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The SDGs System: a longitudinal analysis through PLS-PM

Il sistema degli SDGs: un'analisi longitudinale attraverso il PLS-PM

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Abstract The Sustainable Development Agenda [24] emphasizes measurement and monitoring progress of the Sustainable Development Goal (SDG) targets, stressing the need for "a data revolution for sustainable development to improve the quality of statistics and information available to citizens and governments". The main problem for researchers is to find appropriate tools to obtain a synthetic indicator able to synthesize these targets and monitor them over the time. The work focuses on using the Structural Equation Modeling and especially Higher Order Partial Least Squares Path Modeling as a valuable way to analyze longitudinal data of SDGs. The paper contributes to the European Community countries-analysis of SDG reporting by performing a longitudinal analysis over the 20-year period encompassing 2000 to 2019. Due to the difficulty of reporting on a paper a detailed analysis of all 17 SDGs, we focus only on social dimension.

Abstract *L'Agenda per lo Sviluppo Sostenibile [24] sottolinea la misurazione il monitoraggio dei progressi degli obiettivi di Sviluppo Sostenibile (Sustainable Development Goal (SDG)), evidenziando la necessità di "una rivoluzione di dati per migliorare la qualità delle statistiche e delle informazioni a disposizione di cittadini e governi". Il problema principale per i ricercatori è trovare strumenti adeguati per ottenere un'indicatore capace di sintetizzare questi target e monitorarli nel tempo. Il presente lavoro si focalizza sull'uso di Modelli ad Equazioni Strutturali e in modo particolare dei modelli gerarchici Partial Least Squares Path Modeling come uno strumento prezioso per analizzare dati longitudinali degli SDGs. Il lavoro si basa*

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sull'analisi degli stati membri dell'Unione Europea eseguendo un'analisi longitudinale su un periodo di 20 anni compreso tra il 2000 e il 2019. A causa della difficoltà di riportare nel documento un'analisi dettagliata di tutti i 17 SDGs, ci siamo focalizzati solo sull'area sociale.

Key words: SDGs, Composite indicator, PLS-PM, longitudinal analysis

1 Introduction

Sustainable development has been at the heart of European policy for a long time, firmly anchored in the European Treaties. The 2030 agenda for Sustainable Development and its 17 Sustainable Development Goals (SDGs), adopted by the UN General Assembly in 2015, have given a new impetus to global efforts to achieve sustainable development. In the last years, the interest towards understanding and measuring the phenomena manifests in numerous researches and publications [3]; [20]; [9]; [6], aiming to review and compare the synthetic indices developed to measure sustainable development. Cataldo et al. [3] in a recent paper proposed Partial Least Squares Path Modeling (PLS-PM) as a method for studying SDGs indicators demonstrating how PLS-PM could help you to define the framework for SDGs indicators in order to provide a better measure of this complex multidimensional social phenomenon. This study can be considered an advancement of that work as it demonstrates how the PLS-PM, that worked with cross-sectional data in Cataldo et al. [3], is very useful in longitudinal data. In this work the statistical aim is to investigate the evolution of the effects between constructs over time and to test them.

According to Banati et al. [2], today "there is growing recognition of the potential of longitudinal research to contribute evidence for policy, insofar as it facilitates understanding of the dynamic nature of developmental trajectories and of the diverse processes that shape outcomes over time". Their paper highlight "how longitudinal data can be a resource for understanding the drivers underpinning SDG indicators and could provide an assessment of the timing of development windows, and related interventions to maximize the impact of interventions". Based on these considerations, in this work we want to demonstrate how PLS-PM can help researchers and funders to analyze the SDGs through a longitudinal analysis. To perform such an analysis, it is necessary to take into account the most important turning points in the evolution of sustainability: 1) the SDGs were born at the United Nations Conference on Sustainable Development in Rio de Janeiro in 2012 (the objective was to produce a set of universal goals that meet the urgent environmental, political and economic challenges facing our world) [23] and 2) the SDGs replace the Millennium Development Goals (MDGs), which started a global effort in 2000 to tackle the indignity of poverty (the MDGs established measurable, universally-agreed objectives for tackling extreme poverty and hunger, preventing deadly diseases, and expanding primary education to all children, among other development priorities) [22]. In this paper, we take into account only some SGDs, due to the difficulty of reporting a detailed analysis of all 17 SDGs, in particular, we will focus on the first six Goals belonging to the social dimensions of SDGs, according to the three-way holistic framework (social, environment and economic area). The indicators at different points in time are used to create the exogenous and endogenous constructs at the different points in time in the PLS-PM [17]; [12]; [18]. The main research objective in this case is to investigate the evolution of the effects between constructs over time.

2 Longitudinal data analysis with PLS-PM approach

The model on longitudinal data can be approached from several perspectives, and the model can be constructed as a Structural Equation Model (SEM). According to Baltes and Nesselroade [1], SEM is a valuable way to analyze longitudinal data because it is both flexible and usefulfor answering common research questions. The explicit invocation of latent variables (LVs) afforded by the SEM makes this framework the one most commonly used to implement and analyze longitudinal data [16]; [19]. Recently, Roemer [17] has proposed using the component-based approach to SEM-PLS-PM in a longitudinal study [7]; [21]. In accordance with Roemer [17], we posit that PLS path modeling is highly appropriate for an analysis of the development and change in constructs in longitudinal studies, since it offers three favorable methodological characteristics. First, constructs often need to be predicted in evolutionary models [12]; [18]. Secondly, model complexity quickly increases when development and change need to be analyzed in longitudinal studies. This is due to the larger number of constructs that are measured at different points in time and the respective effects between those constructs [12]. PLS-PM is well suited to dealing with such complex models [8]; [27]. Thirdly, sample sizes can become quite small in longitudinal studies [13]. PLS path modeling is particularly appropriate in such cases [11]; [14]. There are many referenced review papers, in the literature, on the PLS approach to SEM [5], [10] and [21]. Recently, Lauro et al. [14] have presented some current developments in PLS-PM for the treatment of non-metric data, hierarchical data, longitudinal data and multi-block data.

3 Data and Analysis

The official data derive from the database of United Nation "Sustainable Development Goals" [1], they were mined in January 2021. The analysis was developed with reference to the European Community countries, including United Kingdom (left on 31 January 2020) over the 20-year period encompassing 2000 to 2019. Four thresholds were considered: 2000 (t_0), 2005 (t_1), 2010 (t_2) and 2015 (t_3); even 2019 (last

[1] https://unstats.un.org/sdgs/indicators/database/

year available) wanted to be included in the analysis but lacked data for almost all indicators, the last full year available was 2015. Considering that each indicators of the considered Goals have different units and values, for comparison purposes all units are first normalized to a value between 0 and 1, where 0 was assigned to the least wellbeing while 1 was the value assigned to the most wellbeing country for each indicators. Some variables are not considered because they are not available in the four periods considered and are not available for all countries. The scheme of theoretical model is shown in Fig. 1. The constructs have been created based on the

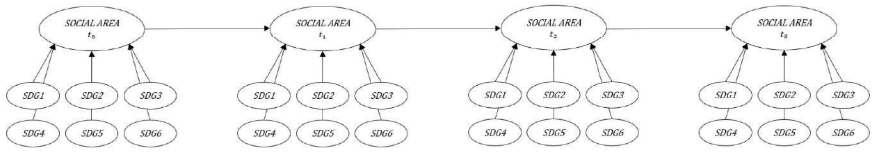

Fig. 1 Theoretical model

indicators at the three points in time. The study focuses on a formative measurement model and the XLSTAT software [2] was used for all the data processing and the PLS-PM. Any missing data was handled by using the NIPALS algorithm [26], while the path weighting scheme was chosen [10] for the model and it was estimated with a maximum of 1,000 iterations. The model, shown in Fig. 1, is a hierarchical model: the block "Social area" in the different time period is the Higher Order Construct (HOC) related to its concrete subdimensions (Lower-Order Components (LOCs)) represented by the six Goals. Different approaches have been developed and proposed in the literature [15]; [25] and [4]. In this work the HOCs have been estimated with the Mixed Two Step Approach [4]: in the first step the indicators of LOCs have been used as indicators of HOCs, and, after running the PLS-PM algorithm, the resulted scores of the blocks are used as indicators of the HOCs, and the PLS-PM algorithm is performed again.

Table 1 reports the main indices to test the overall model quality: R^2 coefficient, the Redundancy index, the Average variance Extracted (AVE) and the Goodness of Fit (GoF) indices. The R^2 coefficients show that the endogenous LV at time t is better predicted by the explanatory LV at the previous time *t-i*, while the values of the redundancy index are appreciably higher for all blocks (the value of 0,50 indicates a sufficient degree of construct validity). The prediction performance of the PLS-PM reflects the high quality of the constructs.

To test the significance of the path coefficients, the bootstrapping procedure was run [10]. Table 2 shows the effects of HOC block at t_1 to t_2 and t_2 to t_3 are positive and highly significant at p-value$<$ 0,001. Only one effect is not significant (t_0 to t_1).

[2] XLSTAT software Copyright © 2017 Addinsoft

Table 1 Overall model quality

Construct	R^2	Redundancies	AVE	GoF
Social Area (t_0)		0,703	0,705	
Social Area (t_1)	0,768	0,659	0,762	0,803
Social Area (t_2)	0,838	0,714	0,716	
Social Area (t_3)	0,821	0,737	0,737	

Table 2 Results of test of significance of the effects over time

Time	Effect	Path Coefficients	Standard Error	t-values	p-values
t_0/t_1	$SocialAreat_0 \rightarrow SocialAreat_1$	0,340	0,217	0,639	0,528
t_1/t_2	$SocialAreat_1 \rightarrow SocialAreat_2$	0,293	0,064	4,578	0,000
t_2/t_3	$SocialAreat_2 \rightarrow SocialAreat_3$	0,358	0,080	4,475	0,000

4 Conclusion

The aim of the work was to use the SEMs and especially Higher-Order PLS-PM as a valuable way to analyze longitudinal data of SDGs. In this analysis we take into account only the first six SGDs belonging to the social dimension of SDGs, due to the difficulty of reporting a detailed analysis of all 17 SDGs. The main research objective was to study the evolution of the effects between constructs of social dimension over time. The overall model quality indices reflect the high quality of the constructs and the path coefficients over time, after 2005, are positive and significant, effects related to the most important turning point in the evolution of sustainability, the Conference on SDG in Rio de Janiero in 2012, which had a very strong impact on the measurement of the indicators of the 17 SDGs. Only the first effect, from 2000 to 2005, results not significant, highlighting the fact that probably the MDGs, which started a global effort in 2000, did not have a strong social impact before 2005.

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