Journal of Research Administration
Society of Research Administrators International

FACTOR ANALYSIS: MEASUREMENT OF COMPANY GREEN FINANCE IN INDONESIA

[1] Syarief Gerald Prasetya, [2] Julia Safitri, [3] Andi Harmoko Arifin, [4] Syamsu Alam
[1] Student of the Doctoral Program in Management Science at the Universitas Terbuka and Lecturer in the Management Department of Universitas Binaniaga Indonesia, Indonesia
[2,3] Lecturer of Department of Management,Universitas Terbuka, Indonesia
[4] Lecturer of Department of Management,Universitas Hasanudin, Indonesia

ABSTRACT

The aim of this study is to test the application of factor analysis to measure the implementation of green finance in Indonesia.This research employs exploratory factor analysis (EFA) to examine the dataset in order to uncover complex relationships between items and groups of items that constitute an integrated concept. The new Green Finance measurement in this study represents a transformative step towards a greener and more equitable future, involving Validity Test, Reliability Test, Measure Of Sampling Adequacy Test, Kaiser-Meyer-Olkin (KMO) Test, and Bartlett's Test of Sphericity. Conservation projects, sustainable investments, and renewable energy are the key factors extracted using the Rotated Component Matrix method to measure green finance implementation. Factor analysis used in measuring green finance requires a holistic evaluation that considers the relationship between environmental, social and economic factors. Green finance indicators are metrics of specific criteria used to assess the environmental and sustainable impact of financial management initiatives. The resulting indicators help evaluate how effectively funds are allocated to environmentally friendly projects, businesses and practices**.** This study's perspective presents a quantitative measurement model aimed at assessing the suitability of green financial practices in Indonesia.

Keywords *: Factor Analysis,Green Finance, Sustainable Investments, Indonesia*

Introduction

Indonesia's commitment to implementing green finance relates to the launch of the Indonesian Green Taxonomy on 20 January 2022, as a guide to promote information transparency in the Financial Services sector and as a reference for encouraging innovation in sustainable financial products and services, an element crucial to this concept is the development of revolutionary and economically acceptable financing or project funding schemes. Current research on green finance is mostly focused on the theoretical aspects of definitions, history and government policies in the field of green finance. However, according to Lindenberg N (2013), until now there has been no consensus regarding the definition of green finance. The results of previous studies such as Falcone, P., & Sica, (2019) and Kissinger et al., (2019) cannot be ruled out as hasanah in understanding relevant theories of green finance. However, to encourage a deeper understanding of green finance, an in-depth study of the measurement aspects of green finance is needed. Measurement of a rational green finance construct can be studied by comparing the dynamic relationship of factors influencing green finance constructs in various countries, which helps in the measurement and evaluation of the green finance development process in Indonesia.

This research analysis primarily centered on the utilization of factor analysis, a multivariate statistical technique employed to discern the relatively strong relationships among variables within subsets, as described (Tabachnick and Fidell,2013). The objective of this research was to employ factor analysis as a means of condensing a large array of interrelated measures into a set of representative constructs or factors, which can subsequently be used for further examination. Numerous studies have previously explored the utility of factor analysis as a method to reduce extensive datasets and identify the resultant factors (MacCallum et al, 1999).

Within the context of the green finance industry, assessing the degree of implementation involves various parameters. Factor analysis can categorize these variables into distinct factors, each of which gauges different facets of green finance implementation. The extraction of significant factors serves the purpose of elucidating the maximum variation within the study group. The application of factor analysis offers valuable insights for decision-makers, enabling them to concentrate on a select number of primary factors from the numerous parameters at hand, thereby guiding policy development.

The update in this study was obtained from the search results for articles with the keyword Green Finance, it is known that there are still very limited studies on measuring the implementation of green finance in various countries using a questionnaire survey method using factor analysis. The question of this research is how to test the application of factor analysis on questionnaire items to measure the implementation of green finance?. Therefore, to identify these factors, it is important to understand the concept and steps for applying factor analysis to a questionnaire survey.

Research Method

Research Samples

The research sample was taken using non-probability sampling with purposive sampling method, with the following criteria:

a. PROPER rated company in 2022 with Gold, Green, Blue, Red and Black ratings.

b. Registered (listing) on the Indonesian Stock Exchange in 2022 A total sample of 304 companies with gold, green, blue and red ratings listed on the Indonesia Stock Exchange were used as samples in the research. In this research, primary data was used by conducting a questionnaire survey with the help of a Google Form survey, aimed at company leaders and financial managers, with the rate of return or filling out the questionnaire only 47 respondents provided responses. Thus the response rate in this study was 15.4% which was considered sufficient. According to Roscoe (1975) in a concept known as the "rule of thumb" which states that a sample size greater than 30 is often considered sufficient to assume a normal distribution or close to a normal distribution, especially in statistical analysis with the aim of testing hypotheses or predictions. Information regarding corporate identity presented by type of company is explained as follows:

Table 1, Respondent Profile Based on Company Type

The type of company	Number of (people)	Percentage (%)
Banking	4	8,51
Garments	7	14,89
Agribusiness	11	23,40
Automotive	12	25,53
Gas and Oil	10	21,28
Transportation	3	6,38
Amount	**47**	**100,00**

Measurement Dimensions

Table 2, Measurement Dimensions in Previous Green Finance Research

Source	Measurement Dimensions	Country
Gilbert *et. al* (2012)	Sustainable development projects, environmentally friendly products and sustainable economic policies	
Zandek and Flyn, (2013)	Operational cost of green investment	
Zeng *et. al* (2014)	Five dimensions and using the subjective method of expert judgment and objective method of measuring assets in various areas of finance	China
PWC (2013)	Environmental investments, eco-friendly technologies, sustainable projects, low carbon industry and business	
Akin *et.al* (2016)	Financial friendliness index based on factor analysis and nonlinear weighting to compare levels of financial risk sharing and interstate support	
Sabine Dörry & Christian Schulz (2018)	Financial services, products, sustainability space and organization	Luxembourg
Hayat *et.al* (2018)	The financial development index and	Pakistan

	energy prices are significantly related with energy consumption	
Li *et.al* (2018)	Green financial market performance index and green financial ecological index	China
Mohsin *et.al* (2020)	Low carbon financial index	
PBoC (2019)	green financing, green investment and green society	China
Street *et.al* (2001)	Performance on green bank services: physical outlets, self-service, and facility automation	
Hof *et. al* (2011)	Climate finance: adequacy, predictability, And justice.	
Bloomberg, 2017	Alternative energy Energy efficiency Pollution Prevention and Control Sustainable Water Green Building Climate Adaptation	
Measurement dimension hypothesis	- Eco-friendly project - Prevention and control of pollution - Conservation and recycling - Climate change adaptation - Clean transportation - Clean energy	

In the table above, it can be seen from previous studies that researchers have used a variety of different green finance dimensions, this can indicate that there is still no agreement regarding the definition and measurement dimensions of green finance

Validity Test

The validity test aims to assess the validity of the indicators for measuring variables. A questionnaire is considered valid if the questions contained in it can describe the things that the questionnaire wants to measure (Ghozali, 2005). A valid measuring instrument will have a small error rate, so that the data collected is reliable. The test criteria used, if r-count > r-table (at a significance level of 0.05), it can be stated that the questionnaire items are valid.

Reliability Test

A reliability test, sometimes referred to as a consistency assessment, is a technique employed to gauge the degree of uniformity or steadiness of a questionnaire when serving as an indicator of a specific variable or concept. In the context of this investigation, the analysis employed for the reliability test was the Cronbach-Alpha coefficient, and it exceeded 0.7 in line with the guidelines outlined (Sekaran, 2010)..

Factor Analysis

In contrast to prior research on the assessment of green finance, the following methodologies have been employed: Zeng et al. (2014) utilized the Analytic Hierarchy Process (AHP), Sabine and Schulz (2018) adopted a qualitative approach, and Li et al. (2018) applied multiple regression analysis. In this research, an exploratory factor analysis (EFA) is employed to scrutinize data collections in order to unveil intricate connections among the constituent items and item groups that constitute the overarching concept. EFA, known for its exploratory approach, does not make a clear distinction between independent and dependent variables. Instead, it amalgamates similar variables into coherent factors with the aim of revealing the underlying variables. The method solely relies on a data correlation matrix, as suggested (Noora, 2021). Within this investigation, principal component extraction is utilized in factor analysis to evaluate whether statements are indicative of distinct factors pertinent to the implementation of green finance. As per Hair et al. (2006), Principal Component Analysis (PCA) is a statistical procedure used to accentuate variations, wherein primary data components are computed, thereby highlighting significant patterns within the dataset. Factor analysis involves several important steps as follows (Thompson, 2004):

a. Correlation or Covariance Matrix: The first step is to calculate the correlation or covariance matrix of the dataset.
b. Deriving Eigenvalues and Eigenvectors : To obtain eigenvalues and eigenvectors, one can perform calculations using the correlation or covariance matrix. This is achieved through the equation $Rv=\lambda v$, in which 'v' represents the eigenvector, 'λ' signifies the eigenvalue, and 'R' corresponds to the correlation or covariance matrix.
c. Determining the Quantity of Factors: Deciding how many factors to extract from the outcomes of the factor analysis involves using a "scree plot." This plot illustrates the eigenvalues in relation to the factor number and identifies the juncture at which eigenvalues begin to decline significantly, often referred to as the "elbow point" on the plot.

d. Calculating Factor Loadings: Factor loadings relate the original variables to the latent factors. The factor weight (lij) for the Xi variable and the Fj factor is calculated as part of the factor loadings matrix. It involves eigenvectors, correlation matrices, and column vectors of factors *loadings* *matrix*:

$$lij = \frac{vij}{\sqrt{\gamma j}}$$

e. Factor Rotation: Factor rotation is used to make factor analysis results easier to interpret by using factor loadings matrix transformation.
f. Interpretation of Results: After calculating the factor loadings, then interpret the factors found. Variables with high factor loadings on certain factors are considered to have a strong relationship with these factors.
g. Determining Factor Names: Giving names to factors based on interpretation of the variables that are most strongly connected to each factor.
h. Calculating the Proportion of Variance: by calculating the proportion of variance explained by each factor by adding up the squares of the factor loadings and dividing it by the total variance of the initial variable.

Results

Selection of indicators

Prior to conducting factor analysis, it is essential to choose and validate the indicators that will be employed. The initial indicator selection process involves subjecting them to validity and reliability assessments. The validity examination entails comparing the correlation value (r-count) with the critical r-table value at a significance level of $\alpha = 0.05$, which was determined to be 0.361. The outcomes of the validity test are presented in the subsequent table.

Table 3, Validity Test Results

No.	Indicator	*Correlation* (r- count)	*Sign*	information
1.	KH1	0,778	0,00	Valid
2.	KH2	0,526	0,00	Valid
3.	KH3	0,856	0,00	Valid
4.	KH4	0,718	0,00	Valid
5.	KH5	0,768	0,00	Valid
6.	KH6	0,681	0,00	Valid
7.	KH7	0,892	0,00	Valid
8.	KH8	0,664	0,00	Valid
9.	KH9	0,743	0,00	Valid
10.	KH10	0,765	0,00	Valid
11.	KH11	0,633	0,00	Valid
12.	KH12	0,707	0,00	Valid

According to the findings from the validity test, it is evident that the correlation value (r-count) for each of the indicators surpasses the critical r-table value of 0.361. Therefore, it is reasonable to conclude that all the indicators employed in the study are indeed valid. Following the validation assessments, the reliability testing of all the indicators was pursued.

The reliability test involved comparing the Cronbach's Alpha value with a threshold of 0.700. The detailed results of the reliability test are provided in the subsequent table:

Table 4, Reliability Test Results

Cronbach's Alpha	*N of Item*
0,919	12

As indicated in the table above, the reliability test yielded a Cronbach's Alpha value of 0.919. This value surpasses the threshold of 0.700, affirming that the measurement instrument, in this case, the questionnaire, is reliable and suitable for subsequent data analysis. The next step involves assessing the selection of indicators to determine the extent of correlation among the initial indicators. The correlation among these indicators can be observed within the correlation matrix representing the initial indicators. This assessment utilizes statistical tests, namely the Measure of Sampling Adequacy (MSA), the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy, and the Bartlett test of sphericity, which are elaborated upon below.

a. *Measure of Sampling Adequacy* (MSA)

The Measure of Sampling Adequacy (MSA) assessment is conducted to identify which indicators are suitable for further analysis, as not all indicators will be retained for subsequent analysis. This examination involves reviewing the MSA values for each indicator, which are found along the diagonal in the anti-image correlation matrix. If any of the initial indicators individually exhibit an MSA value below 0.5, they are eliminated and excluded from the subsequent analytical process. The process entails systematically removing indicators one by one, commencing with the ones having the smallest MSA values. Then, the remaining initial indicators that meet the specified criteria are re-evaluated until their MSA values reach the threshold of 0.5. The outcomes of the MSA test are presented in the table below.

Table 5, Measure of Sampling Adequacy Test Results

Anti-image Matrices													
		KH 1	KH 2	KH 3	KH 4	KH 5	KH 6	KH 7	KH 8	KH 9	KH 10	KH 11	KH 12
Anti-image Correlation	KH1	,726[a]	,243	-,216	-,234	,025	-,178	-,782	,276	-,003	,199	,257	,440
	KH2	,243	,744[a]	-,449	,004	,181	-,193	-,244	-,025	,108	,091	,153	,227

	KH3	-,216	-,449	,817[a]	,172	-,088	,228	-,040	-,153	-,481	,100	-,163	-,537
	KH4	-,234	,004	,172	,906[a]	-,177	-,042	,005	-,069	-,305	,155	-,068	-,162
	KH5	,025	,181	-,088	-,177	,883[a]	-,357	-,205	-,190	-,192	,050	,238	,197
	KH6	-,178	-,193	,228	-,042	-,357	,861[a]	,136	-,164	-,182	-,107	-,184	-,086
	KH7	-,782	-,244	-,040	,005	-,205	,136	,715[a]	-,045	,375	-,602	-,485	-,471
	KH8	,276	-,025	-,153	-,069	-,190	-,164	-,045	,840[a]	,138	-,245	-,428	,066
	KH9	-,003	,108	-,481	-,305	-,192	-,182	,375	,138	,773[a]	-,509	-,220	-,120
	KH10	,199	,091	,100	,155	,050	-,107	-,602	-,245	-,509	,735[a]	,534	,223
	KH11	,257	,153	-,163	-,068	,238	-,184	-,485	-,428	-,220	,534	,661[a]	,279
	KH12	,440	,227	-,537	-,162	,197	-,086	-,471	,066	-,120	,223	,279	,743[a]

From the table above the MSA values of the 12 indicators used can be seen in the diagonal matrix which shows that each indicator has an MSA value of more than 0.5. Thus, it can be concluded that the 12 indicators used are feasible or adequate for further analysis.

b. *Kaiser-Meyer-Olkin* (KMO) *Measure of Sampling Adequacy and* B*artlett Test of Sphericity*

This analysis was carried out to evaluate the suitability of the sample by utilizing two criteria: the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy index and the p-value associated with Bartlett's Test of Sphericity. The assessment primarily focuses on the KMO value. If the KMO value falls within the range of 0.5 to 1 (or exceeds 0.5), and the p-value from Bartlett's Test of Sphericity is below the predetermined significance level (α = 0.05), it indicates the appropriateness of applying factor analysis, and it is advisable to proceed with the analysis. The outcomes of this assessment, along with the respective values, are presented in the table provided below.

Table 6, KMO Test Results and Bartlett's Test of Sphericity

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,777
Bartlett's Test of Sphericity	*Approx. Chi-Square*	424,952
	df	66
	Sig.	,000

Based on the test results, the KMO value was 0.777 and the Bartlett's Test of Sphericity significance value was 0.000, thus it can be concluded that factor analysis can be used or continued to simplify the collection of 12 indicators.

Factor formation

Having chosen the 12 indicators and ensured their eligibility for analysis, the subsequent phase involves constructing factors with the aim of uncovering the underlying structure that interconnects these indicators. The process of establishing these factors entails determining the quantity of factors and implementing factor rotation. The steps for forming this factor are described as follows:

a. Determining the number of factor

The determination of the optimal number of factors to be generated involves amalgamating various criteria to align with the characteristics of the research data. This analysis is executed with reference to the provided table.

Table 7, Total Variance Explained

Component	*Initial Eigenvalues*			*Extraction Sums of Squared Loadings*			*Rotation Sums of Squared Loadings*		
	Total	*% of Variance*	*Cumulative %*	*Total*	*% of Variance*	*Cumulative %*	*Total*	*% of Variance*	*Cumulative %*
1	6,469	53,908	53,908	6,469	53,908	53,908	3,773	31,440	31,440
2	1,218	10,148	64,056	1,218	10,148	64,056	2,605	21,709	53,149
3	1,076	8,963	73,020	1,076	8,963	73,020	2,384	19,871	73,020
4	,776	6,467	79,486						
5	,688	5,734	85,220						
6	,535	4,462	89,682						
7	,368	3,068	92,750						
8	,313	2,612	95,362						
9	,289	2,409	97,771						
10	,154	1,286	99,057						
11	,080	,670	99,727						
12	,033	,273	100,000						

By consolidating the initial indicators into 3 factors, a substantial cumulative total variance of 73.020% was achieved. This implies that the 3 factors formed effectively encapsulate the 12 green financial indicators, elucidating approximately 73.020% of the concept of green finance. Hence, it is confirmed that extracting the 3 factors aligns with the second criterion.

The third criterion involves ascertaining the number of factors using Scree plots. A Scree plot depicts the eigenvalues corresponding to the extracted factors, and the precise number of factors is determined by identifying the point where the Scree plot begins to exhibit a flattening pattern. The Scree Plot image is explained as follows:

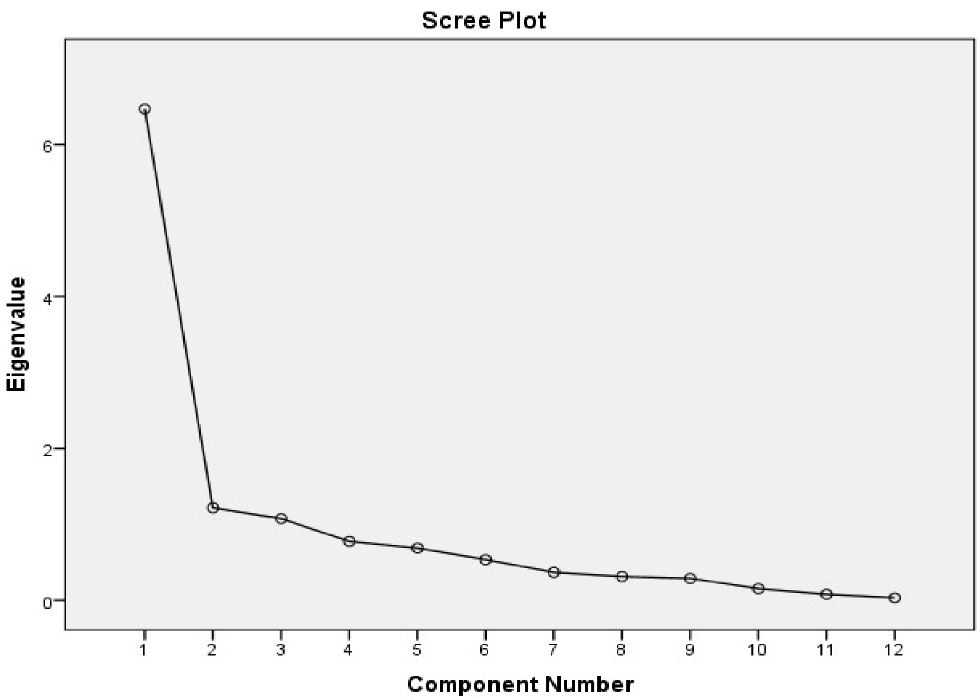

Figure 1, Scree Plot

In the depicted graph, it's evident that the Scree plot begins to plateau when extracting the initial indicators into 3 factors. Therefore, it can be deduced that the optimal factor extraction involves using 3 factors. From the aforementioned explanation, it's apparent that all three criteria yield congruent results, indicating that the most suitable number of factors is indeed 3.

b. Communalities

Communality is basically the amount of variance of an indicator that can be explained by existing factors. Communality can be said to be the ability of indicators to explain factors. The greater the communality value, the higher the role of the indicator in explaining the factors formed. The table below shows the communality values of the indicators.

Table 8, Communalities

No.	*Variable*	*Indicator*	*Extraction*
1.	Project	KH1	,813
		KH2	,622
		KH3	,888
2.	Pollution Prevention and Control	KH4	,579
		KH5	,783
3.	Conservation and Recycling	KH6	,711
		KH7	,886
4.	Clean Transportation	KH8	,751
5.	Clean Energy	KH9	,610
		KH10	,723
6.	Climate Change Adaptation	KH11	,696
		KH12	,701

The numbers in the table show the magnitude of the variance of the indicators that can be explained by the factors formed. For example, the KH1 indicator has a correlation of 81.3% to the formed factor, the KH2 indicator has a 62.2% correlation to the formed factor and so on.

c. Component Matrix

The table depicting the component matrix visually presents the allocation of the 12 indicators among the three identified factors. In this component matrix, the values within it signify factor loadings, which reflect the degree of correlation between each indicator and the three distinct factors, specifically referred to as factor 1, factor 2, and factor 3. Below, you will find the Component Matrix table.

Tabel 9, *Compenent Matrix*

	Component		
	1	2	3
KH1	,763	-,261	-,404
KH2	,522	,554	-,205
KH3	,871	,329	-,146
KH4	,714	-,250	,087
KH5	,768	-,419	,135
KH6	,673	-,320	,394
KH7	,885	-,042	-,317
KH8	,660	,206	,522
KH9	,761	-,029	,172

KH10	,765	-,295	-,224
KH11	,621	,382	,406
KH12	,731	,341	-,224

The table above explains that the correlation values of each indicator with the three factors formed include: (1) indicator KH1 with factor 1 correlation 0.763; with factor 2 correlation -0.261; with a correlation factor of -0.404, (2) KH2 indicator with a correlation factor of 1.522; with factor 2 correlation 0.554; with a factor 3 correlation -0.205, (3) KH3 indicator with a factor 1 correlation 0.871; with factor 2 correlation 0.329; with factor 3 correlation -0.146 and so on.

d. Rotation

The rotation matrix component is a correlation matrix that provides a more transparent and accurate representation of variable distribution compared to the component matrix. The generation of factors based on their constituent indicators can be observed through the outcomes of the Rotated Component Matrix test. The indicator that assumes the role of forming a factor is identified by the highest factor loading value. Below, you will find the Rotated Component Matrix table.

Table 10, *Rotated Component Matrix*

	Component		
	1	2	3
KH1	,821	,373	-,010
KH2	,062	,769	,162
KH3	,436	,758	,351
KH4	,637	,148	,389
KH5	,771	,030	,432
KH6	,565	-,055	,623
KH7	,739	,562	,157
KH8	,176	,275	,803
KH9	,501	,301	,518
KH10	,793	,273	,142
KH11	,067	,435	,709
KH12	,353	,727	,217

To determine whether the grouping of indicators into each factor formed is appropriate or not, a significance test of the loading factor value has not been carried out. The test is carried out with the requirement that the factor loading value of 0.5 is considered significant.

The results of the analysis show that the indicators KH1, KH4, KH5 KH7 and KH10 have the highest loading factor value (> 0.5) in forming factor 1. Then the indicators KH2, KH3 and KH12 have the highest loading factor value (> 0.5) in forming factor 2. Meanwhile, indicators KH6, KH8, KH9 and KH11 have the highest loading factor value (0.5) in forming factor 3. Thus, the grouping of indicators into each factor is explained in the following table:

Table 11, Grouping of Indicators into Factors

Factor	Indicator
Factor 1	KH1, KH4, KH5, KH7, KH10
Factor 2	KH2, KH3, KH12
Factor 3	KH6, KH8,KH9, KH11

Factor Naming

After the formation of 3 factors, each of which consists of the initial indicators studied, the next step is to name the factors based on the characteristics that correspond to the members of each factor.

a. Factor 1
   Members or indicators in factor 1 consist of projects supported by the company aiming to improve the welfare of the surrounding community (KH1), the company implements environmentally friendly technology and production processes to reduce pollutant emissions (KH4), the company routinely carries out monitoring and control pollution in its operations (KH5), the company actively supports recycling programs and the use of environmentally friendly raw materials (KH7) and the use of renewable energy is a top priority in company policy (KH10). By generalizing the four indicators, factor 1 is then referred to as the conservation project factor.
b. Factor 2
   Members or indicators in factor 2 consist of companies investing in projects that support the development of environmentally friendly technologies (KH2), company projects actively considering positive impacts on the environment (KH3) and in making long-term decisions, companies consider factors -climate change factors (KH12). By generalizing the four indicators, factor 2 is then referred to as the sustainability investment factor.
c. Factor 3
   Members or indicators in factor 3 consist of companies implementing energy and water conservation policies in their operations (KH6), companies prioritizing the use of more efficient and environmentally friendly transportation fleets (KH8), companies actively seeking ways to reduce energy consumption and improve energy efficiency in operations (KH9) and companies investing in research and technology that can help reduce vulnerability to climate change (KH11). By generalizing the four indicators, factor 3 is hereinafter referred to as the renewable energy factor.

Determine the accuracy of the factors

After determining the new factors, it is necessary to test the accuracy of the factors formed. To carry out the test, Component Transformation Matrix analysis is used which serves to prove the magnitude of the correlation value of the factors formed. Factor formation is said to be correct if the correlation of each factor is greater than 0.5. Based on the results of the analysis, the Component Transformation Matrix is obtained as shown in the table below:

Table 12, Component Transformation Matrix

Component	1	2	3
1	,699	,519	,492
2	-,653	,743	,145
3	-,290	-,423	,858

The correlation value of each factor can be seen from the diagonal table above which is obtained: factor 1 correlation value 0.699, factor 2 correlation value 0.743 and factor 3 correlation value 0.858. These three factors are proven to have a correlation value greater than 0.5. Each factor has a positive relationship which is explained by the correlation value of each factor which is positive. With this test it can be concluded that the three factors formed are appropriate in summarizing the 12 existing indicators. Where based on these three factors is used to measure green finance.

Discussion

It should be noted that the development of sustainable business practices in Indonesia has significant potential for growth. However, at present, it is still in progress and faces many challenges. Full support from all stakeholders, including the government, companies, society, and relevant institutions, is needed to achieve significant changes towards a more sustainable business in the future. Arifin and Syahruddin's study (2011) suggests that Indonesia has the potential to boost its economic growth between 1971 and 2008 by increasing the utilization of renewable energy sources and reducing the use of fossil fuels. Indonesia is also striving to shift towards an eco-friendly model, with the objective of producing 5% of its total electricity from geothermal, wind, biomass, hydro, and solar sources by 2025. As a substantial step in steering Indonesia's economy toward a low-carbon trajectory, the nation has initiated the Low Carbon Development Initiative (LCDI), detailing a number of policies and transformation programs across various economic sectors. This approach is expected to result in consistent economic growth of 5.6% by 2024 and reaching 6.0% by 2045. In a more positive outlook, it is anticipated that an increase of approximately \$5.4 trillion will be added to the Gross Domestic Product (GDP) by 2045, resulting in the creation of more than 15.3 million sustainable employment opportunities. Additionally, these endeavors are projected to decrease the poverty rate from 9.8% of the overall population in 2018 to 4.2% and lead to approximately 40,000 lives saved through enhanced air quality (Brodjonegoro et al. 2019).

The Indonesian Financial Services Authority (OJK), as the regulator of sustainable finance, currently does not have a specific or separate green finance measurement framework. However, OJK has shown concern for green and sustainable finance issues through a number of initiatives. In 2019, OJK issued Circular No. 37/SEOJK.04/2019 concerning the Application of the Principles of Sustainable Development for Financial Services Institutions. This circular provides guidance to financial services institutions (including banks, insurance and capital markets) to implement sustainable development principles in their operations. Although not specifically about measuring green finance, this circular covers several aspects relevant to sustainable investment. Apart from that, OJK has also encouraged sustainable financial reporting through principles adopted from global frameworks such as the Global Reporting Initiative (GRI) and the Sustainability Accounting Standards Board (SASB).

The current implementation of sustainable finance from OJK is based on KUBL (Environmentally Aware Business Activities) which refers to "POJK 60/2017" which refers to Financial Services Authority (OJK) Regulation Number 60 of 2017 concerning the application of sustainability principles in managing sector financing risks banking and non-bank financial industries. These regulations cover 11 sectors regulated in managing financing and investment risks in the context of the environment and sustainability. These principles require financial institutions to consider environmental and social impacts in their financial decisions.

Suggestion

This research approach to measuring green finance involves a multidimensional framework that considers not only the environmental impact of investments, but also their social and economic implications. Factor analysis used in measuring green finance requires a holistic evaluation that considers the relationship between environmental, social and economic factors. Green finance indicators are metrics of specific criteria used to assess the environmental and sustainable impact of financial management initiatives. These indicators help evaluate how effectively funds are allocated to environmentally friendly projects, businesses, and practices.

Implications

This research provides investors, businesses, and policymakers with the benefit of being able to make more informed choices by considering factors beyond traditional financial metrics. These measures encourage and incentivize investments that align with sustainable development goals, sparking greater interest in green finance initiatives.

Limitations

This research still has a lot to develop due to the limited number of respondents who are willing to fill out the questionnaire, so it is necessary to develop responsive data collection methods to capture a larger sample.

Further Research

Requires specifications for the type of industry being studied, so that it will influence the determination of the quantity and specific factors involved in measuring green finance in a particular industry.

ACKNOWLEDGEMENT

The author extends their gratitude to the Republic of Indonesia's Ministry of Education and Culture for their valuable support in the form of research grant.

ETHICAL STATEMENT

This article does not contain any studies with human participants performed by any of the authors.

CONFLICT OF INTEREST

The authors declare that they have no competing interests.

AUTHORS' CONTRIBUTIONS

Both authors contributed equally to the conception and design of the stud

DATA REQUEST

Requests for materials should be addressed to Syarief Gerald Prasetya.

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