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STRUCTURAL EQUATION MODELING AS A TOOL FOR ECONOMIC RESEARCH

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Abstract: In this paper, the benefits of applying the Structural equation modelling (SEM) technique to economic research are methodologically analyzed. SEM is a second-generation multivariate analysis technique for simultaneously measuring and analyzing complex cause-effect relationships. Interest in this technique has grown since a large amount of software has been developed for applied SEM, where the theoretical model is created using simple drawing tools (Arbuckle, 2017). SEM allows simultaneous standard and non-standard modeling of relationships between latent and observed variables with the ability to process longitudinal data, time series, elimination of autocorrelation and analysis of non-normally distributed variables. Techniques such as multiple and logistic regression and analysis of variance, have certain initial disadvantages that can affect the accuracy of the measurement: 1. simplification of the model structure, 2. they require that all variables be considered observable from the start, and 3. they assume that all variables are measured without error. With the SEM technique, often unobservable constructs, that are indirectly measured by several indicators, can be modelled simultaneously, taking into account measurement errors, so that the results are more accurate compared to standard techniques. To illustrate the methodological features of SEM, this paper uses a theoretical background, a small graphical manual and an own applied empirical analysis from practice. The study presents the results of an applied empirical research on corporate social responsibility conducted on a sample of 105 companies in the Italian region of Campania. The data were collected using a questionnaire, and the methodological technique applied was an adapted SEM that involved a wider range of factors. PCA was used to identify preliminary factors, which were rotated to reduce the number of variables. The generated principal components were integrated into SEM, where the testing of various inter-associations and the measurement of the impact on the company's profit were simultaneously carried out. Company profit was measured on a Likert scale, for the period covering the last two years. All three principal components, GEWR, APG and EFO had a significant and positive impact on the growth of company profits. An increase in GEWR by one point leads to an increase in profit by 0.57. A jump in APG by one point leads to an increase in profit by 0.45. The growth of EFO by one point, causes an increase in profit by 0.3. Following the size of the company, the type of activity, the size of the budget and the ecological situation in the local community, this study gives recommendations to managers for an effective choice of strategy.

Keywords: Structural equation modeling, methodology of economic research, corporate social responsibility, environmental protection, Italian companies, profit

Field: Economics

1. INTRODUCTION

The paper examines the scope of applications for Structural Equation Modeling (SEM). The primary aim of this research paper is to methodically validate the benefits of the SEM technique in economic research. For this purpose, the theoretical background, a mini graphic manual and an empirical example from practice were used. SEM is a second-generation multivariate analysis technique that enables high-quality econometric analyses. Interest in utilizing this technique in economic research has been steadily increasing (Elangovan & Rajendran, 2015). SEM tests and evaluates causal relationships using a combination of statistical data and qualitative causal assumptions (Kumar et al., 2013). A large amount of software has been developed for the application of SEM, which allows a theoretical model to be created quickly and with simple drawing tools (Arbuckle, 2017). SEM enables the fitting of non-standard models, including the flexible processing of longitudinal data, time series with autocorrelation errors as well as non-normally distributed variables (Arbuckle, 2017). In addition, SEM enables the simultaneous modeling of complex relationships between multiple independent and dependent variables as well as latent variables (Baretto & Howland, 2006). According to Hox and Bechger (1998), the main reason for choosing SEM over traditional regression and factor analysis techniques, is its flexibility and greater potential for modeling complex relationships between constructs. SEM comprises a measurement model and a structural model. The measurement model has the task of linking observed variables with latent constructs. The structural model shows the relationship between the constructs (Kyndt, & Onghena, 2014). First-generation multivariate analysis techniques such as multiple regression, logistic regression, and analysis of variance have three major limitations (Haenlein & Kaplan, 2004):

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1. At the start they assume a simple model structure.
2. The structure requires that all variables be considered visible.
3. It is assumed that all variables are measured without error.

Regarding the first limitation, techniques such as multiple regression assume simple models that contain one layer of dependent and usually one independent variable (Hair et al., 2021). Causal models of type A leads to B leads to C, and more complex structures that include a larger number of intervening variables can only be partially explained by regression techniques, but not simultaneously, which affects the accuracy of the results. Regarding the 2nd limitation, the presence of unobserved variables can only be considered ex-post, through confirmatory factor analysis, which also brings various disadvantages (Bagozzi & Philipps, 1982; Hair et al., 2021). Regarding the third limitation, the methodological techniques of the first generation of multivariate analysis are only applicable if the measured variables contain neither systematic nor random errors, which is a rare case due to the nature of the social sciences. The use of SEM allows the simultaneous modelling of unobservable constructs measured indirectly by multiple indicators, taking into account measurement errors, so that the final results are more accurate compared to standard techniques. Therefore, SEM has become an attractive technique for researchers in fields such as entrepreneurship (Manley et al., 2020), knowledge management (Cepeda Carrión et al., 2019), marketing (Hair et al., 2012a; Sarstdetd et al., 2022; Guenther et al., 2023), circular economy (Babic et al., 2024; Zhang & Berhe, 2022), strategic management (Hair et al., 2012b), accounting (Nitzl, 2016., Nitzl & Chin, 2017), tourism economics (Do Valle & Assaker, 2016), human resources management (Ringle et al., 2020, Legate et al., 2023) and in other areas of management (Magno et al., 2024).

2. MATERIALS AND METHODS

Observed variables are standardly marked with rectagle in SEM. An ellipsis is used as a marking symbol for unobserved variables.The single-headed arrows are used to show direct relationships, factor loadings and correlations. A double-headed arrow we use to display the covariance. Smaller circles, usually labeled e, are used to mark the error (Table 1).

Table 1 Mini Graphic Manual for SEM

X Y	Observed, Measured, Manifest, Indicator, Reference variable
	Unobserved, Latent Variable, Factor or Construct, Error or distrubance
	Direct effect, Factor loading, Path loading, Correlation between variables, Parameter, Path
	Non directional, Bidirectional association, Correlation and covariance, Parameter, Path
e X e Y	Measurement error on observed variable
e e	Disturbance or error on latent variable

Source: Adapted from Elangovan & Rajendran, 2015

An exogenous variable is one whose value is determined by factors external to the model in which it is included. Exogenous variables explain other variables within the model. Endogenous variables (Lleras, 2004) are those whose variability can be explained by one or more variables within the model. Endogenous variables are influenced by other variables in the model, including exogenous and other endogenous variables.

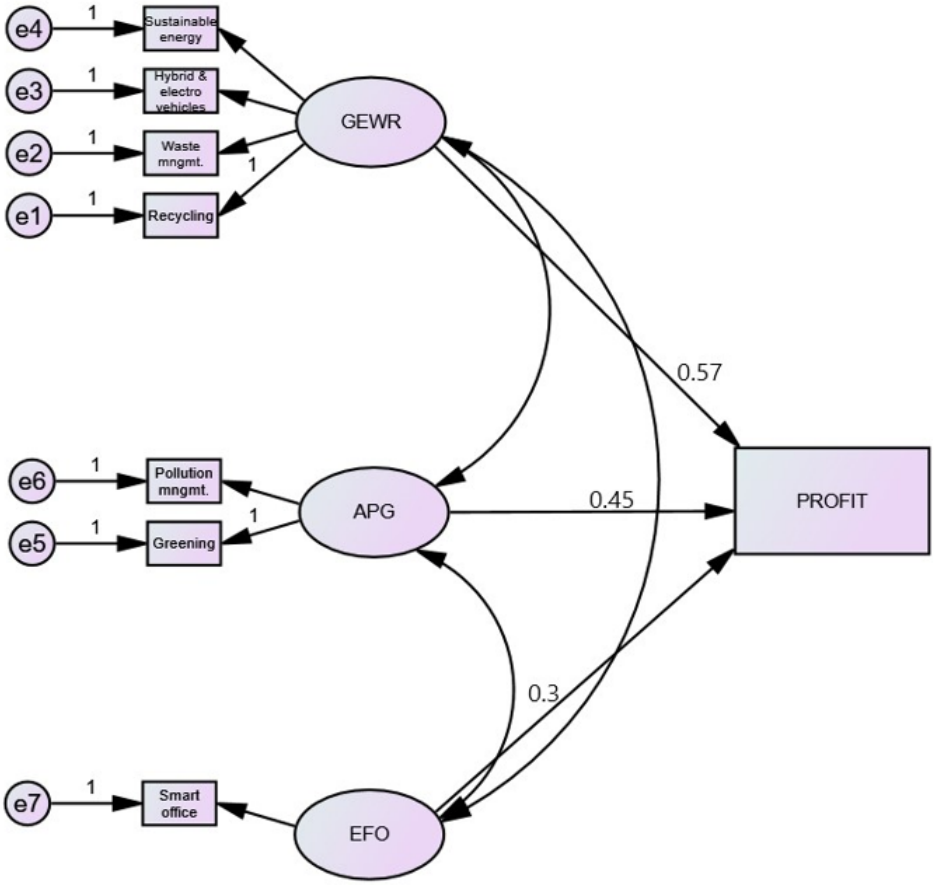
The research used data from an extended sample for the purposes of this work, which included 105 companies in the Campania region, Italy (Babic et al., 2024). Seven key indicators of companies'

participation in CSR (sustainable energy, hybrid & electro vehicles, waste management, recycling, anti-pollution, greening & smart office) were processed using the PCA technique followed by SEM to measure the impact on company profits. The change in the profit variable in the past two years, was measured on a 4-point Likert scale. The assumption that CSR indicators influence the profit growth of companies was analyzed. Calculations were performed in Amos 25 software.

3. RESULTS AND DISCUSSIONS

The threshold for factor loadings in our sample size is set at ±0.55 (Hair et al., 2019). Figure 1 shows isolated significant factor loadings that enter the structure of 3 complex principal components: GREEN ENERGY WASTE & RECYCLING (GEWR), ANTI-POLLUTION & GREENING (APG) and ECO-FRIENDLY OFFICE (EFO).

Figure 1 SEM, Conceptual Model



Source: Author

Looking at the fit indices (Table 2), a perfect value (1) for Comparative Fit Index (Hu & Bentller, 1999) is indicated. And the values for IFI and NFI are in the prescribed range (Marsh et al., 1996):

Table 2 Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	1.000		1.000		1.000
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

Source: Author's calculation

Based on the insight into the value of BETA unstandardized coefficients (Figure 1), three factor scores have a significant effect on the increase of the company's profit. If GEWR jumps by one point,

profit increases by 0.57. When APG jumps by one point, there is an increase in profit by 0.45, while if EFO increases by one point, the company's profit jumps by 0.3. GEWR leads to the highest profit growth, but requires the largest investments and is therefore suitable for large companies. The strategy includes investments in systems for generating energy from sustainable sources, the purchase of hybrid and electric vehicles and investments in technologies for waste management and recycling. APG's strategy of avoiding harmful gases leads to a slightly lower, but equally significant increase in profit. The strategy is suitable for medium-sized companies. The EFO strategy leads to the lowest profit growth, but also requires the lowest investment. EFO is suitable for start-ups and small companies. It includes options such as using smart lighting, buying recycled equipment, reducing paper use in offices and increasing cooperation with environmentally conscious suppliers. Before choosing a strategy, managers are advised to take into account the size of the company, the type of activity, the budget, the composition of the staff and the environmental situation in local community.

4. CONCLUSIONS

The aim of this study was to validate the mechanism of the predictive models in SEM. In this way, the advantages of this technique are made clear to the researcher, and confidence in SEM as a tool for deriving management implications is strengthened. SEM and path analysis are used to solve complex problems in many areas of economic science. SEM is a technique suitable for multidimensional simultaneous measurement of complex cause-and-effect relationships, which cannot be performed through classical multiple regression. SEM is a precise technique because it can estimate parameters with maximum likelihood, which provides consistent and asymptotically efficient results. The most important steps in this process are the establishment of appropriate scientific theories and the formulation of hypotheses. Otherwise, the researcher may fall into a trap in which SEM becomes a goal per se. In this case, the whole strategy loses its meaning and the obtained are unfounded. For research purposes, an adaptive SEM model is applied to measure the impact of CSR on the company's profits in the Campania region. Using PCA, we obtained preliminary factors that we rotated, leading to a reduction in the number of variables. The generated principal components (GEWR, APG and EFO) were integrated into SEM, simultaneously testing various relationships and measuring the impact on company profits. It was found that GEWR, APG and EFO each have a positive impact on profit growth. The GEWR strategy requires greater investment, but yields the highest profit growth, so its implementation is recommended for large and ambitious medium-sized companies. The APG strategy is suitable for medium-sized companies. The EFO management strategy requires the least financial resources and is therefore recommended for start-ups and small companies.

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