchase intention, which involves complex variables such as brand imagery, and behavioural and attitudinal factors (Witek & Kuźniar, 2021).

Studies have found ANN models effective in analysing cause-and-effect relationships in complex systems. In fields such as health sciences, where data is limited and complexity is high, feedforward ANNs with backpropagation have effectively modelled nonlinear relationships while avoiding overfitting through careful design (Pasini, 2015). Similarly, in small-sample purchase prediction studies (Prashar et al., 2016), ANN has proven effective. Thus, ANN was chosen for this study due to its suitability for small datasets with nonlinear variables. The proposed model entailed the model architecture depicted in Figure 1.

Figure 1: Model architecture.



Source: Author's creation.

An 80:20 split in the data was used for training and testing datasets, respectively. The proportions of the binary class distribution in the overall dataset were maintained in both the training and testing datasets. The proposed ANN model consisted of an input layer with nine neurons representing input and target variables. The hidden layers were optimised using hyperparameter tuning, adjusting layer depth, neuron count, activation functions and optimisers to identify the best configuration. The output layer had two neurons for binary classification, using the sigmoid activation function for probability-based interpretation (Bigarella, 2024).

The network depth was found to be crucial for effective predictive power (Kalliola et al., 2021). A study used to predict purchase behaviour tested three and five hidden layers with 64 and 128 neurons for optimal learning. Previous studies have suggested that increasing hidden layers and neurons up to five layers with 128 neurons enhances prediction (Chaudhuri et al., 2021).

Additionally, to improve learning and generalisation, various optimisers and activation functions were tested. ReLU and tanh, effective in deep learning and preventing vanishing gradients, were explored (Bonaccorso, 2018; Kalliola et al., 2021). Hyperparameters such as batch sizes, epochs and optimisation functions were also fine-tuned to maximise predictive accuracy. A summary of these hyperparameters is presented in Table 4.

Table 4. Hyperparameters for ANN model.

Hyperparameters	Selected Values
Neurons in the input layer	8
Number of hidden layers	3, 5
Number of neurons in hidden layer	32, 64, 128
Batch size	32, 64
No. of epochs	100, 200
Activation function – hidden layer	ReLU, tanh
Activation function – output layer	Sigmoid
Optimiser	Adam, SGD

Note: This table presents the hyperparameters tested in the tuning phase.
Source: Authors' own creation.

3.2.4. *Model performance and evaluation*

The ANN model's performance was evaluated by assessing its accuracy in distinguishing between 1s (purchase) and 0s (non-purchase). Performance was measured using the test dataset, ensuring the model generalised well. Overfitting occurs if the model performs better on training data than on testing data (Vora & Bhatia, 2023). Key performance metrics included Accuracy, F1 score, Recall and Precision, calculated for both training and testing datasets to detect overfitting or underfitting issues. Furthermore, the ANN model was compared with RF, SVM, XGBoost, gradient boosting and decision tree models, following methodologies from similar studies (Chaudhuri et al., 2021; Choudhury et al., 2024). The model was implemented in Python, utilising NumPy and Pandas for data structuring, Matplotlib and Excel for visualisation, and TensorFlow and Keras for ANN construction.

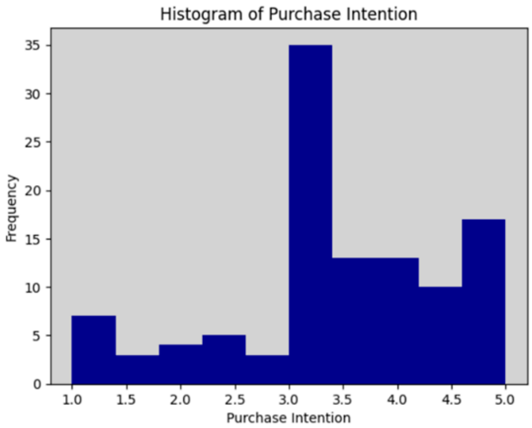
4. Results and Discussion

4.1. Results

4.1.1. *Preprocessed data*

After the preprocessing tasks outlined in 3.2.2 were carried out, the data distribution was depicted (Figure 2 and Figure 3).

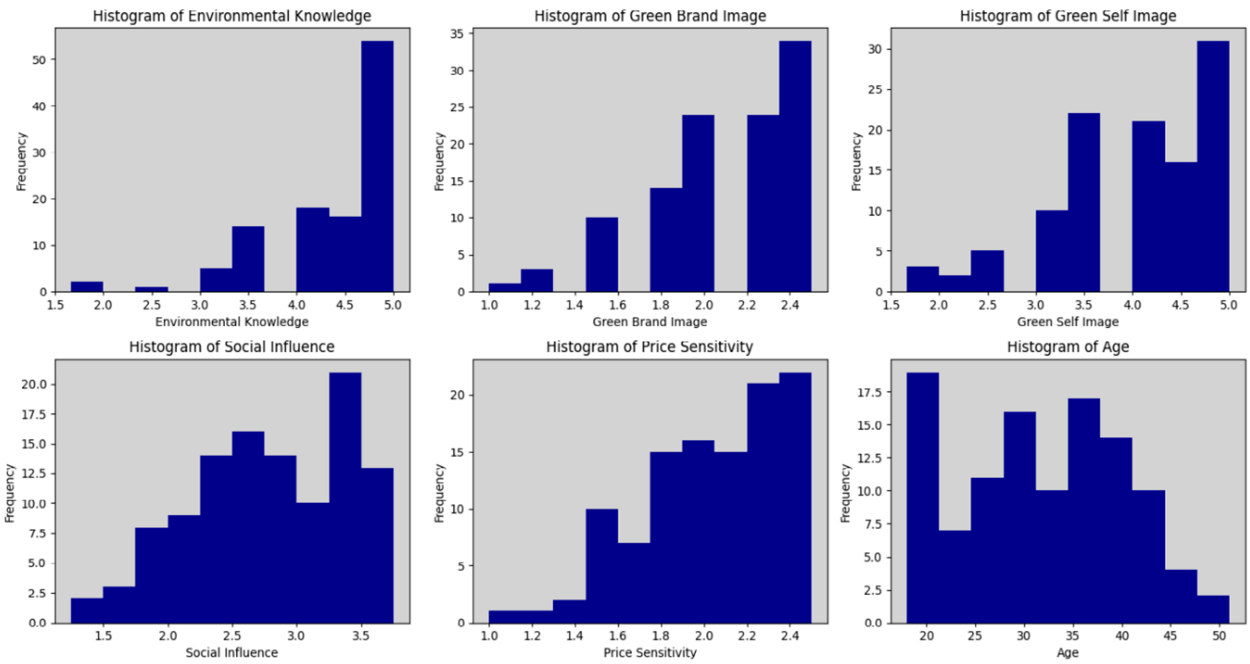
Figure 2: Histogram of Purchase Intention.



Source: Authors' own creation.

The Purchase Intention histogram depicts the highest frequency of responses around the mid-point of 3, indicating that most respondents were indecisive about purchasing green personal-care products. A smaller number of respondents favoured purchasing green products, with fewer observations between the ranges of 1 and 2.5, indicating a lower inclination towards negative purchase behaviour.

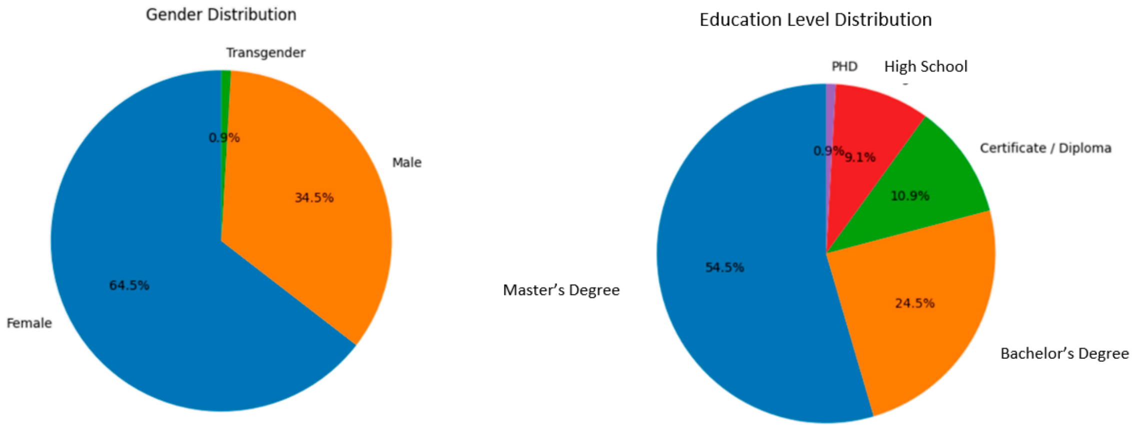
Figure 3: Histograms for independent variables.



Source: Authors' own creation.

The histograms for six variables (excluding Gender and Education Level) show their aggregated mean scores after data transformation. None follows a normal distribution, with most variables exhibiting positive skewness. Environmental Knowledge, Green Brand Image, and Green Self-Image have responses clustered around 4.5–5, while Price Sensitivity is more evenly distributed but slightly concentrated between 4.5–5. The Age variable displays a bimodal distribution, peaking at 20, 30 and 35–40 years.

Figure 4: Proportions of Gender and Education Level variables.



Source: Authors' own creation.

The Gender composition was skewed, with 64.5% being female, followed by 34.5% male and less than 1% in other genders. In terms of Education Level, over 75% of respondents had bachelor's and master's degrees.

As the next steps, categorical variables such as Gender and Education Level were converted to dummy variables using one-hot encoding, enabling the preparation of their use in the prediction model. Table 5 depicts the resulting types of data after the data preprocessing.

Table 5. Data types.

Variable	**Data Type**
Environmental Knowledge	Float
Green Brand Image	Float
Price Sensitivity	Float
Purchase Intention	Float
Green Self-Image	Float
Social Influence	Float
Age	Integer
Gender_Male	Boolean
Gender_Transgender	Boolean
Education Level_Certificate/Diploma	Boolean
Education Level_High School	Boolean
Education Level_Master's Degree	Boolean
Education Level_PhD	Boolean

Source: Authors' own creation.

4.1.2. *Descriptive statistics: Post-processing of data*

The dataset consisted of data for nine variables, of which Environmental Knowledge, Green Brand Image, Price Sensitivity, Purchase Intention, Green Self-Image and Social Influence are categorical in nature. Gender_Male, Gender_Female, Gender_Non-Binary, Gender_Transgender, Education Level_High School, Education Level_Certificate/Diploma, Education Level_Bachelor's Degree, Education Level_Master's Degree and Education Level_PhD are Boolean-type data which result from the transformation of the Gender and Education Level variables. Age is presented as integers.

The statistics in Table 6 depict significant variability in the respondents' attitudes and behaviours concerning the purchase intention of green personal-care products. Environmental Knowledge and Green Brand Image depict high mean scores over 4 with moderate variability, indicating respondents feel well informed about environmental issues. Green Self-Image (3.94) and Price Sensitivity (3.99) also score relatively high, though Green Self-Image shows greater individual differences (SD = 0.84). Social Influence reflects a moderate mean (3.36) but high variability (SD = 1.1). Purchase Intention scores of 3.42 with moderate variability (SD = 1.06) indicate mixed intentions toward eco-friendly personal-care products.

Table 6. Descriptive statistics of the numeric variables.

	Environmental Knowledge	Green Brand Image	Price Sensitivity	Purchase Intention	Green Self-Image	Social Influence	Age
Count	110.00	110.00	110.00	110.00	110.00	110.00	110.00
Mean	4.29	4.20	3.99	3.42	3.94	3.36	31.70
Std	0.71	0.73	0.81	1.06	0.84	1.10	8.60
Min	1.67	2.00	2.00	1.00	1.67	1.00	18.00
25%	4.00	3.62	3.50	3.00	3.33	2.50	26.00
50%	4.33	4.50	4.00	3.33	4.00	3.50	32.00
75%	5.00	5.00	4.50	4.00	4.67	4.00	38.75
Max	5.00	5.00	5.00	5.00	5.00	5.00	51.00

Source: Authors' own creation.

Table 7 depicts the distribution in respondents' demographics: respondents' ages ranged from 18 to 51 years (mean = 31.7, SD = 8.6), representing a young sample. Gender distribution was somewhat unbalanced (65% female, 35% male, 1% transgender). Most respondents were highly educated, with 55% holding a master's degree and 25% a bachelor's degree. The dataset includes 110 responses.

Table 7. Descriptive statistics of the categorical variables.

	Gender_ Female	Gender_ Male	Gender_ Transgender	Education Level_ Bachelor's Degree	Education Level_ Certificate/ Diploma	Education Level_ High School	Education Level_ Master's Degree	Education Level_ PhD
Count	110.00	110.00	110.00	110.00	110.00	110.00	110.00	110.00
Mean	0.65	0.35	0.01	0.25	0.11	0.09	0.55	0.01
Std	0.48	0.48	0.10	0.43	0.31	0.29	0.50	0.10
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
25%	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
50%	1.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00
75%	1.00	1.00	0.00	0.00	0.00	0.00	1.00	0.00
Max	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Source: Authors' own creation.

4.1.3. *Deep learning model*

This study developed a prediction model using ANN to forecast purchase intention. Taking the learnings of similar studies (Prashar et al., 2016), a base model was constructed consisting of an input layer with 16 neurons, three hidden layers with 64 neurons each, and an output layer with one neuron. A batch size of 64 and 100 epochs per run was adopted. The ReLU activation function was applied to hidden layers, while the Adam optimiser was used for optimisation. The architecture was based on similar studies utilising ANN for purchase behaviour prediction (Chaudhuri et al., 2021). The performance of this base model is presented in Table 8.

Table 8. Performance of the base model.

Epochs: 100 Batch No: 64 Activation (Hidden Layers): ReLU Optimiser: Adam

Configuration			Evaluation: Training				Evaluation: Testing				Difference			
Run #	Hidden Layers	Neurons	Acc	F1	Recall	Precision	Acc	F1	Recall	Precision	Acc	F1	Recall	Precision
Baseline	3	64	1.0	1.0	1.0	1.0	0.77	0.86	0.84	0.88	0.23	0.14	0.16	0.12

Note: This table presents the evaluation results of the base model for both training and testing data. The configuration includes three hidden layers with 64 neurons, ReLU activation function, and Adam optimiser. The metrics shown are Accuracy (Acc), F1 score, Recall and Precision for both the training and testing sets, along with the differences between training and testing scores.
Source: Authors' own creation.

To optimise the model for improved accuracy, hyperparameter tuning was carried out in three stages, where hyperparameters such as the number of hidden layers, neurons per layer, epochs, batch size, activation functions and optimisers were systematically optimised. The first stage of tuning explored configurations with three and five hidden layers consisting of 64 and 128 neurons per layer. The batch number, number of epochs, optimiser and activation were maintained the same as the base model. The performance scores, as indicated in Table 9, reflect that the training accuracy reached 1.0 for all models, but testing accuracy ranged between 0.77 and 0.88. However, runs with higher neurons (128) and additional layers (five) demonstrated an increased performance, F1, Recall and Precision scores of 0.89, suggesting better classification ability compared to the baseline model in Table 8 (0.86, 0.84, 0.88), with the exception of five layers with 128 neurons. However, differences between training and testing scores indicate overfitting, requiring further refinements.

Table 9. Performance of the model with different network configurations.

Epochs: 100 Batch No: 64 Activation (Hidden Layers): ReLU Optimiser: Adam

Configuration			Evaluation: Training				Evaluation: Testing				Difference			
Run #	Hidden Layers	Neurons	Acc	F1	Recall	Precision	Acc	F1	Recall	Precision	Acc	F1	Recall	Precision
1	3	128	1.0	1.0	1.0	1.0	0.81	0.89	0.89	0.89	0.19	0.11	0.11	0.11
2	5	64	1.0	1.0	1.0	1.0	0.81	0.89	0.89	0.89	0.19	0.11	0.11	0.11
3	5	128	1.0	1.0	1.0	1.0	0.77	0.86	0.88	0.84	0.23	0.14	0.12	0.16

Note: This table presents the evaluation results of the model with different configurations for hidden layers and number of neurons, ReLU activation function, and Adam optimiser. The metrics shown are Accuracy (Acc), F1 score, Recall and Precision for both the training and testing sets, along with the differences between training and testing scores. Thus, the configurations in Runs 1, 2 and 3 are used for the next stage in hyperparameter tuning.
Source: Authors' own creation.

The impact of batch number and epoch configurations was evaluated in the second hyperparameter tuning stage. To mitigate overfitting, the number of epochs was increased to 200, and the batch size was reduced to 32. This stage evaluated models with the best-performing configurations from Stage 1. As illustrated in Table 10, despite changes in batch size and epoch configurations, the testing performance remained unchanged compared to Stage 1. The model with three hidden layers and 128 neurons (Run 4) performed slightly worse than those with five hidden layers (Runs 5 and 6), indicating that increasing epochs and reducing batch size does not improve generalisation but may exacerbate overfitting. The results are compared with Runs 1, 2 and 3, along with the baseline model, presented in Table 10.

Table 10. Performance of the model configurations with 200 epochs and a batch size of 32.

Epochs: 200 Batch No: 32 Activation (Hidden Layers): ReLU Optimiser: Adam

Configuration			Evaluation: Training				Evaluation: Testing				Difference			
Run #	Hidden Layers	Neurons	Acc	F1	Recall	Precision	Acc	F1	Recall	Precision	Acc	F1	Recall	Precision
4	3	128	1.0	1.0	1.0	1.0	0.77	0.86	0.84	0.88	0.19	0.11	0.11	0.11
5	5	64	1.0	1.0	1.0	1.0	0.81	0.89	0.89	0.89	0.19	0.11	0.11	0.11
6	5	128	1.0	1.0	1.0	1.0	0.81	0.89	0.89	0.89	0.19	0.11	0.11	0.11

Note: This table presents the evaluation results of the model, with the same configurations for number of hidden layers and number of neurons as in Table 9, but different configurations for the number of epochs and batch sizes, ReLU activation function, and Adam optimiser. The metrics shown are Accuracy (Acc), F1 score, Recall and Precision for both the training and testing sets, along with the differences between training and testing scores.
Source: Authors' own creation.

The impact of the activation and optimiser functions was evaluated in Stage 3. The tanh activation function and SGD optimiser were introduced to further improve generalisation while maintaining the best configurations from Stage 2. Table 11 depicts the results showing increased testing Accuracy (0.90) and F1, Recall and Precision scores (0.95–1.0), indicating better generalisation. Notably, Run 7 (three hidden layers, 128 neurons, 100 epochs, batch size 64) demonstrated the best performance, with testing accuracy slightly surpassing training accuracy. The reduced gap between training and testing scores suggested a decline in overfitting compared to ReLU-Adam models. However, models with five hidden layers (Runs 8 and 9) showed slightly lower performance, emphasising that additional layers do not necessarily enhance generalisation.

Table 11. Model performance with tanh activation function and SGD optimiser.

Epochs: 100 Batch No: 64 Activation (Hidden Layers): Tanh Optimiser: SGD

Configuration			**Evaluation: Training**				**Evaluation: Testing**				**Difference**			
Run #	**Hidden Layers**	**Neurons**	**Acc**	**F1**	**Recall**	**Precision**	**Acc**	**F1**	**Recall**	**Precision**	**Acc**	**F1**	**Recall**	**Precision**
7	3	128	0.86	0.92	0.97	0.92	0.90	0.95	1.0	0.95	-0.04	-0.03	-0.03	-0.03
8	5	64	0.86	0.92	0.95	0.88	0.86	0.92	0.94	0.90	0.00	0.00	0.01	-0.02
9	5	128	0.85	0.91	0.94	0.88	0.90	0.95	1.0	0.95	-0.05	-0.04	-0.06	-0.07

Note: This table presents the evaluation results of the model, with different configurations, the activation function, and the optimiser. The number of hidden layers and neurons is the same as in Table 9. The metrics shown are Accuracy (Acc), F1 score, Recall and Precision for both the training and testing sets, along with the differences between training and testing scores.
Source: Authors' own creation.

4.1.4 *Comparison test*

The model performance was further assessed by comparing its performance with other machine learning prediction models. The comparison analysis is represented in Table 12. At first glance, the ANN model appears to have lower training scores (Accuracy = 0.86, F1 = 0.92, Recall = 0.97, Precision = 0.92), compared to random forest, XGBoost, gradient boosting, and decision trees, which achieve perfect training scores (1.0). However, ANN excelled in testing performance, achieving higher testing scores than training scores, and demonstrating superior generalisation compared to other models that struggle with unseen data. ANN's training–testing differences (-0.04, -0.03, -0.03, -0.03) across Accuracy, F1, Recall, and Precision indicated minimal overfitting.

Table 12. Comparison of ANN model performance with other ML models.

Configuration	Evaluation: Training				Evaluation: Testing				Difference			
	Acc	**F1**	**Recall**	**Precision**	**Acc**	**F1**	**Recall**	**Precision**	**Acc**	**F1**	**Recall**	**Precision**
ANN	0.86	0.92	0.97	0.92	0.90	0.95	1.00	0.95	-0.04	-0.03	-0.03	-0.03
Random Forest	1.0	1.0	1.0	1.0	0.90	0.95	1.00	0.90	0.10	0.05	0.00	0.10
SVM	0.87	0.92	0.95	0.89	0.86	0.92	0.94	0.90	0.01	0.00	0.01	-0.01
XGBoost	1.0	1.0	1.0	1.0	0.81	0.89	0.89	0.89	0.19	0.11	0.11	0.11
Gradient Boosting	1.0	1.0	1.0	1.0	0.81	0.90	0.94	0.85	0.11	0.10	0.06	0.15
Decision Tree	1.0	1.0	1.0	1.0	0.86	0.92	0.94	0.90	0.14	0.08	0.06	0.10

Note: This table presents a comparison of the performance of the ANN model with other ML models. The metrics shown are Accuracy (Acc), F1 score, Recall and Precision for both the training and testing sets, along with the differences between training and testing scores. Source: Authors' own creation.

ANN achieved the highest testing Accuracy (0.90), while F1 and Recall scores match random forest. ANN and random forest achieved perfect Recall scores (1.0) in testing, meaning they consistently detected positive instances. ANN's Precision improved from training (0.86) to testing (0.95), with only a -0.03 difference, whereas gradient boosting showed the largest discrepancy (0.15). SVM achieved a lower Precision difference (-0.01), but its testing score (0.90) was lower than ANN (0.95), indicating overfitting. Random forest, gradient boosting and decision trees suffered from overfitting, showing a significant performance drop from training to testing (0.81–0.95 in testing). XGBoost and gradient boosting performed the worst.

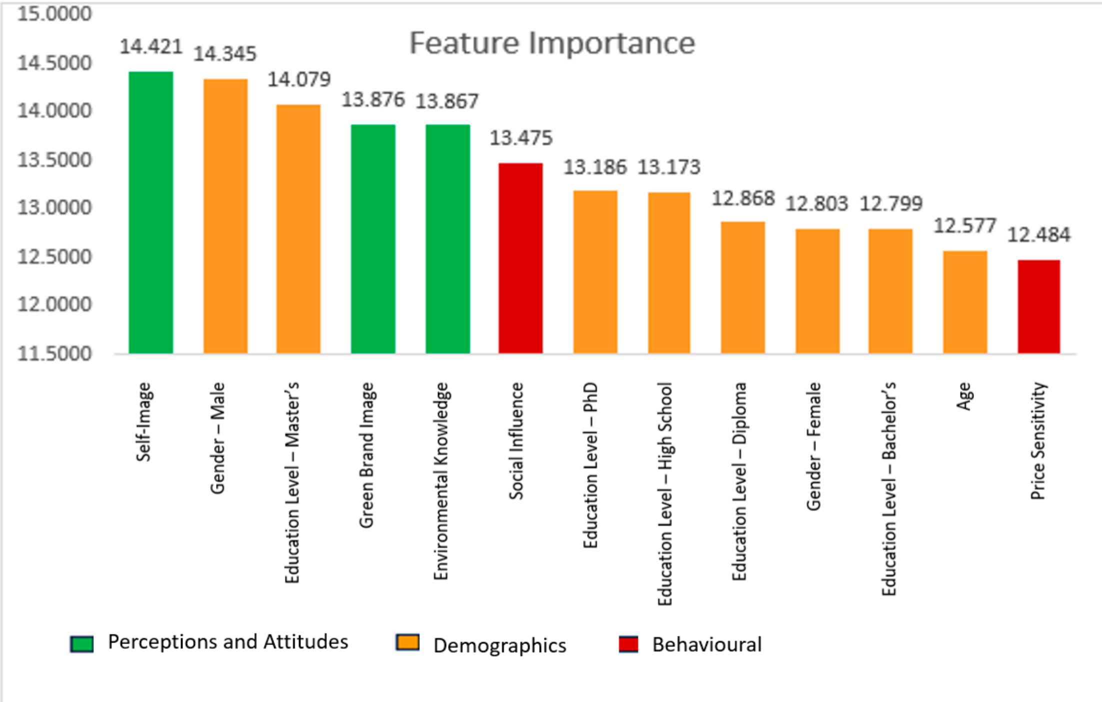
In summary, the ANN prediction model demonstrated consistent performance compared to other machine learning models. While the random forest algorithm achieved comparable F1 and Recall scores during testing, ANN exhibited a closer alignment between training and testing results, reinforcing its robustness and predictive effectiveness. Similar studies on purchase-intention prediction have also demonstrated ANN's superiority over traditional machine learning models, further validating its applicability in consumer behaviour forecasting.

Our finding that ANN can provide a good prediction is similar to Prasad and Ghosal's (2021) findings. In their study, they used ANN to predict the purchase intention for direct-to-consumer (DTC) brands with non-linear variables such as 'safety of transactions', 'availability of innovative products' and 'product quality', where a small dataset of 100 valid responses was used. They found that the ANN's accuracy was 96%. Moreover, a study to predict restaurant check-ins using ANN with a dataset of 120,825 check-ins in a geographical area in New York found that the prediction accuracy was 93%. Despite using different model architectures with a range of hidden layers and number of neurons, the highest accuracy was found to be with one hidden layer (Zheng et al., 2013).

4.1.5. *Feature importance*

The individual importance of each independent variable to the overall prediction of purchase behaviour of green personal-care products was assessed through the 'feature importance' analysis. This analysis was constructed based on the learned weights of the first layer of the neural network. This approach assumed that the larger weight magnitudes in the first layer contribute more significantly to the model's prediction, making these features more important. The feature importance was constructed based on the optimised model used in Run 7. Figure 5 depicts the independent variables' importance in descending order in this model.

Figure 5: Feature importance of the independent variables of the ANN model.



Source: Authors' own creation.

The feature importance scores indicate that all variables contributed meaningfully to predicting purchase intention, though some stood out more than others. The analysis highlighted that perception and attitudinal factors, particularly Green Self-Image, ranked the highest, with a score of 14.421, suggesting that self-perception of environmental consciousness strongly influences purchase decisions. Demographic factors such as Gender_Male also played a significant role, indicating that gender differences may influence purchasing behaviour, though Gender_Female was slightly less important. Similarly, Education Level_Master's followed closely, with scores of 14.345 and 14.078, demonstrating that education, particularly at higher levels, is a critical predictor.

Brand perception also played a moderate role, with Green Brand Image scoring 13.875, reflecting the impact of sustainability perceptions on purchase decisions. Environmental Knowledge followed closely, with a score of 13.866, emphasising the importance of awareness regarding environmental issues. Social Influence was another moderate factor, scoring 13.475, indicating that peer opinions contribute to green purchasing decisions. Various educational qualifications contributed differently, with Education Level_PhD ranking in the top half at 13.185, while Diploma, Master's, and High School qualifications showed varied contributions in the lower half of the ranking.

While age played a role in predicting purchase intention, a lower impact on Purchase Intention than other variables was observed. Similarly, Price Sensitivity was seen to have the least influence, suggesting that price was not a primary driver of environmentally conscious purchasing behaviour. Overall, attitudinal factors such as Green Self-Image and Environmental Knowledge, along with demographic factors such as Gender and Education Levels, were the strongest predictors of purchase intention. Age, some Gender considerations, and Price Sensitivity contributed to a lesser extent. These findings confirm that the ANN prediction model effectively learns and generalises on unseen data, making it a reliable tool for real-world applications.

5. Conclusion, Implications, Limitations and Future Research

This study developed a deep-learning model to predict purchase intentions for green personal-care products. A multi-layer ANN classification model was rigorously optimised and evaluated against key performance metrics and other machine learning models. The findings confirmed the ANN's superiority in predictive accuracy, highlighting its potential as a robust tool for forecasting consumer behaviour in sustainability-driven markets. The study also underscored the importance of network structure optimisation, revealing that deeper architectures can enhance training performance and may lead to overfitting in smaller datasets. The optimal model configuration consisted of three hidden layers with 128 neurons each, using the tanh activation function and the stochastic gradient descent (SGD) optimiser. These refinements ensured a stable and generalised model capable of delivering consistent performance on unseen data.

Feature importance analysis further validated the impact of attitudinal, behavioural and demographic factors, aligning with prior research. The study has significant academic and managerial implications. From an academic perspective, it advocates for the adoption of machine learning models – particularly ANNs – over traditional regression-based methods, which are often constrained by assumptions of linearity and normal distribution. For managers, the predictive insights generated by ANNs can enhance green marketing strategies, improve customer segmentation and optimise CRM systems. Businesses can also tailor marketing efforts to high-intent consumers through targeted promotions while increasing awareness among lower-intent buyers. Additionally, ANN-based predictions can improve demand forecasting, optimise inventory and supply-chain management, and assess marketing campaign effectiveness by tracking changes in purchase intent. In summary, by leveraging ANNs, businesses can better identify key purchase drivers and forecast demand across various personal-care product categories.

Despite its contributions, the study acknowledges limitations, including potential sample and respondent biases due to its focus on Tāmaki Makaurau Auckland and the use of purposive sampling via online questionnaires. Responses collected from 110 participants may constrain the generalisability of the findings. Small datasets also increase the risk of overfitting, where the model captures patterns specific to the sample rather than generalisable trends. Therefore, future research should consider validating the model on larger and more diverse datasets to enhance the robustness and predictive reliability of the results. Expanding the sample across different demographic groups, industries or geographic regions would strengthen the model's external validity and practical applicability.

Future research could explore more diverse data-collection methods, such as face-to-face interviews or social media surveys, to enhance representativeness. Further refinement of model hyperparameters, including learning rates and loss functions, could also be explored to enhance predictive accuracy and adaptability. In addition, future research may re-examine the issue using larger or more diverse samples from various regions and segments to provide additional evidence regarding purchase intentions for green personal-care products.

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