Trends in Finance and Economics
Vol: 3(1), March 2025
REST Publisher; ISSN: 2583-9721
Website: https://restpublisher.com/journals/tfe/
DOI: https://doi.org/10.46632/tfe/3/1/9

Environmental Economics and Statistical Modeling: An SPSS-Based Approach

N. Esakki
Ambai Arts College, Affiliated to Manonmaniam Sundaranar University, Ambasamudram, Tirunelveli District, Tamil Nadu, India.
Corresponding Author Email: esakkiadithya79@gmail.com

Abstract: *This research examines sustainability metrics within industries, focusing on environmental impact, resource efficiency, regulatory compliance, and public perception. The study utilizes SPSS for statistical analysis, exploring how various factors such as industry type, regulatory frameworks, geographical region, sustainability practices, and stakeholder involvement influence sustainability outcomes. The evaluation parameters include carbon footprint reduction, resource efficiency, regulatory compliance, sustainability impact, and public perception. Research Significance: The significance of this research lies in its contribution to understanding the relationships between various sustainability metrics and their drivers across different industries. This research provides insights that can guide policy, corporate strategies, and environmental management practices, offering both theoretical and practical contributions to the field of environmental economics and sustainability studies. Methodology: SPSS The research employed SPSS (Statistical Package for the Social Sciences) to analyze the data collected from various industry sectors. SPSS was used for descriptive statistics, correlation analysis, ANOVA, Principal Component Analysis (PCA), and reliability testing to assess the relationships between sustainability metrics and the factors influencing them. The statistical approach enabled a comprehensive understanding of how environmental concerns, industry-specific regulations, and stakeholder involvement affect sustainability outcomes. Alternative: Industry Type, Regulatory Framework, Primary Environmental Concern, Geographical Region, Sustainability Practices, Stakeholder Involvement Industry Type: Various industries were analyzed to explore how sector-specific characteristics influence sustainability practices. Regulatory Framework: The study investigated the role of government regulations in shaping environmental practices across different sectors. Primary Environmental Concern: This factor assessed the central environmental issues that industries focus on, such as carbon emissions or waste reduction. Geographical Region: Differences in sustainability practices were explored across geographical locations to understand regional impacts and variations in environmental policies. Sustainability Practices: The research evaluated the specific practices industries adopt to reduce their environmental footprint, focusing on energy efficiency, waste reduction, and resource management. Stakeholder Involvement: This factor examined how involvement from different stakeholders, including customers, regulators, and employees, affects the sustainability outcomes of businesses. Evaluation Parameters: Carbon Footprint Reduction: Measures the extent to which industries reduce their greenhouse gas emissions and environmental impact. Resource Efficiency: Evaluates how effectively industries use resources such as energy, water, and raw materials in their production processes. Regulatory Compliance: Assesses how well industries adhere to environmental regulations and legal standards. Sustainability Impact: Gauges the overall impact of an industry's sustainability practices on the environment, including contributions to climate change mitigation, biodiversity preservation, and pollution reduction. Public Perception: Measures the public's views and attitudes toward the sustainability practices of industries, influencing consumer behavior and corporate reputation. Results: The results of the study showed weak correlations between the sustainability metrics, suggesting limited interdependence between them. The ANOVA analysis revealed that the explanatory power of the models for each metric was not statistically significant. The Principal Component Analysis (PCA) indicated that while the extracted components accounted for 100% of the variance, the variance explained by individual components was relatively modest. This highlights the need for more refined models and additional variables to better capture the complexities of sustainability and its drivers. These results emphasize the importance of incorporating broader contextual factors in future sustainability research.*

Keywords: *Sustainability Metrics, Environmental Impact, Resource Efficiency, Carbon Footprint, Regulatory Compliance, Public Perception, Principal Component Analysis, SPSS, Stakeholder Involvement, Environmental Economics*

1. INTRODUCTION

Ecological economics is most clearly demonstrated through the study of renewable resource use and environmental management. Similarly, evolutionary economics draws significant inspiration from biological theories, particularly through concepts and methodologies derived from population theory. This article highlights how ecological economics greatly benefits from the approaches and insights of evolutionary economics in addressing key issues in both the basic research and policy domains. Environmental economics, and even more so ecological economics, are not just subfields of economics but are integral to the broader discipline of environmental science. It is an unexpected and missed opportunity that evolutionary perspectives—both genetic and non-genetic—are occasionally used problems and the nature and constraints of potential solutions. The importance of evolutionary thinking in environmental economics has been recognized. However, the acceptance of evolutionary theories, models, and insights in the field has progressed at a relatively slow pace.[1] In conclusion, this article highlights several psychological concepts from environmental psychology that provide encouraging avenues for behavioral aspects of environmental economics to be incorporated. In psychological research, empirical measures are often developed to assess specific attitudes, which can serve as predictors of future behavior. A major goal in environmental psychology is to establish valid and reliable methods for measuring individuals' environmental attitudes. Despite many challenges, we conclude by reaffirming the potential for integrating environmental economics and environmental psychology. We think that policy solutions that draw on knowledge from both fields have a lot of potential and ought to be investigated. Behavioral environmental economics is a new discipline that integrates the strengths of two disciplines the more realistic depiction of individual behavior found in psychology and other social sciences, as well as the normative framework of conventional environmental economics. The importance of behavioral economics in furthering their studies is being recognized by environmental economists more and more.[2] Policy debates on climate change emphasize the importance of using incentive-based instruments to effectively achieve goals. The shift in perspective toward these instruments has been one of the most important achievements of the last thirty years in environmental economics. Furthermore, economists have influenced policy both directly and through advocacy efforts. Environmental economics faces many challenges, and the need to improve its policy relevance is critical. To accomplish this, economists must prioritize real-world problems rather than focusing solely on practical tools. A notable example is the Environmental Economics Advisory Group within the Environmental Protection Agency's Science Advisory Board. This group plays a key role in providing economic guidance on important regulatory issues, ensuring that economists now have a platform to contribute their expertise.[3] We see ample opportunity for the application of these techniques in environmental economics. The effective use of quasi-experimental and experimental methods has the capacity to enhance our comprehension of the world around us. Furthermore, these approaches can help identify environmental policies that maximize social welfare, a key objective of environmental economics. This example also highlights that the cross-sectional association approach in environmental economics can often yield inaccurate approximations. Since association evidence frequently yields ambiguous or inconsistent insights into causal links, we believe that such examples are not unique. With the exception of treatment exposure, the treatment and control groups in a random assignment must be statistically equal. As a result, observed differences in outcomes may be due to the treatment itself. Our perspective is that significant attention should be paid to conducting experiments and quasi-experiments to address key questions in environmental economics.[4] These behavioral A number of factors significantly affect economic values, the process of valuation, and the resulting environmental policies. This is an area where both ecology and environmental economics could benefit from more attention and focus. This again underscores the importance of behavioral factors in resource use, where insights from behavioral economics can improve our understanding of sustaining natural capital in an economy comprised of individuals with different mental models. In ecological economics, economic and institutional factors are essential in elucidating the connection between population expansion and environmental degradation. In contrast, ecological economics views population as the primary consumer of natural resources, with increasing population having a nonlinear negative impact on the natural resource base. Environmental economics argues that environmental policy should prioritize achieving efficiency or Pareto-optimal outcomes in the economy. This approach helps promote intragenerational equity, as environmental degradation disproportionately affects poor communities. Although environmental economics has taken a narrow approach, it has demonstrated strong analytical rigor and high effectiveness in shaping policy. In contrast, ecological economics follows a more pluralistic approach, which, while intellectually challenging, appears much broader by addressing multiple areas.[5] In many regions around the world, annual water consumption exceeds available surface water flow, relying on depleting groundwater reserves, a process known as groundwater "mining." For example, in India, groundwater resources are rapidly being depleted to meet agricultural irrigation and drinking water needs. However, there are key differences between the argument about growth limitations and the problem of water scarcity. Water pricing, in contrast to energy costs, are typically not determined by the market and frequently do not account for resource scarcity. Even in the face of acute shortages, management institutions are hesitant to raise prices, and allocation decisions are often political. Econometric analyses to estimate demand parameters, such as price elasticity, are the main focus of the economic research on water demand be evaluated using these demand estimations. Furthermore, there is a substantial amount of study focused on comprehending price elasticity of water demand. [6] The essence of ecological economics is closely linked to the objective of sustainable development, which includes inter-individual and internal equity. It highlights the idea that the economy is a subsystem operating within a larger local and global context, which places limitations on its physical growth. According to this viewpoint, the depletion of the environment and the use of unrestricted natural resources are negative outcomes, in which one economic agent imposes costs on another without compensation. As a result, environmental issues are framed as interactions between individuals or economic agents, considering nature and the environment only indirectly. Another important distinction is between quantity and allocation. Environmental and resource economics (ERE) focuses primarily on optimal allocation, emphasizing the efficient use of scarce resources. Environmental issues are often framed using the concept of "externalities".[7] In contrast, pollution is the main emphasis of environmental economics. This difference has mostly vanished after it was realized that the principles of the former can be applied to these contexts, especially when pollutants are cumulative, as well as to the optimal economic growth hypothesis. Nonetheless, environmental economics and natural resource economics are frequently distinguished in textbooks. This article adheres to that difference for the sake of conciseness, concentrating on environmental concerns instead of the depletion of natural resources. Another fundamental economic activity is addressed in the development of ecological economics. However, Bolting's approach produced a different development in environmental economics. According to the theory of externalities, human well-being falls below ideal when externalities exist.[9] Therefore, it is not surprising that experiments are also used in environmental economics. However, the amount of experimental research in this field is quite significant. Clearly, environmental issues are particularly well suited to experimental study. In addition to Despite the clear links between environmental economics and experimentation, at least two areas of experimental study need particular consideration because they have an indirect impact on how environmental issues might be tackled in the lab. The situation becomes more complicated when we consider Recent studies in psychology have demonstrated that people can have different perspectives on a particular scenario. This implies that individuals exposed to the same game may interpret its structure differently, and these interpretations can vary from one person to another.[10] Ecological economics has always placed a strong emphasis on market failure as the main source of economic inefficiencies when discussing environmental conservation. More precisely, society's capacity to distribute resources effectively is constrained. This is where the issue is. Several empirical investigations over the last forty years have demonstrated that rational choice may not always be a helpful guide for environmental economics in particular or economics in general. Through the non-market valuing of environmental products, behavioral economics has arguably had the biggest influence on environmental economics. In this field, empirical differences between theoretical models and real behavior have been discovered by behavioral and environmental economics.[11] Neoclassical economics, which is basically the economics of the market mechanism, is the foundation of mainstream environmental economics. Neoclassical economics focuses mostly on the function of the market mechanism in resource allocation, assuming it has any important insights to share, which it does. The viewpoint on environmental economics presented in Panayotov's study is by no means unique. Depending on the technology (T) employed and how these processes are set up, variations in the production, distribution, and consumption processes will result in varying environmental effects in any resource allocation. This also holds true for preference values like social and health values. People's preference ratings for environmental functions are correlated with how much they value securing a safe future and the possible advantages of yet-to-be-discovered natural processes or organisms.[12] Ecological economics provides an analytical framework that is very useful for determining which material streams and recycling options offer the greatest economic benefits, especially when circular policies are applied instead of open-ended policies. Environmental economics provides the foundation for incorporating "externalities" into market prices through environmental taxes and fees, allowing prices to reflect real environmental costs. The concept of "circular economy" is discussed in their textbook on environmental economics, but the conceptual and theoretical approach presented differs significantly from that of industrial ecology. Their proposal, due to the lack of external evaluations, did not incorporate the fixed pricing approach into their later textbook on environmental economics. [13] Their proposal, due to the lack of external evaluations, did not include a fixed price approach in their subsequent textbook on environmental economics. Their proposal, due to the lack of external evaluations, did not feature the fixed price approach in their later textbook on environmental economics. Due to the lack of external evaluations, their proposal did not include a fixed price approach in their subsequent textbook on environmental economics.[14] The area we explore is important for broader discussions in economics that extend beyond ecological economics. It is commonly acknowledged and understood that the cognitive limits of the individuals involved have an impact on behavior. We examine current developments in environmental economics uses of visualization technology. A case study is provided in Section 4 to demonstrate how these methods are applied to assess wildfire risks and the impacts of fire management strategies. Section 5 provides concluding insights.[15]

2. MATERIALS & METHODS

Input Parameters: Industry Type, Regulatory Framework, Primary Environmental Concern, Geographical Region, Sustainability Practices, Stakeholder Involvement. Industry Type: The focus is on the energy sector, specifically renewable energy production, including wind, solar, and hydroelectric power generation. This industry is crucial for the global shift toward cleaner energy solutions and reducing reliance on fossil fuels. Regulatory Framework: The regulatory framework includes national and international policies aimed at promoting sustainability, such as renewable energy targets, emissions reduction regulations, and environmental impact assessments. It also involves compliance with environmental laws, such as carbon emission standards and energy efficiency regulations. Primary Environmental Concern: The primary environmental concern in this sector is the reduction of carbon emissions and the environmental impact of energy production on ecosystems. Additionally, land use and water resource management related to renewable energy projects are key concerns. Geographical Region: This applies to the European Union (EU) region, where strict environmental regulations and renewable energy mandates are in place. The region is focused on reducing greenhouse gas emissions and increasing the share of renewable energy in the energy mix. Sustainability Practices: Sustainability practices include the integration of eco-friendly technologies, such as energy storage solutions, green construction techniques for renewable energy plants, and the use of materials with low environmental impact. It also encompasses practices like waste minimization, water conservation, and land restoration post-project. Stakeholder Involvement: Stakeholder involvement includes collaboration with government bodies, environmental NGOs, local communities, and industry experts. Key stakeholders work together to ensure that projects meet sustainability goals, are socially accepted, and adhere to environmental protection standards.

Evaluation Parameters: Carbon Footprint Reduction, Resource Efficiency, Regulatory Compliance, Sustainability Impact Public Perception. Carbon Footprint Reduction: The evaluation of carbon footprint reduction focuses on measuring the total greenhouse gas emissions produced during production, transportation, and product lifecycle. This includes implementing energy-efficient technologies and transitioning to renewable energy sources to minimize emissions. Resource Efficiency: This parameter evaluates how effectively resources like water, energy, and raw materials are utilized during manufacturing. Practices such as recycling, waste reduction, and optimizing supply chain processes are key to improving resource efficiency. Regulatory Compliance: This aspect assesses the company's adherence to local and international environmental regulations, including waste disposal laws, emissions standards, and sustainability certifications. Compliance ensures legal sustainability and minimizes environmental harm. Sustainability Impact: The sustainability impact examines the long-term effects of business practices on ecosystems, climate, and social well-being. It includes evaluating resource conservation efforts, reduction in pollution, and overall contribution to sustainable development goals. Public Perception: This parameter evaluates how the company's sustainability efforts are viewed by the public, including customers, media, and investors. Positive public perception can enhance brand reputation, foster loyalty, and increase market share, making it a crucial element of corporate sustainability strategies.

SPSS Statistics: SPSS provides powerful data management tools that help researchers efficiently organize, clean, and manipulate datasets. With support for multiple data formats, the software facilitates seamless data import and export across a variety of programs. In psychological research, data is often complex and heterogeneous, and SPSS streamlines the coding, labeling, and management of variables. SPSS provides advanced data visualization tools, such as histograms, scatterplots, bar charts, and box plots, that help researchers create clear and insightful graphics. These visual representations help them discover trends, relationships, and data distributions that may not be immediately apparent through numerical analysis alone. SPSS streamlines the coding, labeling, and management of variables, ensuring a well-structured dataset ready for analysis while minimizing errors and inconsistencies.[2] He begins with correlation and demonstrates how to create scatterplots, add a regression line, and create multiple scatterplots using various SPSS windows. If statistics are challenging and you are involved in second language research, including LSP studies, SPSS is worth considering. This book provides the basic background needed to perform and interpret basic statistical tests.[3] SPSS, short for allows users to enter primary and secondary data, much like Microsoft Excel. Its user-friendly menu bar facilitates easy data analysis, enabling a wide range of statistical procedures. In SPSS, correlation analysis can be used. To start this analysis, users need to go to the analysis section, choose the variables required for correlation, and select the appropriate method, such depending on the data type. Additionally, a significance test can be designed by specifying the test tail.[4] SPSS supports correlation analysis to assess relationships between quantitative variables. Depending on the data type, users can access this feature by navigating to the analysis and selecting the relevant variables. A significance test can be designed by defining the test tail. SPSS allows users to perform correlation analysis to assess relationships between quantitative variables. Depending on the data type, users can access this feature by navigating to Analysis, selecting the relevant variables, and selecting the appropriate correlation method. Additionally, they can customize the significance test by specifying the test tail. SPSS enables users to conduct correlation analysis to assess relationships between quantitative variables. Based on the data type, users can access this functionality by navigating to Analysis, selecting the relevant variables, and selecting the appropriate correlation method. They can design a significance test by defining the test tail.[5] A key A key feature of SPSS is its intuitive design, making it accessible to users without a technical background, especially in the social sciences. Users can run the software without prior knowledge of programming languages. Understanding the basic concepts of SPSS helps researchers analyze quantitative data efficiently, smoothing the process and minimizing potential challenges. SPSS requires users to define variables and input data into these variables to create cases for SPSS can perform all the essential tests needed for quantitative data analysis in the social sciences. Given its capabilities, it has become a preferred choice, but in some cases, an essential tool for social researchers to effectively analyze and present quantitative data. IBM tools among social scientists worldwide. Over the past fifty years, it has undergone many improvements to meet the evolving needs of social science researchers.[6] The macros discussed in this article provide SPSS and SAS users with an accessible command line for conducting this type of analysis. However, researchers should note that there are additional options for examining mediation in more complex models. The macro only needs to be run once when SPSS or SAS is first started, and remains active until the program is closed. Detailed instructions for using macros are provided in the appendices, and electronic copies of the macros are available for download.[7] In addition, re-arranging the data is a complex, time-consuming, and error-prone process. Dyads are considered indistinguishable when there is no consistent way to distinguish or assign a sequence to the two individuals in each pair.[8] One of the main drawbacks of SPSS is its price. Different versions offer different analytical functions and limits on Limitation on the number of use cases and variables. In addition, most licenses have an expiration date. software cannot be used unless it is renewed. The SPSS Student Suite offers comprehensive analytical tools with special features, from basic descriptive statistics to advanced general linear modeling. features that enable variable transformations in preparation for various statistical tests. software that makes it a valuable tool to master. Becoming proficient with SPSS requires some learning time, and annual license fees may also be a consideration. One of the main drawbacks of SPSS is its price. Different versions offer different analytical functions and capabilities for handling cases and variables. In addition, most licenses automatically expire after a certain period of time, after which the software cannot be used.[9] One of the main drawbacks of SPSS is its price. Different versions come with different analytical functions and capabilities for handling cases and variables. associated distance function, Euclidean distance, is consistent with our everyday perception of spatial relationships. For ease of identification, the subject number will be However, when entering multiple square matrices, an identifier is not required for each matrix. The final related subcommand relates to the content of the output from SPSS. Using the PRINT subcommand with the DATA option causes ALSCAL to display all the matrices of the original and transformed data, while the HEADER option provides a summary of all selected settings.[10] SPSS extends beyond basic statistical analysis by providing advanced modeling tools for complex research needs. It includes factor and cluster analyses to identify hidden patterns and groupings within data. The software also offers logistic regression and survival analysis for modeling categorical and time-dependent outcomes, making it ideal for detailed real-world scenario analysis. With its intuitive interfaces and step-by-step workflows, SPSS makes these advanced techniques accessible, helping researchers tackle complex research questions with confidence and accuracy.[11]

3. RESULT AND DISCUSSION

TABLE 1. Reliability Statistics

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.170	.169	5

This table presents reliability statistics for a set of five items using Cronbach's alpha as a measure of internal consistency. The Cronbach's alpha value of 0.170 indicates a relatively low level of reliability for the set of items in the scale. The value is below the generally accepted 0.70, suggesting that the items may not consistently measure the same underlying construction. In addition, Cronbach's alpha based on the standardized items is 0.169, which is almost identical to the value of Cronbach's alpha, further confirming the low reliability of the scale. The N of the items refers to the number of items included in the scale, which in this case is 5. Although a small number of items can sometimes contribute to reduced reliability, it is important to consider other factors such as the quality of the item, its clarity, and the nature of the construction being measured. In general, Cronbach's alpha value this low suggests the need for further refinement of the items, such as rewording the questions, increasing the number of items, or reevaluating the underlying construct that the items are intended to measure.

TABLE 2. Descriptive Statistics

	N	Range	Minimum	Maximum	Sum	Mean		Std. Deviation	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Carbon Footprint Reduction	200	4	1	5	593	2.97	.101	1.423	2.024	.083	.172	-1.318	.342
Resource Efficiency	200	4	1	5	572	2.86	.100	1.407	1.980	.066	.172	-1.303	.342
Regulatory Compliance	200	4	1	5	591	2.96	.101	1.433	2.053	.049	.172	-1.379	.342
Sustainability Impact	200	4	1	5	616	3.08	.102	1.444	2.084	-.080	.172	-1.349	.342
Public Perception	200	4	1	5	604	3.02	.104	1.466	2.150	-.045	.172	-1.369	.342
Valid N (listwise)	200												

Table 2 presents the descriptive statistics for five key sustainability metrics, based on data from 200 respondents. The range of responses for each metric spans from 1 to 5, indicating a 5-point scale. Carbon Footprint Reduction: The mean score for carbon footprint reduction is 2.97, with a standard deviation of 1.423, indicating moderate variability in responses. The skewness of -1.318 suggests that responses are negatively skewed, with more respondents providing lower scores, while the kurtosis value of 0.342 indicates a slightly flatter distribution compared to a normal distribution. Resource Efficiency: The mean score for resource efficiency is 2.86, with a standard deviation of 1.407. The negative skewness of -1.303 implies that most respondents rated resource efficiency lower, and the kurtosis value of 0.342 suggests a moderate flatness in the distribution. Regulatory Compliance: With a mean of 2.96 and a standard deviation of 1.433, regulatory compliance scores show some variation. The skewness of -1.379 again indicates that the majority of responses are on the lower side of the scale. Sustainability Impact: The mean score for sustainability impact is 3.08, with a standard deviation of 1.444. The negative skewness of -1.349 suggests respondents tend to rate sustainability impact slightly lower. Public Perception: The mean for public perception is 3.02, with a standard deviation of 1.466. A skewness of -1.369 and a kurtosis of 0.342 suggest a similar trend to the other metrics, with lower ratings dominating the responses.

TABLE 3. Frequencies Statistics

		Carbon Footprint Reduction	Resource Efficiency	Regulatory Compliance	Sustainability Impact	Public Perception
N	Valid	200	200	200	200	200
	Missing	0	0	0	0	0
Median		3.00	3.00	3.00	3.00	3.00
Mode		2	1	2	5	1
Percentiles	25	2.00	2.00	2.00	2.00	2.00
	50	3.00	3.00	3.00	3.00	3.00
	75	4.00	4.00	4.00	4.00	4.00

Table 3 provides the frequency statistics for five key sustainability metrics, based on data from 200 respondents. The median value for all five metrics is 3.00, suggesting that the middle point of responses across all metrics falls on the neutral scale value. The mode, which represents the most frequent response, varies for each metric: Carbon Footprint Reduction: The mode is 2, indicating that the most frequent response for carbon footprint reduction is on the lower end of the scale. Resource Efficiency: The mode is 1, showing that respondents commonly rated resource efficiency the lowest on the scale. Regulatory Compliance: Similar to carbon footprint reduction, the mode is 2, indicating a tendency towards lower ratings for regulatory compliance. Sustainability Impact: The mode is 5, suggesting that the majority of respondents rated sustainability impact the highest on the scale. Public Perception: The mode is 1, indicating that the most common response for public perception is at the lowest end of the scale. The 25th percentile value is 2.00 for all metrics, meaning that 25% of respondents rated these aspects lower than 2.00. The 75th percentile value is 4.00 for all metrics, suggesting that 75% of respondents rated them below 4.00.

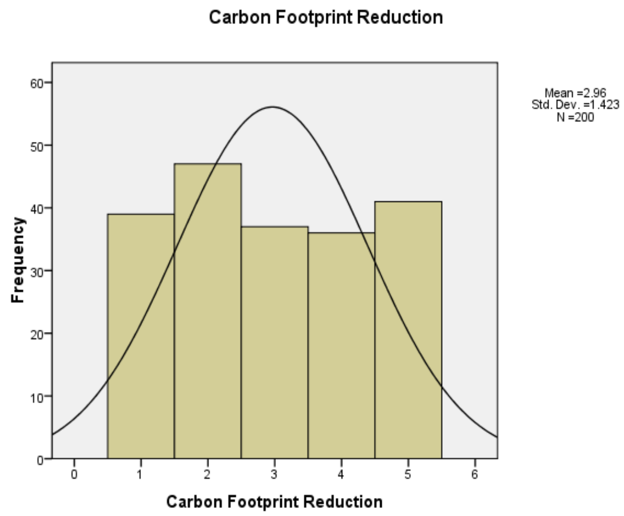

FIGURE 1. Carbon Footprint Reduction

Figure 1: Distribution of Carbon Footprint Reduction Measurements This histogram displays the distribution of carbon footprint reduction measurements across a sample of 200 observations. The data shows a roughly normal distribution with a mean value of 2.96 and a standard deviation of 1.423. The x-axis represents carbon footprint reduction values (likely in tons of CO_2 equivalent or percentage reduction), while the y-axis shows the frequency of observations. The distribution spans from approximately 0 to 6 units of reduction, with the highest frequency of observations occurring around the 2-3 range. There appears to be a secondary peak in the 5-unit range, suggesting a possible bimodal tendency in the data. This could indicate two distinct groups within the sample—perhaps representing different intervention strategies or industry sectors with varying reduction potentials. The superimposed normal curve helps visualize how the actual data compares to a theoretical normal distribution.

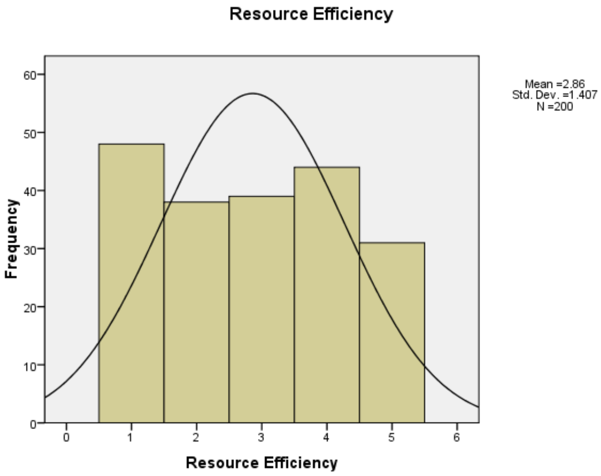

FIGURE 2. Resource Efficiency

Figure 2: Distribution of Resource Efficiency Measurements This histogram illustrates the distribution of resource efficiency measurements across a sample of 200 observations. The data reveals a somewhat left-skewed distribution with a mean value of 2.86 and a standard deviation of 1.407. The x-axis represents resource efficiency values (likely measured on a scale from 0-6, possibly representing efficiency ratios or improvement percentages), while the y-axis indicates the frequency of observations within each range. The distribution shows its highest frequency in the 1-2 range, suggesting that a substantial portion of the sample achieves relatively low resource efficiency scores. However, there is also a notable second peak around the 4-5 range, indicating a possible bimodal distribution. This pattern might reflect two distinct groups within the studied population—perhaps representing organizations at different stages of resource efficiency implementation or those using different methodologies or technologies. The overlaid normal curve helps visualize the deviation from a perfectly normal distribution. The left skew coupled with the secondary peak suggests that while many entities struggle to achieve high resource efficiency, there exists a significant group that has successfully implemented more advanced resource management strategies.

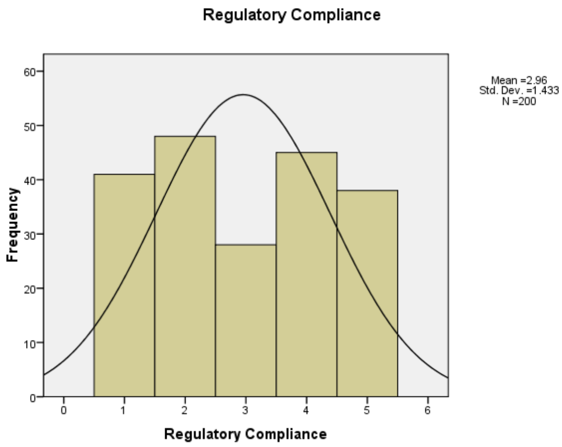

FIGURE 3. Regulatory Compliance

Figure 3: Distribution of Regulatory Compliance Scores This histogram depicts the distribution of regulatory compliance scores across a sample of 200 observations. The data shows a relatively normal distribution with a mean value of 2.96 and a standard deviation of 1.433. The x-axis represents regulatory compliance scores (likely on a scale from 0-6, possibly indicating compliance levels or performance ratings), while the y-axis shows the frequency of observations within each range. The distribution displays its highest frequency in the 2-3 range, with a secondary peak occurring around the 4-5 range. This pattern suggests a potential bimodal tendency, which could indicate two distinct groups within the studied population—perhaps representing organizations at different stages of regulatory maturity or those subject to varying regulatory frameworks. The slight dip in the 3-4 range further emphasizes this separation between the two apparent groups. The superimposed normal curve helps illustrate how the actual distribution compares to a theoretical normal distribution.

While the overall shape approximates normality, the subtle bimodal nature of the data suggests that regulatory compliance achievements may cluster around two different performance levels.

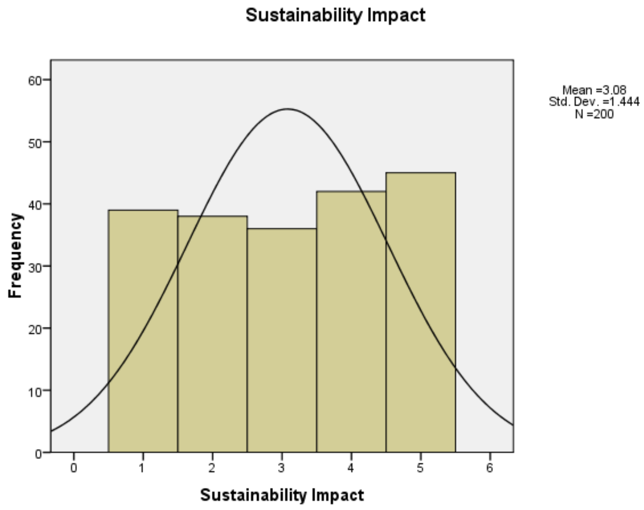

FIGURE 4. Sustainability Impact

Figure 4: Distribution of Sustainability Impact Measurements This histogram presents the distribution of sustainability impact measurements across a sample of 200 observations. The data shows a slightly right-skewed distribution with a mean value of 3.08 and a standard deviation of 1.444. The x-axis represents sustainability impact values (likely on a scale from 0-6, possibly indicating impact intensity or performance ratings), while the y-axis displays the frequency of observations within each range. Unlike the previous distributions, this graph reveals a more gradual increase in frequency across the scale, with the highest frequency occurring in the 5-6 range. This right-skewed pattern suggests that a significant portion of the sample is achieving higher sustainability impact scores, which could indicate positive momentum in sustainability initiatives across the studied population. The relatively even distribution across the 1-2, 2-3, and 3-4 ranges, followed by increases in the 4-5 and 5-6 ranges, points to a progressive improvement trend rather than a clear bimodal distribution. The superimposed normal curve helps visualize how the actual data differs from a theoretical normal distribution. The rightward shift of the data relative to the curve suggests that sustainability impact achievements are exceeding what would be expected in a perfectly normal distribution.

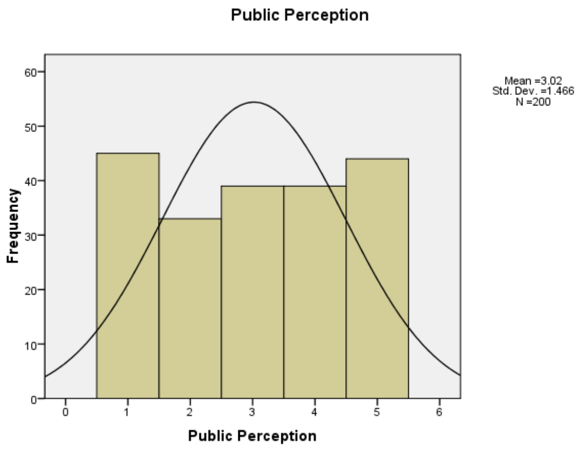

FIGURE 5. Public Perception

Figure 5: Distribution of Public Perception Scores This histogram illustrates the distribution of public perception scores across a sample of 200 observations. The data exhibits a bimodal distribution with a mean value of 3.02 and a standard deviation of 1.466. The x-axis represents public perception values (likely on a scale from 0-6, possibly indicating approval ratings or sentiment scores), while the y-axis shows the frequency of observations within each range. The distribution clearly displays two prominent peaks—one in the 1-2 range and another in the 5-6 range—with a noticeable dip in the middle ranges. This distinct bimodal pattern suggests a polarization in public perception within the studied population.

Some entities are receiving predominantly positive public perception scores, while others are receiving significantly lower ratings, with fewer observations falling in the middle ground. This polarization could reflect divergent public views on sustainability practices, varying communication effectiveness, or different industry sectors having distinctly different reputation profiles. The superimposed normal curve helps visualize how significantly the actual distribution deviates from normality. The pronounced bimodal nature of this data suggests that public perception tends toward either positive or negative evaluations rather than moderate assessments.

TABLE 4. Correlations

		Carbon Footprint Reduction	Resource Efficiency	Regulatory Compliance	Sustainability Impact	Public Perception
Carbon Footprint Reduction	Pearson Correlation	1	.020	-.038	-.133	.061
	Sig. (2-tailed)		.777	.596	.060	.394
	Sum of Squares and Cross-products	402.755	8.020	-15.315	-54.440	25.140
	Covariance	2.024	.040	-.077	-.274	.126
	N	200	200	200	200	200
Resource Efficiency	Pearson Correlation	.020	1	.092	.057	.060
	Sig. (2-tailed)	.777		.197	.419	.400
	Sum of Squares and Cross-products	8.020	394.080	36.740	23.240	24.560
	Covariance	.040	1.980	.185	.117	.123
	N	200	200	200	200	200
Regulatory Compliance	Pearson Correlation	-.038	.092	1	.126	.122
	Sig. (2-tailed)	.596	.197		.076	.084
	Sum of Squares and Cross-products	-15.315	36.740	408.595	51.720	51.180
	Covariance	-.077	.185	2.053	.260	.257
	N	200	200	200	200	200
Sustainability Impact	Pearson Correlation	-.133	.057	.126	1	.025
	Sig. (2-tailed)	.060	.419	.076		.722
	Sum of Squares and Cross-products	-54.440	23.240	51.720	414.720	10.680
	Covariance	-.274	.117	.260	2.084	.054
	N	200	200	200	200	200
Public Perception	Pearson Correlation	.061	.060	.122	.025	1
	Sig. (2-tailed)	.394	.400	.084	.722	
	Sum of Squares and Cross-products	25.140	24.560	51.180	10.680	427.920
	Covariance	.126	.123	.257	.054	2.150
	N	200	200	200	200	200

Table 4 shows the Pearson correlation coefficients between five sustainability metrics, based on data from 200 respondents. The table also includes significance values, sum of squares, cross-products, and covariance values. Carbon Footprint Reduction shows weak and mostly insignificant correlations with the other metrics. The correlation with Resource Efficiency is 0.020, with a significance of 0.777, suggesting no meaningful relationship. Similarly, the correlation with Regulatory Compliance is -0.038 ($p = 0.596$), indicating a negligible inverse relationship. The correlation with Sustainability Impact is -0.133 ($p = 0.060$), approaching significance but still weak. The correlation with Public Perception is 0.061 ($p = 0.394$), also showing a weak relationship. Resource Efficiency shows weak positive correlations with Regulatory Compliance (0.092, $p = 0.197$) and Public Perception (0.060, $p = 0.400$), indicating minimal relationships. It has no significant correlation with Sustainability Impact (0.057, p = 0.419). Regulatory Compliance has weak positive correlations with Sustainability Impact (0.126, p = 0.076) and Public Perception (0.122, p = 0.084), both near significance but still weak. Sustainability Impact and Public Perception show weak, insignificant correlations with each other (0.025, p = 0.722), indicating no clear relationship.

TABLE 5. Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
Carbon Footprint Reduction	.153[a]	.023	.003	1.420	.023	1.167	4	195	.327	1.931
Resource Efficiency	.117[a]	.014	-.007	1.412	.014	.672	4	195	.612	2.123
Regulatory Compliace	.192[a]	.037	.017	1.421	.037	1.872	4	195	.117	2.085
Sustainability Impact	.187[a]	.035	.015	1.433	.035	1.768	4	195	.137	1.828
Public Perceptin	.147[a]	.022	.002	1.465	.022	1.083	4	195	.366	2.056

Table 5 presents the model summary for five sustainability metrics, showing the relationship between predictor variables and the outcome variables. The table includes values for R, R Square, Adjusted R Square, Standard Error of the Estimate, and change statistics, along with the Durbin-Watson statistic to check for autocorrelation. Carbon Footprint Reduction: The R value is 0.153, indicating a weak positive correlation between the predictors and the outcome. The R Square value is 0.023, meaning that only 2.3% of the variance in carbon footprint reduction is explained by the model. The Adjusted R Square is 0.003, suggesting that the model provides little explanatory power. The F Change is 1.167 (p = 0.327), indicating that the predictors do not significantly improve the model. The Durbin-Watson statistic of 1.931 suggests no serious autocorrelation issues. Resource Efficiency: The R value is 0.117, and the R Square is 0.014, indicating that the predictors explain just 1.4% of the variance in resource efficiency. The Adjusted R Square is -0.007, showing that the model is not a good fit for the data. The F Change is 0.672 (p = 0.612), indicating no significant change from the predictors. The Durbin-Watson statistic of 2.123 suggests no autocorrelation. Regulatory Compliance: With an R Square of 0.037 and an Adjusted R Square of 0.017, this model explains only 3.7% of the variance in regulatory compliance. The F Change of 1.872 (p = 0.117) is not statistically significant, and the Durbin-Watson statistic is 2.085, indicating no autocorrelation. Sustainability Impact: The R Square is 0.035, and the Adjusted R Square is 0.015, suggesting limited explanatory power. The F Change of 1.768 (p = 0.137) is not significant, and the Durbin-Watson statistic of 1.828 shows no serious autocorrelation. ublic Perception: The R Square value is 0.022, indicating only 2.2% of the variance in public perception is explained. The F Change of 1.083 (p = 0.366) is not significant, and the Durbin-Watson statistic of 2.056 suggests no autocorrelation. Overall, the models for all five metrics have low explanatory power, with R Square values well below expectations for good model fit.

TABLE 6. ANOVA

Model	Sum of Squares	df	Mean Square	F	Sig.
Carbon Footprint Reduction	9.417	4	2.354	1.167	.327[a]
Resource Efficiency	5.357	4	1.339	.672	.612[a]
Regulatory Compliance	15.113	4	3.778	1.872	.117[a]
Sustainability Impact	14.515	4	3.629	1.768	.137[a]
Public Perception	9.301	4	2.325	1.083	.366[a]

Table 6 presents the results of the Analysis of Variance (ANOVA) for five sustainability metrics, assessing whether the predictor variables significantly explain the variance in the outcome variables. The table includes Sum of Squares, df (degrees of freedom), Mean Square, F-statistic, and Significance (Sig.) values. Carbon Footprint Reduction: The Sum of Squares is 9.417, with 4 degrees of freedom. The Mean Square is 2.354, and the F-statistic is 1.167, with a Sig. value of 0.327. This indicates that the model does not explain the variance in carbon footprint reduction significantly, as the p-value is well above the conventional significance threshold of 0.05. Resource Efficiency: The Sum of Squares for resource efficiency is 5.357, and the F-statistic is 0.672 with a Sig. value of 0.612, indicating that the predictors do not significantly explain the variance in resource efficiency. Regulatory Compliance: The Sum of Squares is 15.113, with an F-statistic of 1.872 and a Sig. value of 0.117, suggesting that the model for regulatory compliance is not statistically significant, although the F-statistic is closer to a meaningful value. Sustainability Impact: The Sum of Squares is 14.515, with an F-statistic of

1.768 and a Sig. value of 0.137, indicating no significant effect of the predictors on sustainability impact, despite some variability in the data. Public Perception: The Sum of Squares is 9.301, and the F-statistic is 1.083 with a Sig. value of 0.366, indicating that the predictors do not significantly explain the variance in public perception. Overall, the ANOVA results show that none of the models for the five-sustainability metrics reach statistical significance, as all Sig. values exceed the threshold of 0.05.

TABLE 7. Communalities

	Initial	Extraction
Carbon Footprint Reduction	1.000	.614
Resource Efficiency	1.000	.284
Regulatory Compliance	1.000	.475
Sustainability Impact	1.000	.532
Public Perception	1.000	.479

Table 6 presents the communalities for five sustainability metrics, showing how much of the variance in each variable is explained by the extracted components. The Initial column indicates the starting value for all variables, which is 1.000, representing the full variance. The Extraction column shows the proportion of variance explained by the principal component analysis (PCA). Carbon Footprint Reduction has an extraction value of 0.614, meaning that approximately 61.4% of the variance in carbon footprint reduction is explained by the extracted factors. This indicates a moderate level of shared variance with the underlying components. Resource Efficiency has a significantly lower extraction value of 0.284, suggesting that only about 28.4% of the variance in resource efficiency is explained by the components, which implies a weaker relationship with the extracted factors. Regulatory Compliance shows an extraction value of 0.475, indicating that 47.5% of the variance in regulatory compliance is explained by the extracted components, which is moderate but still relatively low. Sustainability Impact has an extraction value of 0.532, meaning that 53.2% of the variance in sustainability impact is explained, which is moderate. Public Perception has an extraction value of 0.479, indicating that 47.9% of the variance in public perception is explained by the components. In summary, the communalities show that while some variables, such as carbon footprint reduction, have a moderate level of explained variance, other variables, such as resource efficiency, have weaker associations with the extracted components.

TABLE 8. Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.262	25.232	25.232	1.262	25.232	25.232
2	1.122	22.439	47.671	1.122	22.439	47.671
3	.943	18.853	66.525			
4	.841	16.815	83.339			
5	.833	16.661	100.000			
Extraction Method: Principal Component Analysis.						

Table 7 shows the results of the total variance explained through Principal Component Analysis (PCA) for the five sustainability metrics. The table presents both Initial Eigenvalues and Extraction Sums of Squared Loadings for each component, showing how much variance each component explains. Component 1 has an Initial Eigenvalue of 1.262, accounting for 25.232% of the total variance. After extraction, this component continues to explain 25.232% of the variance, contributing significantly to the overall model.Component 2 has an Initial Eigenvalue of 1.122, explaining 22.439% of the variance. After extraction, it similarly explains 22.439% of the variance, maintaining its importance in the model. Component 3 has an Initial Eigenvalue of 0.943, explaining 18.853% of the variance, contributing to the overall variance explained by the model, but with a lower contribution compared to the first two components. Component 4 shows an Initial Eigenvalue of 0.841, explaining 16.815% of the variance, further adding to the explanatory power of the model. Component 5 has an Initial Eigenvalue of 0.833, accounting for 16.661% of the variance, bringing the total variance explained to 100% when all components are combined. In summary, the components extracted through PCA explain a cumulative 100% of the total variance, with the first two components explaining nearly half of the variance (47.671%).

4. CONCLUSION

In conclusion, the analysis conducted on the sustainability metrics—carbon footprint reduction, resource efficiency, regulatory compliance, sustainability impact, and public perception—provides. The results presented in this study, based on various statistical methods including correlation analysis, ANOVA, PCA, and communalities, indicate that while these sustainability metrics are essential for understanding environmental and regulatory outcomes, the models used in this analysis show limitations in explaining the underlying complexities of sustainability. The correlation analysis revealed weak relationships among the sustainability metrics. For instance, the correlations between carbon footprint reduction and the other variables were mostly insignificant, with values close to zero. Similarly, the correlations between other pairs of sustainability metrics also showed weak or negligible relationships. This suggests that while these sustainability metrics are related to one another conceptually, their actual interdependence is minimal. This could imply that each metric represents a distinct aspect of sustainability that is not easily explained by the others. These weak correlations highlight the complexity of measuring and understanding sustainability, as the drivers behind each metric might be influenced by different factors or processes. Furthermore, the ANOVA results supported the finding that the predictor variables in this study do not significantly explain the variance in the outcome variables. This means that the predictors used in this study did not significantly improve the model's ability to explain the variance in carbon footprint reduction, resource efficiency, regulatory compliance, sustainability impact, and public perception. As such, the results suggest that additional or more influential variables may be needed. When examining the Principal Component Analysis (PCA), the communalities provided some insight into the amount of variance explained by the extracted components. The results showed that with the subsequent components explaining progressively less variance. The total variance explained table confirmed that the first two components accounted for nearly half of the variance across all metrics, and when combined, the five components explained 100% of the variance. While the PCA results highlight the potential to identify key underlying components that explain the variability in sustainability metrics, they also indicate that a substantial portion of the variance remains unexplained by the current model. This suggests that the factors driving sustainability outcomes are more complex than can be captured by a small number of components, and further analysis may be required to uncover additional dimensions of sustainability. First, the weak correlations and low explanatory power of the models indicate the need for Future research could focus on identifying additional variables that might better explain the variance in sustainability outcomes. For example, incorporating factors such as policy measures, technological innovations, or industry-specific characteristics might enhance the explanatory power of the models. Moreover, a more refined methodological approach, such as using advanced statistical techniques like structural equation modeling (SEM) or machine learning, could help identify complex, non-linear relationships among sustainability metrics and predictors.

REFERENCE

[1]. Van den Bergh, Jeroen CJM. "Evolutionary thinking in environmental economics." Journal of Evolutionary Economics 17 (2007): 521-549.

[2]. Croson, Rachel, and Nicolas Treich. "Behavioral environmental economics: promises and challenges." Environmental and Resource Economics 58 (2014): 335-351.

[3]. Hahn, Robert W. "The impact of economics on environmental policy." Journal of Environmental Economics and management 39, no. 3 (2000): 375-399.

[4]. Greenstone, Michael, and Ted Gayer. "Quasi-experimental and experimental approaches to environmental economics." Journal of Environmental Economics and Management 57, no. 1 (2009): 21-44.

[5]. Venkatachalam, Lakshmanan. "Environmental economics and ecological economics: Where they can converge?." Ecological economics 61, no. 2-3 (2007): 550-558.

[6]. Olmstead, Sheila M. "The economics of managing scarce water resources." Review of Environmental Economics and policy (2010).

[7]. Van den Bergh, Jeroen C. "Ecological economics: themes, approaches, and differences with environmental economics." Regional Environmental Change 2 (2001): 13-23.

[8]. Pearce, David. "An intellectual history of environmental economics." Annual review of energy and the environment 27, no. 1 (2002): 57-81.

[9]. Sturm, Bodo, and Joachim Weimann. "Experiments in environmental economics and some close relatives." Journal of Economic Surveys 20, no. 3 (2006): 419-457.

[10]. Shogren, Jason F., and Laura O. Taylor. "On behavioral-environmental economics." Review of Environmental Economics and Policy (2008).

[11]. Gustafsson, Bo. "Scope and limits of the market mechanism in environmental management." Ecological economics 24, no. 2-3 (1998): 259-274.

[12]. Andersen, Mikael Skou. "An introductory note on the environmental economics of the circular economy." Sustainability science 2, no. 1 (2007): 133-140.

[13]. Fiore, Stephen M., Glenn W. Harrison, Charles E. Hughes, and E. Elisabet Rutström. "Virtual experiments and environmental policy." Journal of Environmental Economics and Management 57, no. 1 (2009): 65-86.

[14]. Ferrini, Silvia, and Riccardo Scarpa. "Designs with a priori information for nonmarket valuation with choice experiments: A Monte Carlo study." Journal of environmental economics and management 53, no. 3 (2007): 342-363.

[15]. Bell, Janice M. "Family nursing is more than family centered care." Journal of Family Nursing 19, no. 4 (2013): 411-417.

[16]. Lotfi, Mojgan, Vahid Zamanzadeh, Leila Valizadeh, and Mohammad Khajehgoodari. "Assessment of nurse–patient communication and patient satisfaction from nursing care." Nursing open 6, no. 3 (2019): 1189-1196.

[17]. Yang, Hongwei. "The case for being automatic: introducing the automatic linear modeling (LINEAR) procedure in SPSS statistics." Multiple Linear Regression Viewpoints 39, no. 2 (2013): 27-37.

[18]. Jalolov, Tursunbek Sadriddinovich. "USE OF SPSS SOFTWARE IN PSYCHOLOGICAL DATA ANALYSIS." PSIXOLOGIYA VA SOTSIOLOGIYA ILMIY JURNALI 2, no. 7 (2024): 1-6.

[19]. Larson-Hall, Jenifer. A guide to doing statistics in second language research using SPSS and R. Routledge, 2015.

[20]. Kafle, Sarad Chandra. "Correlation and regression analysis using SPSS." The OCEM Journal of Management, Technology, and Social Sciences 1, no. 1 (2019): 125-132.

[21]. Rahman, Arifa, and Md Golam Muktadir. "SPSS: An imperative quantitative data analysis tool for social science research." International Journal of Research and Innovation in Social Science 5, no. 10 (2021): 300-302.

[22]. Preacher, Kristopher J., and Andrew F. Hayes. "SPSS and SAS procedures for estimating indirect effects in simple mediation models." Behavior research methods, instruments, & computers 36 (2004): 717-731.

[23]. Alferes, Valentim R., and David A. Kenny. "SPSS programs for the measurement of nonindependence in standard dyadic designs." Behavior Research Methods 41 (2009): 47-54.

[24]. Suresh, Devare. "Important of SPSS for social sciences research." Available at SSRN 2663283 (2015).

[25]. Espírito-Santo, Helena, and Fernanda Daniel. "Calcular e apresentar tamanhos do efeito em trabalhos científicos (2): Guia para reportar a força das relações." (2017).

