National Research Journal of Banking and Finance Management ISSN: 2349-6762
Volume No: 12, Issue No: 2, Year: 2025 (July-December) Peer Reviewed & Refereed Journal (IF: 7.56)
PP: 102-119 Journal Website www.nrjbfm.in

SEM ANALYSIS OF IMPACT OF COST AND RETURN ON INVESTMENT ON CHOICE OF INVESTMENT IN RENEWABLE ENERGY SECTOR

Meenakshi Swami

Research Scholar, School of Commerce, IIS Deemed to be University.

Sarabjeet Kaur

Assistant Professor, selection grade, Department of business studies, School of Commerce, IIS Deemed to be University

ABSTRACT:

This study investigates the impact of cost and return on investment in renewable energy sources on investor preferences and decision-making. Using Structural Equation Modeling (SEM), a structural model was developed to examine these relationships based on various indicators. Primary data from investors and prospective investors in renewable energy sector were collected for items representing latent variables, and the analysis confirmed the robustness of the findings. The results revealed that both cost and return on investment significantly influence investment evaluation metrics, highlighting the critical role of financial factors in renewable energy investment decisions. The findings suggest that cost and return are major drivers in investment decisions, with small investors particularly influenced by financial risks and opportunities. To stimulate investment, it is recommended that attractive financial packages, government support, and incentives be provided to enhance investor confidence and promote greater participation in renewable energy investments.

Keywords: SEM Analysis, initial cost, Cost and return on investment, choice of investment, renewable energy sector, renewable energy, RE investments, investors preference, zero emissions, public opinion, policy, public and private sectors, investors and prospective investors, investment evaluation metrics, financial factors, investment decisions, drivers in investment decisions, financial risks and opportunities, financial packages, government support, and incentives, participation, growth potential of renewable energy, long-term financial returns, opportunities, social and environmental, funds, SDG

INTRODUCTION

Renewable energy is becoming the primary source of power in nations worldwide, regardless of economic level. Despite its high initial cost, these energies cause little environmental impact. Renewable energy sources (RES) have the potential to deliver zero or near-zero emissions of air pollutants and greenhouse gases, making them suitable for meeting residential energy needs (Qazi et al., 2019). Promoting the use of renewable energy requires legislative changes and public opinion research (Bayulgen & Benegal, 2019).

Analysing public opinion on renewable energy is vital for shaping policy. RE investment is the focus of a more recent surge of reform (Pueyo, 2018). Renewable energy has become a critical component of the global agenda for sustainable development as nations endeavour to reduce their carbon footprints and achieve climate objectives (Harasheh et al., 2024). The public and private sectors have both expressed interest in the exponential growth of renewable energy investment. Investors are acknowledging the potential of renewable energy as a profitable avenue for long-term financial returns. This sector provides a wide range of opportunities.

SDG investment have positive social and environmental consequences, including renewable energy projects, pure water initiatives, and affordable housing alternatives. These funds can facilitate the acceleration of progress toward the SDGs by designating financing to specific sectors (Zhan & SantosPaulino, 2021). Given the growing global emphasis on sustainability, organizations that integrate sustainable practices into their operations may experience superior outcomes in the long term (Pizzi et al., 2021). As a result, these funds can contribute to the profitability and expansion of businesses.

Tailing the release of the Intergovernmental Panel on Climate Change (IPCC) (IPCC, 2014) and the historic Paris accord (UNFCCC, 2015), the worldwide mitigating and adaptation initiatives have attracted impetus (Kul et al., 2020). REI has grown steadily to help the economies depend more on low-carbon energy sources.

BENEFITS OF RE INVESTMENTS

A substantial increase in the demand for energy is necessary for the dynamic development of national economies (Cai et al., 2022). The global economy's demand is no longer met by conventional energy resources, such as oil, natural gas, and carbon (Rosales-Calderon & Arantes, 2019) due to rapid increase in energy intensity in numerous industries. Another issue is the increasing contamination of the environment and the climate change that is caused by conventional energy sources (Zawalińska et al., 2020).

Currently, the provision of energy is one of the most critical objectives of developing countries, as there is a direct correlation between economic development and energy supply (Z. Liu, 2017b) Consequently, developing nations, including China and India, have been the most significant contributors to the emission of greenhouse gases (Z. Liu, 2017a)

Renewable energy is a viable substitute for fossil fuels due to its environmental sustainability and its availability in the majority of the globe (Balakrishnan et al., 2020). Although these sources are capable of generating electricity, they are not frequently employed. The majority of the world continues to rely on fossil fuels to generate energy, while only a handful of countries, including the United States, Germany, and China, have made substantial investments.

Therefore, the primary benefits of renewable energy alternatives are the reduction of dependence on foreign countries for energy supply and the development of sustainable energy production (F. Liu et al., 2020).

RENEWABLE ENERGY AS PART OF SUSTAINABLE ENERGY GOALS

Sustainable development is foundation of a strategy to move towards a progressive future keeping in mind not to constraint with the needs of the future generations. One of the most important indicators for sustainable development is energy usage (Gyamfi et al., 2018).

Providing everyone with access to energy services, guaranteeing energy supply to meet rising demand, and reducing energy's role to climate change are the three main energy concerns facing the world today.

INVESTORS ATTITUDE TOWARDS RENEWABLE ENERGY INVESTMENTS

Renewable energy sources are recognized as environmentally favourable. An additional benefit of this energy source is that it enhances the energy independence of nations. Considering these favourable features, nations are formulating many approaches to augment their investments in renewable energy. Within this particular framework, the states provide the following incentives: tax reductions and loans with low interest rates. As this would provide a cost benefit to investors, it will be feasible to attract these investments.

It is essential to do a thorough cost-benefit analysis of the planned investment. An inherent drawback of investments in renewable energy is the substantial initial cost (Nathaniel & Khan, 2020). Another crucial aspect of this process is the progressive augmentation of technical investments by firms. By adopting this approach, accelerated implementation of contemporary advancements in renewable energy investments will be feasible. Therefore, it will be feasible to decrease the exorbitant initial capital expenditure.

There are many factors that impact the success of these investments. The primary rationale for this is that these investors shall efficiently use their resources. The first step in this procedure is to accurately identify the elements that influence the effectiveness of investments in renewable energy (Q. Wang et al., 2020). The balanced scorecard approach suggest that the performance of firms is influenced by four distinct dimensions: finance, customer, internal process, and learning and development thereby including both financial and non-financial measures simultaneously. Technological advancements have a direct impact on renewable energy. The energy industry's instruments and equipment are evolving as a result of technological advancements (Tang & Dinçer, 2019). The new technology improves energy efficiency and reduces expenses in the process. The IEA (2019) has reported a 17% increase in investment in renewable energy, which is a positive sign for environmental sustainability and technological innovation and also cost reductions and technical improvements.

RENEWABLE ENERGY INVESTMENTS RISING TRENDS

The UAE is a top innovator in RER projects and renewable energy conversion in the Middle East.

Climate change is causing increasing temperatures, sea levels, and severe weather events, highlighting the need for urgent action (Adetomi Adewnmi et al., 2023). This calls for a shift away from traditional energy models towards more sustainable alternatives. Renewable energy technology' fast developments and promise to change energy production serve as the foundation for this investigation.

REVIEW OF LITERATURE

(Baumli & Jamasb, 2020) The research sought to accurately determine the financial and nonfinancial indicators that impacted investment decisions. The primary issue faced by investors was the degree of confidence in the effectiveness of laws. Primary options considered were the enhancement of local capabilities and the use of policy instruments designed to address institutional inflexibilities. The findings indicated that more than only financial reasons influenced the challenges of private energy investment in Africa.

(Oluoch et al., 2020) This research focuses on a national survey of 1020 Kenyan respondents to provide an evaluation of popular knowledge, acceptability, and attitude toward renewable energy. This research emphasizes how important it is for politicians to abandon conventional methods that prioritize supplying Kenya's energy needs at the expense of public opinion. Thus, it is essential to look into public acceptability, understanding, and attitudes toward renewable energy in order to get the knowledge required to formulate policies that work.

(Lagerkvist et al., 2020) A study involving 559 private investors in Sweden found that sustainability strategies and environmental focus were more important than other fund characteristics. Negative affect related to Sustainable and Responsible Investment (SRI) contributed to variance heterogeneity, while experience in fund savings, positive product involvement, and positive affect were not significant. The study found that latent behavioural characteristics of investors are strong predictors of latent class membership, distinguishing nontrivial investor sub-groups. Sociodemographic characteristics were not supported. The results can help identify market segments for equity fund offerings, including those related to SRI, to meet demand among private investors.

(Bortolotti, 2020) This study adopted the adaptive conjoint analysis (ACA) method for investigating the policy preferences of 41 European investors engaged with different investment firms. The findings demonstrated how the characteristics of investors, such as the kind of institution they worked for and the quantity of assets they handled, impacted their preferences over several aspects of e-mobility policies. This research also showed that investors' policy decisions were impacted by behavioral factors. These behavioral characteristics specifically included investors' pre-existing beliefs about the COVID-19 pandemic and the consequences of climate change. This research provided an analysis of investor behavior with the goal of assisting policymakers in developing more potent regulatory instruments to promote investments in electric mobility both during and after the COVID-19 crisis.

(Yee et al., 2022) The study explores the intention of Malaysian investors to invest in renewable energy using the theory of planned behavior (TPB). A survey conducted in three major states revealed that investors' intentions are influenced by attitude, subjective norm, perceived behavioral control, and regulatory framework evaluation. Risk aversion did not affect investors' intentions. The evaluation of regulatory framework was found to be the most important determinant, contradicting previous studies that focused on investment behaviors or proenvironmental intentions. The study also examined the indirect effects of TPB on investors' intentions through regulatory framework evaluation. The results suggest that attitude and perceived behavioral control indirectly influence investors' intentions, while subjective norms do not. The study offers practical implications for policymakers to improve renewable energy investments.

(Vardopoulos et al., 2023) The guiding factor of this research is examining the relationship between homeowners' views on the resale value of green or sustainable buildings and their interest in installing renewable energy sources and energy efficiency upgrades to their own houses. One hundred and eighty-five adults residing in the Paphos urban complex on the island of Cyprus were polled. The participants were chosen at random and, with respect to age, and income, they were reflective of the community at large. They were asked about their views on energy efficiency, renewable energy, and the value of green buildings in the market. Statistical approaches such as Cronbach's α coefficient, descriptive statistics, factor analysis, and the nonparametric Friedman test were used to examine the acquired data. Coding and analysis were carried out using the Statistical Package for the Social Sciences (SPSS). A total of 64% of households expressed interest in putting money into renewable energy sources, while 72% expressed interest in ways to reduce energy consumption. Furthermore, homeowners' perceptions of the market value of green buildings are favorably correlated with their moderate interest level (58%) in investing in renewable energy sources. Also, green buildings are more valuable to homeowners with greater incomes and education levels, and these same homeowners are more likely to invest in renewable energy and value energy efficiency measures. This research sheds light on the link between homeowners' views of the market value of green buildings and their interest in investing in renewable energy sources and energy efficiency measures. It also offers insights into the variables that motivate this investment.

(Petrovich & Kubli, 2023) This research uses a choice experiment to look at how small and medium-sized enterprises (SMEs) in four European nations feel about buying energy from local sources and renewable energy sources. Decisions made by 823 make up the sample. The research concludes that energy communities may maximize their potential if their business models are tailored to the needs of corporate users. According to the findings, small and medium-sized enterprises (SMEs) see power suppliers favorably as possible sources of energy community solutions. It is suggested that when the European policy directive is implemented at the national level, the power companies' potential contributions to energy community creation and management be considered.

(Wagenaar, 2024) The ambition of this research is to examine the factors that determine investor preference for sustainable investing strategies and to assess the impact of financial sacrifice upon such preferences. A binary logistic regression analysis reveals that the variables of political preference and anticipated return have a favorable impact on an investor's choice for sustainable investment within the study group. Conversely, investing expertise has a negative effect on this preference. (Xuan et al., 2024) By using data collected from ASEAN nations specifically, the elements that contribute to the use of renewable energy sources during the fifth technological revolution have been studied. An ARDL (autoregressive distributed lag) method is used in the research. The study also makes use of random panel data and unconstrained fixed data. Combining econometric modelling with machine learning methods, the study examines data covering the two-decade period from 2000 to 2022. Renewable energy use in these nations is greatly influenced by public

ISSN: 2349-6762
Peer Reviewed & Refereed Journal (IF: 7.56)
Journal Website www.nrjbfm.in

knowledge, government policy, and technology progress, according to preliminary data. For stakeholders and legislators interested in harnessing technology advances for sustainable energy development, the empirical findings provide valuable insights.

METHODOLOGICAL FRAMEWORK

Acquisition of Data

Data collection for the study was done from the investors and prospective investors of renewable energy instruments which included business owners in the field of mining, engineering, petroleum products, wood and wood products, stone industry and other factory owners in the state of Rajasthan. The data was collected by filling schedules personally. Schedules were filled by 400 respondents out of which 379 were selected after data screening. The data collected was put to analysis in IBM SPSS AMOS software.

DATA ANALYSIS TECHNIQUE

Structure equation modelling (SEM) technique was adopted to test the model. In SEM measurement model is created to confirm the variability and reliability of the data set used for analysis. Then the hypothesis formulation is done to test the impact of independent variables on dependent variables by formulation of structural model In the current paper the following hypothesis was formed and the structural model was created as shown in Figure 1.

***Null Hypothesis H0*: Cost of renewable energy and return on investment does not affect the choice of investment of Investors in renewable energy sector.**

***Alternative Hypothesis* H2: Cost of renewable energy and return on investment affect the choice of investment of Investors in renewable energy sector.**

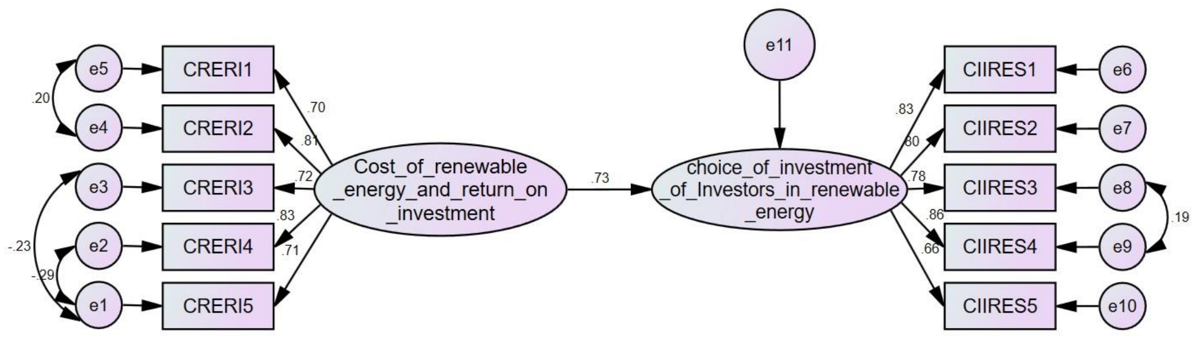

Figure 1: structural model of Hypothesis under Analysis

In the structural model in Figure 1 the independent variable being Cost of renewable energy and return on investment and the dependent variable being Choice of investment of investors and renewable energy has been shown in ovals and connected through arrow pointing from the independent variable to dependent variable. Both these variables are the main latent variables or constructs under study on the basis of which hypothesis have been formulated. The latent constructs are studied using certain items. These items are basically the questions

ISSN: 2349-6762
Peer Reviewed & Refereed Journal (IF: 7.56)
Journal Website www.nrjbfm.in

asked from respondents during data collection indicating the preferences of respondents relative to latent variables. These indicators or items have been shown in rectangles in the structure model shown in figure 1. Items or indicators and dependent variable are also marked with respective error terms indicated by circle with arrows pointing towards each item and denoted by "e". Covariances between error terms are drawn with arc arrows wherever necessary to achieve model fit.

After the formulation of structural model, the regression weights or factor loadings, standard error, critical ratio and p value for each path has been calculated and shown in table 1. This table presents the results of a Structural Equation Modelling (SEM) analysis, which is employed to examine the relationships between variables in the context of investors' decisions to invest in renewable energy. Specifically, it appears to assess the influence of factors such as the cost of renewable energy and return on investment on investors' choices regarding renewable energy, as well as their evaluation criteria (e.g., CRERI and CIIRES factors). Here's a more detailed explanation of the analysis:

OVERVIEW OF THE MODEL

The model examines the paths of influence between two primary latent variables:

1. **Cost of Renewable Energy and Return on Investment**: This construct represents the financial aspects of renewable energy, including both the initial investment costs and expected returns over time.
2. **Choice of Investment of Investors in Renewable Energy**: This latent variable captures the decision-making process of investors, where higher values represent a greater likelihood of choosing renewable energy projects for investment.
3. **CRERI** and **CIIRES**: These are secondary constructs or indicators or items to measure above latent constructs indicated by (CRERI)'s for Cost of Renewable Energy and Return on Investment and (CIIRES)'s for Choice of Investment of Investors in Renewable Energy. These factors act as mediators, reflecting how the primary variables influence investment choices.

The SEM framework allows for the estimation of direct and indirect relationships between these constructs, providing insights into how cost and return on investment influence investor behaviour and choice evaluation criteria.

To obtain the model fit 11 model fit indices and their associated values from a Structural Equation Modelling (SEM) analysis has been calculated and a depicted in table 2 which shows obtained value as well as standard or ideal value of each index. These indices are used to assess how well the proposed model fits the observed data Complete description of indices is as follows:

1. Chi-Square Value (χ^2)

The **Chi-square** statistic tests the null hypothesis that the model fits the data perfectly. A smaller chi-square value indicates a better fit. However, chi-square is sensitive to sample size, and it tends to be significant in large samples even when the model is a good fit. Byrne, B. M. (2016).

2. Degrees of Freedom (df)

Degrees of freedom (df) indicate the number of independent pieces of information available to estimate the parameters in the model. It is important to understand that the larger the degrees of freedom, the more reliable the model estimation.

There is no "ideal" value for degrees of freedom, but it should be sufficiently large relative to the number of parameters estimated. A low df (relative to the number of parameters) can indicate that the model is overfitted, which may make it harder to generalize.

3. CMIN/DF (Chi-Square Divided by Degrees of Freedom)

This ratio is a normalized version of the chi-square statistic. It is used to adjust for the degrees of freedom and is less affected by sample size than chi-square alone. The **CMIN/DF** value provides a measure of the relative size of the chi-square statistic compared to the number of degrees of freedom.

Kline, R. B. (2015).

4. P-Value (Associated with Chi-Square Test)

The **P-value** is determined from the Chi-Square distribution

The p-value for the chi-square test evaluates whether the observed data significantly deviates from the expected model. A **p-value less than 0.05** generally indicates that the model does not fit the data well. However, due to the sensitivity of the chi-square test in large samples, researchers often rely on other fit indices.

5. Goodness of Fit Index (GFI)

The **GFI** indicates the proportion of variance in the observed data that is explained by the model. It is an overall measure of fit, with higher values indicating better fit.

A **GFI** value close to **1.0** is desirable. A value of **0.90** or higher is considered acceptable, and values below **0.80** suggest poor fit. Jöreskog, K. G., & Sörbom, D. (1993).

6. Relative Fit Index (RFI)

The **RFI** compares the model's fit to a baseline (null) model. Higher values suggest a better relative fit to the null model. A value above **0.90** indicates a good fit.

7. Normed Fit Index (NFI)

The **NFI** compares the fit of the proposed model to the baseline model (no relationships between variables). It measures the reduction in chi-square as a proportion of the baseline chi-square. A value greater than **0.90** indicates a good fit. Values approaching **1.0** suggest a very good fit.

8. Incremental Fit Index (IFI)

ISSN: 2349-6762
Peer Reviewed & Refereed Journal (IF: 7.56)
Journal Website www.nrjbfm.in

The **IFI** is similar to the NFI but adjusts for the degrees of freedom in the model. It measures how much better the model fits compared to the null model. A value **above 0.90** indicates a good fit, and values closer to **1.0** are even better.

9. Comparative Fit Index (CFI)

The **CFI** is one of the most widely used fit indices. It compares the fit of the proposed model to the fit of the null model and adjusts for sample size. A **CFI** value above **0.90** indicates an acceptable fit, with values closer to **1.0** indicating excellent fit.

10. Root Mean Square Residual (RMR)

The **RMR** represents the average of the residuals (the difference between observed and expected values). A lower **RMR** indicates a better fit. **RMR** values closer to **0** indicate a better fit. However, the ideal cutoff varies, but generally, **values below 0.05** suggest a good fit.

11. Root Mean Square Error of Approximation (RMSEA)

The **RMSEA** assesses how well the model approximates the population covariance matrix. It is particularly sensitive to model complexity and the number of parameters. A value **below 0.06** is generally considered a good fit. Values between **0.06 and 0.08** are acceptable, while values greater than **0.10** suggest poor fit.

All these techniques are utilized to collectively achieve Model fit and establish the relationship to be tested in hypothesis under study.

ANALYSIS AND INTERPRETATION OF RESULTS

Table 1 Regression Weights:

Path			Standard Estimate	S.E.	C.R.	P
Choice of investment of Investors in renewable energy	<---	Cost of renewable energy and return on investment	.725	.087	10.844	***
CRERI5	<---	Cost of renewable energy and return on investment	.709			
CRERI4	<---	Cost of renewable energy and return on investment	.830	.102	12.757	***

ISSN: 2349-6762
Peer Reviewed & Refereed Journal (IF: 7.56)
Journal Website www.nrjbfm.in

CRERI3	<---	Cost of renewable energy and return on investment	.720	.101	11.323	***
CRERI2	<---	Cost of renewable energy and return on investment	.811	.099	12.880	***
CRERI1	<---	Cost of renewable energy and return on investment	.705	.097	11.542	***
CIIRES1	<---	Choice of investment of Investors in renewable energy	.833			
CIIRES2	<---	Choice of investment of Investors in renewable energy	.802	.056	17.880	***
CIIRES3	<---	Choice of investment of Investors in renewable energy	.777	.060	16.639	***
CIIRES4	<---	Choice of investment of Investors in renewable energy	.859	.059	19.295	***
CIIRES5	<---	Choice of investment of Investors in renewable energy	.656	.062	13.671	***

Table1 depicts a hypothetical structural equation model that shows cases of interdependence between two variables, namely the Cost of renewable energy and return on investment and Choice of investment of Investors in renewable energy. In the present model, the independent variable is the Cost of renewable energy and return on investment, whereas the dependent variable is the Choice of investment of Investors in renewable energy. Using the relationship between these factors with investor preferences in a regression model test, a hypothesis was tested. This displayed an intensive positive correlation of the cost and return on investment with the choice of investment, and the standardized estimate was 0.725. The C.R of 10.844 and a highly significant p-value of less than 0.001 underlined the statistical significance of this effect. This means that renewable energy projects that offer attractive returns and favourable cost structures can attract preference from investors.

The factor loadings for indicators (CRERI1 to CRERI5) of cost and return on investment and Choice of investment of Investors in renewable energy (CIIRES1 to CIIRES5) were all substantial and statistically significant, which enhances the validity of the measures used to test the relationship. A high factor loading of 0.830 for CRERI4 and 0.859 for CIIRES4 signifies that renewable energy investors value the economic aspects viz upfront costs and expected returns with great significance. Overall, it verifies that the alternative hypothesis is valid and that cost of renewable energy and expected return on investment plays a significantly prominent role in this sector while choosing investor preferences. More capacity projects are mainly more alluring to investors as these tend to have more favourable economies of scale and higher returns.

However, may vary for smaller investors looking at residential or smaller-scale renewable energy installations. To these investors, higher up-front costs may present an obstacle despite long-run advantages. Therefore, special targeted solutions in the form of subsidies, low-cost financing, or incentives to small-capacity projects become very important in luring smaller investors, who at times focus more on affordability and manageable size of investment. By lowering the initial financial barriers, such measures can make renewable energy investments more attractive to small individual investors and investors at smaller scales. Thus, From the above findings; the null hypothesis, H0 is rejected, while the alternative hypothesis, H1 is accepted.

INTERPRETATION AND IMPLICATIONS

Impact of Cost and Return on Investment:

The cost of renewable energy and return on investment emerges as a critical determinant of investor choice in renewable energy. This finding aligns with economic theory suggesting that investment decisions are heavily influenced by expected financial returns and the perceived risk associated with costs. The substantial influence of this construct implies that financial metrics remain a primary driver for investors in the renewable energy sector.

Investor Evaluation Criteria (CRERI):

The **CRERI factors** likely represent specific investment criteria or evaluation metrics (e.g., sustainability, long-term returns, or project feasibility) that investors use to assess renewable energy projects. The strong influence of cost and return on investment on these criteria underscores the importance of financial considerations in shaping investors' perceptions and evaluations of renewable energy opportunities.

Investor Sentiment and Choice (CIIRES):

The **CIIRES factors**, which might reflect investor sentiment, risk tolerance, or additional qualitative criteria, are significantly impacted by the investors' **choice of renewable energy investments**. This suggests that as investors choose to engage in renewable energy, their evaluation of projects becomes more aligned with specific investment metrics, possibly reflecting a shift toward more informed or confidence-based investment decisions.

ISSN: 2349-6762
Peer Reviewed & Refereed Journal (IF: 7.56)
Journal Website www.nrjbfm.in

Statistical Significance:

The high **C.R.** values and low **p-values** across all paths confirm that the relationships in this model are robust and reliable. The fact that all the p-values are marked as "*" suggests that the evidence supporting these relationships is very strong, and the results can be generalized with a high degree of confidence.

MODEL FIT ANALYSIS

Table 2 Model fit summary

Variable	Obtained Value	Standard Value
Chi-square value(χ^2)	58.739	>0.05
Degrees of freedom (df)	30	Higher the better
CMIN/DF	1.958	1-3
P value	0.001	>0.05
GFI	0.970	>0.90
RFI	0.960	>0.90
NFI	0.973	>0.90
IFI	0.987	>0.90
CFI	0.987	>0.90
RMR	0.031	<0.05
RMSEA	0.050	<0.06

The quality of fit was acceptable representation of the sample data (χ^2 = 58.739), NFI (Normed Fit Index) =0.973; IFI (Incremental fit index) = 0.987, GFI (Goodness of Fit) = 0.970, RFI (Relative Fit Index) = 0.960 and CFI (Comparative Fit Index) =0.987 which is much larger than the 0.90. Similarly, RMR (Root Mean Square Residuals) =0.033 and RMSEA (Root mean square error of approximation) = 0.031 values are lower the 0.080 critical value**.** Results indicated a good fit for the model presented including RMSEA of 0.050, RMR of 0.031, GFI of 0.970, and CFI of 0.987.

All the indices are briefly described as below:

1. Chi-Square Value (χ^2): 58.739

- **Interpretation**: The **Chi-Square value** tests the null hypothesis that the model perfectly fits the data. A larger chi-square value suggests a poor fit, as it indicates a large discrepancy between the observed and predicted data. However, chi-square is sensitive to sample size, meaning that with large samples, chi-square values are often significant even when the model fits well.
- **Insight**: In this case, **58.739** is the chi-square statistic, but its significance must be evaluated in combination with the degrees of freedom and other fit indices. Given that chi-square values are affected by sample size, it is often not the sole criterion for determining model fit.

2. Degrees of Freedom (df): 30

- **Interpretation**: The **degrees of freedom** (df) represent the number of independent values that can vary in the model. It is the difference between the number of data points (observed variables) and the number of estimated parameters in the model. A model with fewer parameters will tend to have a higher degree of freedom, allowing more flexibility.
- **Insight**: A **df** of **30** suggests a moderately complex model with several free parameters. This is typical for a model with multiple latent and observed variables, where the degrees of freedom allow enough flexibility to model the relationships but do not overfit the data.

3. CMIN/DF (Chi-Square Divided by Degrees of Freedom): 1.958

- **Interpretation**: The **CMIN/DF** ratio is a normalized version of the chi-square statistic. This ratio adjusts the chi-square value by dividing it by the degrees of freedom. It helps to provide a more balanced measure of fit, which is less sensitive to sample size than chi-square alone.
- **Insight**: A **CMIN/DF** value of **1.958** indicates a very good fit. In SEM, a **CMIN/DF** value between **1.0 and 3.0** is generally considered acceptable. Since the value is below **3.0**, this suggests that the model fits the data well and the chi-square statistic is appropriately adjusted for the complexity of the model.

4. P-value: 0.001

- **Interpretation**: The **p-value** tests the null hypothesis that the model perfectly fits the data. A **p-value of 0.001** indicates that the chi-square test is statistically significant, suggesting that there is a significant discrepancy between the observed and expected data. However, as mentioned earlier, the p-value is sensitive to large sample sizes, and it often becomes significant in SEM analyses with large sample sizes even when the model fits well.
- **Insight**: While the **p-value** is statistically significant (less than 0.05), this is typical in SEM with larger samples, and it does not necessarily indicate that the model is poorly fitting. Other fit indices should be considered to assess the model's quality.

5. Goodness of Fit Index (GFI): 0.970

- **Interpretation**: The **GFI** measures the proportion of variance in the data that is explained by the model. It ranges from 0 to 1, where **1** indicates perfect fit and **0** indicates no fit. Values closer to 1.0 suggest a good fit.
- **Insight**: A **GFI of 0.970** indicates a very good fit, as values above **0.90** are considered acceptable, with **0.95** or higher being very good. This suggests that the model explains 97% of the variance in the observed data, reflecting that the model captures the relationships well.

6. Relative Fit Index (RFI): 0.960

- **Interpretation**: The **RFI** compares the fit of the proposed model to a baseline model, where the baseline model assumes no relationships between the variables (a "null model"). It ranges from 0 to 1, where values closer to **1.0** indicate better fit.
- **Insight**: An **RFI of 0.960** indicates a very good fit. Typically, values above **0.90** suggest an acceptable fit, so this value indicates that the model fits well relative to the null model.

7. Normed Fit Index (NFI): 0.973

- **Interpretation**: The **NFI** also compares the fit of the proposed model to the null model. Like the RFI, it measures the proportionate improvement in fit from the null model to the fitted model. Values above **0.90** suggest an acceptable model fit, while values closer to **1.0** indicate a better fit.
- **Insight**: The **NFI of 0.973** is excellent, suggesting that the proposed model significantly improves on the null model, with the model fitting well based on the standard criteria.

8. Incremental Fit Index (IFI): 0.987

- **Interpretation**: The **IFI** is an index that compares the proposed model's fit to that of the null model, adjusting for the number of parameters. It generally provides an accurate measure of model fit. Values greater than **0.90** indicate good fit, with values approaching **1.0** indicating an excellent fit.
- **Insight**: The **IFI of 0.987** indicates an outstanding fit, showing that the model explains a large proportion of the variation in the data compared to the baseline model.

9. Comparative Fit Index (CFI): 0.987

- **Interpretation**: The **CFI** is one of the most commonly used fit indices. It compares the fit of the proposed model to the fit of the null model, adjusting for sample size. Values greater than **0.90** indicate good fit, and values closer to **1.0** suggest an excellent fit.
- **Insight**: A **CFI of 0.987** is excellent, suggesting that the proposed model has a very high degree of fit, making it one of the strongest indicators of a good model fit.

10. Root Mean Square Residual (RMR): 0.031

- **Interpretation**: The **RMR** is a measure of the average difference between the observed and predicted values. A smaller **RMR** indicates a better fit, as it means that the model's residuals (the differences between the model's predictions and the observed data) are small.
- **Insight**: An **RMR of 0.031** is quite good. A value of **0.05** or lower is considered an indicator of a good fit. This suggests that the model's residuals are small and that the model fits the data well.

11. Root Mean Square Error of Approximation (RMSEA): 0.050

- **Interpretation**: The **RMSEA** measures the fit of the model per degree of freedom, penalizing the model for complexity. Lower values of RMSEA indicate a better fit. The value is typically interpreted as:
  - **RMSEA ≤ 0.05**: Excellent fit
  - **0.05 < RMSEA ≤ 0.08**: Acceptable fit
  - **0.08 < RMSEA ≤ 0.10**: Mediocre fit
  - **RMSEA > 0.10**: Poor fit
- **Insight**: The **RMSEA of 0.050** indicates an excellent fit, as it is below the threshold of **0.06** that typically signifies good fit. This suggests that the model fits the data well, taking into account its complexity.

CONCLUSION AND RECOMMENDATION:

The primary objective of this study was to analyse the effect of cost and return on investment in renewable energy sources on investor preferences and choices. SEM analysis was employed to develop a structural model assessing these relationships based on various indicators. Responses were collected for items representing latent variables, and subsequent analyses confirmed the robustness of the findings, as presented in the tables above.

This Structural Equation Modeling (SEM) analysis provided valuable insights into the decision-making process of investors in renewable energy markets. The findings indicated that both financial considerations—specifically, cost and return on investment—significantly influence investment evaluation metrics. The high statistical significance of these relationships underscored the importance of financial factors in renewable energy investment decisions. These insights hold practical implications for policymakers, energy providers, and financial analysts aiming to promote investment in this sector.

The fit indices collectively suggest that the model is a good fit for the data, with values such as the Comparative Fit Index (CFI) of 0.987, Incremental Fit Index (IFI) of 0.987, and Root Mean Square Error of Approximation (RMSEA) of 0.050 indicating strong support for the hypothesized relationships in the model. These indices confirm that the relationships between the variables in the model are well-represented by the proposed structure. This further confirms the acceptance of the alternate hypothesis, thereby establishing a strong relationship between the cost and return of renewable energy sources and investors' choices to invest in renewable energy technologies. Cost and return emerge as major drivers in making such investment decisions.

The study highlighted a strong likelihood of investor participation when reasonable costs and attractive returns are available, in the form of cost savings and potential earnings. Cost and return levels may vary based on the size of the investor, with small investors being particularly influenced by financial risks and available opportunities. To encourage investment, attractive financial packages, government support, and incentives should be provided. These measures could enhance investor confidence and drive greater participation in renewable energy investments.

REFERENCES:

1. Qazi, A., Hussain, F., Rahim, N. A. B. D., Hardaker, G., Alghazzawi, D., Shaban, K., & Haruna, K. (2019). Towards Sustainable Energy: A Systematic Review of Renewable Energy Sources, Technologies, and Public Opinions. *IEEE Access*, *7*, 63837–63851. https://doi.org/10.1109/ACCESS.2019.2906402
2. Bayulgen, O., & Benegal, S. (2019). Green Priorities: How economic frames affect perceptions of renewable energy in the United States. *Energy Research & Social Science*, *47*, 28–36.
3. Pueyo, A. (2018). What constrains renewable energy investment in Sub-Saharan Africa? A comparison of Kenya and Ghana. *World Development*, *109*, 85–100. https://doi.org/10.1016/j.worlddev.2018.04.008
4. Harasheh, M., Bouteska, A., & Manita, R. (2024). Investors' preferences for sustainable investments: Evidence from the U.S. using an experimental approach. *Economics Letters*, *234*, 111428. https://doi.org/https://doi.org/10.1016/j.econlet.2023.111428
5. Zhan, J. X., & Santos-Paulino, A. U. (2021). Investing in the Sustainable Development Goals: Mobilization, channeling, and impact. *Journal of International Business Policy*, *4*(1), 166.
6. Pizzi, S., Rosati, F., & Venturelli, A. (2021). The determinants of business contribution to the 2030 Agenda: Introducing the SDG Reporting Score. *Business Strategy and the Environment*, *30*(1), 404–421
7. Kul, C., Zhang, L., & Solangi, Y. A. (2020). Assessing the renewable energy investment risk factors for sustainable development in Turkey. *Journal of Cleaner Production*, *276*, 124164. https://doi.org/10.1016/j.jclepro.2020.124164
8. Cai, Y., Mignon, V., Saadaoui, J., Liu, X., Lin, Z., Wolff, M., Becker, T., Walther, G., Li, L., Meinrenken, C. J., Modi, V., Culligan, P. J., Zhou, X. Y. X., Lu, G., Xu, Z., Yan, X., Khu, S. T., Yang, J., Zhao, J., … Yousaf, I. (2022). Determining the Optimal Directions of Investment in Regional Renewable Energy Development. *Energies*, *15*(August), 1–23.
9. Rosales-Calderon, O., & Arantes, V. (2019). A review on commercial-scale high-value products that can be produced alongside cellulosic ethanol. *Biotechnology for Biofuels*, *12*(1), 240.
10. Zawalińska, K., Kinnunen, J., Gradziuk, P., & Celińska-Janowicz, D. (2020). To whom should we grant a power plant? Economic effects of investment in nuclear energy in Poland. *Energies*, *13*(11), 2687.

11. Balakrishnan, P., Shabbir, M. S., Siddiqi, A. F., & Wang, X. (2020). Current status and future prospects of renewable energy: A case study. *Energy Sources, Part A: Recovery,*
12. *Utilization and Environmental Effects*, *42*(21), 2698–2703. https://doi.org/10.1080/15567036.2019.1618983
13. R. Akram, F. Chen, F. Khalid, Z. Ye, and M. T. M. (2020). *'"Heterogeneous effects of energy efficiency and renewable energy on carbon emissions: Evidence from developing countries,."'*
14. Gyamfi, S., Derkyi, N. S. A., Asuamah, E. Y., & Aduako, I. J. A. (2018). Renewable energy and sustainable development. In *Sustainable Hydropower in West Africa: Planning,*
15. *Operation, and Challenges*. Elsevier Inc. https://doi.org/10.1016/B978-0-12-813016-
16. 2.00006-X
17. Nathaniel, S., & Khan, S. A. R. (2020). The nexus between urbanization, renewable energy, trade, and ecological footprint in ASEAN countries. *Journal of Cleaner Production*, *272*, 122709.
18. Tang, Z., & Dinçer, H. (2019). Selecting the house-of-quality-based energy investment policies for the sustainable emerging economies. *Sustainability*, *11*(13), 3514.
19. Adetomi Adewnmi, Kehinde Andrew Olu-lawal, Chinelo Emilia Okoli, Favour Oluwadamilare Usman, & Gloria Siwe Usiagu. (2023). Sustainable energy solutions and climate change: A policy review of emerging trends and global responses. *World Journal of Advanced Research and Reviews*, *21*(2), 408–420. https://doi.org/10.30574/wjarr.2024.21.2.0474
20. Maithani, P. C. (2008). Renewable energy policy framework of India. *India: Narosa Publication Delhi*, 41–54.
21. Baumli, K., & Jamasb, T. (2020). Assessing private investment in african renewable energy infrastructure: A multi-criteria decision analysis approach. *Sustainability (Switzerland)*, *12*(22), 1–19. https://doi.org/10.3390/su12229425
22. Oluoch, S., Lal, P., Susaeta, A., & Vedwan, N. (2020). Assessment of public awareness, acceptance and attitudes towards renewable energy in Kenya. *Scientific African*, *9*, e00512. https://doi.org/10.1016/j.sciaf.2020.e00512
23. Lagerkvist, C. J., Edenbrandt, A. K., Tibbelin, I., & Wahlstedt, Y. (2020). Preferences for sustainable and responsible equity funds - A choice experiment with Swedish private investors. *Journal of Behavioral and Experimental Finance*, *28*, 100406. https://doi.org/10.1016/j.jbef.2020.100406
24. Bortolotti, E. (2020). What Drives Them to Invest in the Sustainable Mobility Transition? Evidence from a Conjoint Experiment on European Investors' Policy

Preferences. *Graduate Institute of International and Development Studies, Centre for International Environmental Studies*, *61*.

25. Yee, C. H., Al-Mulali, U., & Ling, G. M. (2022). Intention towards renewable energy investments in Malaysia: extending theory of planned behaviour. *Environmental Science and Pollution Research*, *29*(1), 1021–1036. https://doi.org/10.1007/s11356-021-15737-x
26. Vardopoulos, I., Vannas, I., Xydis, G., & Vassiliades, C. (2023). Homeowners' Perceptions of Renewable Energy and Market Value of Sustainable Buildings. *Energies*, *16*(10), 1–18.
27. https://doi.org/10.3390/en16104178
28. Petrovich, B., & Kubli, M. (2023). Energy communities for companies: Executives' preferences for local and renewable energy procurement. *Renewable and Sustainable Energy Reviews*, *184*(June), 113506. https://doi.org/10.1016/j.rser.2023.113506
29. Wagenaar, A. L. (2024). *Sustainable investment preferences among the clients of a fund manager in the Netherlands*.
30. Xuan, P., Ngoc, V., Thi, N., & Thu, P. (2024). Journal of Open Innovation : Technology ,
31. Market , and Complexity Determinants of renewable energy consumption in the Fifth Technology Revolutions : Evidence from ASEAN countries. *Journal of Open Innovation:*
32. *Technology, Market, and Complexity*, *10*(1), 100190. https://doi.org/10.1016/j.joitmc.2023.100190
33. Byrne, B. M. (2016). *Structural Equation Modelling with AMOS: Basic Concepts, Applications, and Programming* (3rd ed.). Routledge.
34. Kline, R. B. (2015). *Principles and Practice of Structural Equation Modeling* (4th ed.). Guilford Press.
35. Jöreskog, K. G., & Sörbom, D. (1993). *Structural Equation Modeling with the SIMPLIS Command Language*. Scientific Software International.