THE RELATIONSHIP BETWEEN STRUCTURAL EQUATION MODELING AND BALANCED SCORECARD: EVIDENCE FROM A SWISS NON PROFIT ORGANIZATION

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ABSTRACT

This paper studies the relationship between structural equation modeling and Balanced Scorecard in a Swiss non-profit establishment. Using financial and non-financial performance indicators collected directly from the organization, the paper proposes a rational construction and analysis of Balanced Scorecard by selecting the factual metrics for the right strategic areas. This choice is made by applying a sequence of Partial Least Squares in the proposed model. Furthermore, the approach establishes the cause-and-effect sequence originally defined by Kaplan and Norton as: the measures of organizational learning and growth will influence the measures of internal business processes, which, sequentially, will impact the measures of the customer perspective that, lastly, will affect the financial indicators. It will be noted that the Kaplan and Norton model of Balanced Scorecard is different from the findings in this study, a case somehow too general to handle today's complex market environment. Following this, the paper puts forward a time-managed approach to identify the evolution of the main contributors to the current company's strategy as well as their behavior in the future organizational performance. This approach will be applied and demonstrated in a detailed real case of a Swiss non-profit organization.

JEL: G39, M19, M40, L31

KEYWORDS: Balanced Scorecard, Key Performance Indicators, Performance Measurement, Structural Equation Modeling (SEM), Partial Least Squares (PLS), Principal Component Analysis (PCA), Non-profit Organization

INTRODUCTION

An innovative approach of strategic management was introduced in the early 1990s by Robert Kaplan from Harvard Business School and David Norton, co-founder and president of Balanced Scorecard Collaborative Inc., based in Boston, USA. They named this approach the Balanced Scorecard (BSC). Pinpointing some of the drawbacks and ambiguity of previous management systems, the BSC method proposes a coherent guidance as to what companies should measure in order to "balance" the financial perspective.The BSC summarizes a series of performance indicators that offers executives a quick but comprehensive representation of their business. The BSC includes financial indicators that illustrate the outcomes of actions already taken and it complements the financial measures with operational indicators on customer satisfaction, internal processes, and the company's innovation and development activities – "operational measures that are the drivers of future financial performance" (Kaplan & Norton, 1992).

However, one of the limitations of the BSC lies in its structure. Despite the fact that the authors provide us with some key points and describe the steps for building the BSC, the concepts are rather ambiguous and can be difficult to apply in an organizational environment. There are three main goals in this study. The first goal is to merge the above concepts and try to advance several statements for a representative construction of a BSC using the Partial Least Square (PLS) technique. The objective is to generate a realistic model that can be applied in any organization environment, thus modeling the concept of BSC. The second goal is to validate the assumptions with a nonprofit organization case where performance indicators selected will outline the different strategic perspectives, and a rational explanation for this selection is established. A cause-and-effect structure will be generated and clarifications made as to which strategic perspectives (latent variables) are influencing and which are to be influenced. One of the main conclusions of this example is that the Kaplan and Norton's model of BSC is nothing more but a particular case of our conclusions. The final aim is to closely monitor on a timely basis the upmost indicators that affected the organizational performance, indicators that will shape the future company's strategy.The paper is structured as follows.

In the next section, the main BSC concepts are presented and underlined from the specialized literature. The "idealistic" process of 4-axes construction is then highlighted followed by a logical structure allowing for the identification of the number of strategic perspectives as well as the performance indicators connected to each perspective. A tentative modeling of BSC that can be implemented in any organization environment is put forward. This is pursued by a real example of a nonprofit establishment in which the PLS method is applied in order to build a coherent BSC. Using this information, one will be able to better predict the future company trends and to take enhanced corrective measures to quickly adapt in a challenging and complex organizational environment. Finally, the paper will conclude with several comments and remarks that underscore the major outcomes of this work.

LITERATURE REVIEW

According to Kaplan and Norton, the BSC is a management tool (not only a measurement model) that enables companies to acknowledge their vision and strategy and convert into action. Consequently, the BSC allows top management a thorough compilation that translates the organizational strategic goals into a coherent set of performance measures. It provides response across the internal company processes as well as external results in order to constantly advance strategic performance and outcomes. When completely set up, the BSC converts strategic planning from an abstract task into the fundamental point of an organization. As mentioned by Fielden's (1999), companies worldwide start on influencing the ability of BSC for translating vision and strategy into measurable objectives. In fact, a recent study approximates that 60 percent of Fortune 1000 companies have tested the BSC (Silk 1998). Adopters involve KPMG Peat Marwick, Allstate Insurance, and AT&T (Chow et al. 1997).

The BSC can manage the base of the organization's efforts in identifying and communicating the crucial key interests to managers, employees, investors and even customers (Kaplan & Norton, 1993). With four strategic perspectives, the BSC reduce information excess by controlling the number of measures used and compels executives to concentrate on the handful of performance indicators that are most essential. Accordingly, it enables companies to contour financial results while simultaneously monitoring the resources and obtaining the intangible assets they would need for future development (Kaplan & Norton, 1996). The BSC poses managers with the facility to identify performance indicators that could accurately predict the wealth and health of an organization. By allowing the capacity to decode strategy in rapid and quantifiable actions, a BSC manages strategy in an organizational environmental and unveil hidden assets and information. Furthermore, by connecting both internal and external people with these strategies, recurrent learning and development can be achieved (Pineno, 2002).

The BSC asserts to recognize cause-and-effect links between the various constituents of an organization (Kaplan & Norton, 1996). From a practical perspective, this represents the essence of the balanced scorecard, enclosing result metrics and performance drivers, related together in a cause-and-effect relationship. In fact, the heart of the model is this hypothesis allowing measurements in non-financial domains to be utilized to forecast future financial performance (Nørreklit, 2000).

In the eyes of Bontis and al (1999), the BSC has three major benefits. First, it operates according to a straightforward and effectual logic, simple to be learnt by the executives. Second, it seeks to establish clear relationships between the financial performance and the indicators. Third, the topic literature is consistent, both theoretically and practically.

However, the BSC has a couple of drawbacks with some of its key assumptions and relations. Firstly, Nørreklit (2000) states that there is not a causal but rather a sound connection between the strategic areas analyzed. Furthermore, the author contends that customer satisfaction does not automatically create superior financial outcomes. Sequences of action that produce a high ratio of customer value at low costs will eventually lead to good financial results, but this is not an issue of causality; it is commonsense since it is integrated in the concepts. Consequently, the BSC makes illogical suppositions, which may conduct to the anticipation of incoherent measures, causing sub-optimal performance. In addition, the BSC is not a representative strategic management tool mainly because it does not certify any rapport between organizational and environmental reality (e.g. competition). As a result, a discrepancy must be accepted between the strategy formulated in the actions actually undertaken and the assumed strategy (Nørreklit, 2000).Kanji (2002) summaries further of the BSC weaknesses highlighting that the model is way too abstract and not easy to transform into a measurement model, the links between criteria are not clearly stated and, lastly, the causal relationships are problematic (more like interdependence).

Finally, Malina & Selto (2001) argues that the BSC is very complicated to put into practice. The authors make observations on how some aspects negatively influences opinions of the BSC and instigates important controversy and friction between the organization and its distributors. They further concluded that the metrics used in the model are biased or inaccurate, the communication about the BSC is strictly top-down (i.e., one-way and not participative) and the benchmarks are inappropriate but employed for assessment.

The Need for a New Validation Approach

Within this broad-spectrum environment of ambiguity and criticism, some authors (Shields, 1997; Shields & Shields, 1998) have called on management accounting researchers to make better use of Structural Equation Modeling (SEM). Structural Equation Modeling is a statistical technique comprising a family of different methods (path analysis, Partial Least Squares models and latent variable SEM) that allows the simultaneous analysis of a series of structural equations. However, there appears to be some consensus that all SEM involve two characteristics: first, the estimation of multiple interrelated dependent relations between variables, and second the ability to represent latent variables in these equations while accounting for estimated measurement error connected to the unsatisfactory measurement of variables. These methods are particularly helpful when a dependent variable in one equation turn into an independent variable in another equation (Hair et al., 1998).

An essential concern to log is the need of a significant sample size for the majority of SEM models. A suggested rule of thumb for latent variable SEM is a minimum sample size of 100 (Medsker et al., 1994). Furthermore, it has been advised that a sample volume of 200 may be required to produce valid fit measures and to prevent making inaccurate conclusions (Marsh, Balla, & McDonald, 1988; James & James, 1989; Boomsma, 1982; Medsker et al., 1994). In spite of these concerns, Smith and Langfield-Smith (2004) conclude in one of their management studies that eleven of the 20 surveys (55%) had sample volumes beneath the accepted threshold of 200. Even if the recommended sample size of 100 is considered the lowest bound of tolerability, three of the 20 researches (Magner, Welker, & Campbell, 1996, Chalos & Poon, 2000, Abernethy & Lillis, 2001) fall underneath this level, denoting that the conclusions drawn from these studies could be questioned.

As a result of that, management accounting researchers may be restrained from using covariance based methods caused by the significant sample size requirements, and puts forward the statement that the technique is only appropriate in areas where theory is relatively robust. Despite the fact that these shortcomings are true for latent variable SEM techniques, Partial Least Squares (PLS) modeling presents an alternative.Compared to others, PLS regression is a fairly recent technique that generalizes and merges features from principal component analysis (PCA) and multiple regressions. It is specifically useful when require predicting a series of dependent variables from a (very) large sequence of independent variables (i.e., predictors). It was employed in the social sciences (specifically economics, Herman Wold 1966) but became popular first in chemometrics (i.e., computational chemistry) due in part to Herman's son Svante, (Geladi & Kowalski, 1986) and in sensory evaluation (Martens & Naes, 1989). However, PLS regression is also becoming an alternative in the social sciences as a multivariate method for non-experimental and experimental data alike (neuroimaging, see Mcintosh, Bookstein, Haxby, & Grady, 1996). It was first pioneered as an algorithm similar to the power method (used for calculating eigenvectors) but was rapidly retained in statistical milieu (Hervé, 2003).

The usage of PLS, despite of its intrinsic limitations (specifically that it is a limited-information method, aimed to maximize prediction, rather than fit), figures out to be a way in which statistical modeling in management accounting research can move forward without the requirement to obtain large samples, something which management accounting researchers have usually found problematic. Another benefit of PLS is the method's ability to accommodate non-normal data, triggered by less demanding assumptions behind the technique (Smith & Langfield-Smith, 2004). Nevertheless, there is some misunderstanding in the terminology utilized in the PLS field. Herman Wold first introduced the notion of Partial Least Squares in his study about principal component analysis (Wold, 1966) where the NILES (nonlinear iterative least squares) algorithm was developed. This algorithm (and its extension to canonical correlation analysis and to specific situations with three or more blocks) was afterwards called NIPALS (nonlinear iterative partial least squares) (Wold, 1973; Wold, 1975). The notion of "PLS approach" is somewhat too broad and combines PLS for path models on one side and PLS regression on the other. Following a suggestion by Martens (1989), this study exploits the term PLS for Structural Equation Modeling to designate the use of "PLS Path Modeling" as illustrated in Figure 1.

Relationships between the observed variables and the latent variables (outer model) Each latent variable ξ_j is implicitly explained by a group of observed variables x_{jh}. Each observed variable is related to its latent variable by a simple regression:

$$x_{jh} = \pi_{jh0} + \pi_{jh}\xi_j + \varepsilon_{jh} \tag{1}$$

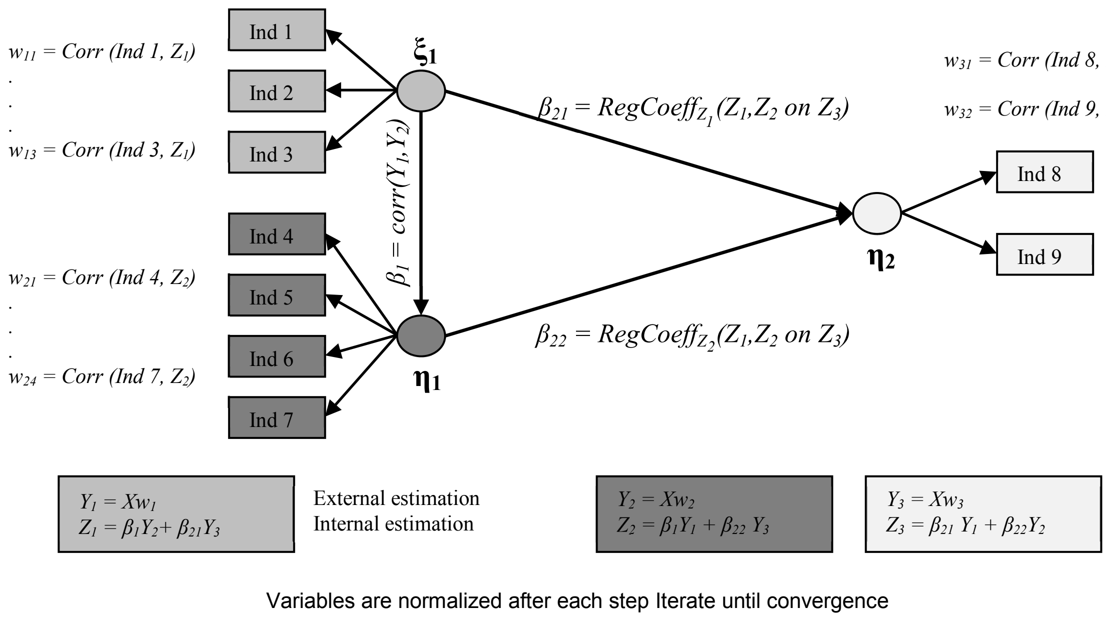
Relation between the latent variables (inner model)
The causality model leads to linear equations connecting the latent variables:

$$\xi_j = \beta_{j0} + \sum_i \beta_{ji}\xi_i + v_j \tag{2}$$

The latent variables related to ξ_j are divided into two categories: the precursors of ξ_j which are latent variables affecting ξ_j and the successors which are latent variables affected by ξ_j.

For any precursor ξ_i of the latent variable ξ_j, the inner weight e_{ji} is equivalent to the regression coefficient of Y_i in the multiple regression of Y_j on all the Y_i's connected to the precursors of ξ_j. If ξ_i is a successor of ξ_j then the inner weights e_{ji} is equivalent to the correlation between Y_i and Y_j (Tenenhaus & Vinzi, 2004).

Figure 1: Example of PLS Path Modeling



Above figure describe the two key relations found in any PLS path model: a first one named the outer model, illustrating the connections between the latent variable and its manifest variables and a second one called the inner model defining the relationships among the latent variables themselves.

The available software has been for many years LVPLS 1.8 developed by Lohmöller (1987, last existing version). Lohmöller has broadened the basic PLS algorithm in numerous ways and published all his research outcomes in 1989. More recently, updated software have been elaborated by Wynne Chin (2001, for the last version) entitled PLS-Graph 3.0 and Christian Ringle labeled SmartPLS. Besides the user-friendly graphical interface to PLS, the algorithm has been further refined and improved with major options being added, like cross-validation of the path model parameters by jack-knife and bootstrap amongst others.Bootstrapping is the technique of gauging components of an estimator (for example its variance) by measuring those aspects when sampling from an estimating distribution.

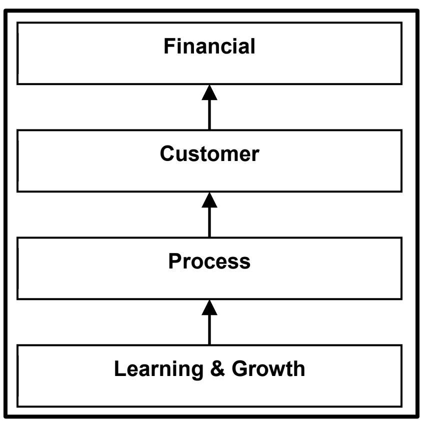
One typical option for computing distribution is the observed distribution of the empirical dataset. In the situation where a group of observed variables are assumed to be from an identically and independent distributed population, this can be solved by creating a number of resamples of the observations (and of same size of the observations), each of which is achieved by random sampling with replacement from the initial set of data. The benefit of bootstrapping compared to analytical techniques is its high simplicity - it is significantly easy to use the bootstrap in order to find estimates of standard errors and confidence intervals for complex estimators of the distribution, such as percentile points, proportions, correlation coefficients and odds ratios. However, even if more, newer and more complex PLS programs are available today (e.g. SmartPLS), a greater examination of the PLS Path Modeling permitted us to develop our own software from scratch with the aim of computing the principal component analysis, path weighting scheme and the bootstrap validation procedure with one tool.

Bonding Balanced Scorecard with Partial Least Squares

Ittner and Larckner concluded in 1998 that "(...) decisions using multicriteria performance measurement systems should be computed using explicit, objective formula that prescribes the weights to be attached to each measure, or should be based on subjective evaluations where the weights to be attached to each measure is implicitly or explicitly chosen by the decision maker". This should be always considered when building, checking and validating assumptions of causality relationships between the performance indicators within the context of the BSC implementation in a company. While this might seem difficult from a practical perspective, the PLS technique offers a valid solution.

As shown in Figure 2, the initial statements of causality relationships between the four strategic perspectives of the Kaplan and Norton's BSC remain subjective. The use of a structural equations model is recommended to establish, in a more objective way, the intensity of the relations between the latent variables defined by groups of observed or measurable indicators. Indubitably, whereas the choice of the perspectives and the hypotheses that link them remain biased in the case of Kaplan and Norton, the model of structural equations aims "to provide a meaningful and parsimonious explanation for observed relationships within a set of measured variables" (MacCallum, 1995).

Figure 2: Generic Relationship Map (Kaplan and Norton 1996)



This figure illustrates the original cause-and-effect chain as defined by the Kaplan and Norton (1996), starting from the learning and growth perspective that will affect the measures of internal business processes which sequentially will influence the measures of the customer perspective which, finally, will affect the financial area.

In a structural equations approach the latent variables cannot be assessed in a direct and precise way. Consequently, these latent variables require measurable variables, which are described through performance indicators that can be directly observed and evaluated. The structural equations method is derived from the principal component analysis of the data (confirmatory or exploratory, in line with each specific case) to distinguish and validate the model of the causal relationships which represent the focal point of BSC. It is essential to highlight that one of the restrictions intrinsic in the application of a system of structural equations in the BSC milieu, are the statistics requirement expected for the data validation, which compels a significant quantity of observations in order to validate the results achieved. The gathering of a large series of data is not easy, particularly in small and medium-sized firms. This is why the use of PLS presents a huge benefit in this particular case or in any case where large datasets are not available.

A Pragmatic Case: Example of a Non-Profit Organization

The suggested method of this study, although universally applicable to any kind of organization, is presented using an example of a non-governmental and non-profit institution. Based in Geneva, Switzerland, this international governmental organization has associative statute active at multinational levels in the field of human rights protection. Devoted to the primacy, the coherence and the application of the international law and the principles that make progress in the human rights field, the association is joining the national and international lawyers, offering their competences in regards to legal expertise for promotion and defense of the previously mentioned rights. The organization has branches in regional offices of Thailand, Nepal, Guatemala and South Africa and is employing a total of around 40 people.

When fully implemented, the proposed method for BSC construction using PLS approach will allow the following: 1.) Identifies the vision and strategy by highlighting the crucial performance indicators. The stress is laid on the fact that financial measurements must be "balanced" with non-financial measurements, coming from other strategic perspectives, 2.) Helps retaining only the key performance indicators dependent on the objectives of the strategic perspectives, while seeking to define the sequences of actions that ultimately create the success of an organization. 3.) Once the strategy and key actions are seized, the organization defines its crucial competences, essential to the development and the improvement of the processes relative to its strategic success. 4.) Finally, it permits the construction of a BSC adapted to the various hierarchical levels, while fixing of short and long-term objectives for the various key indicators.

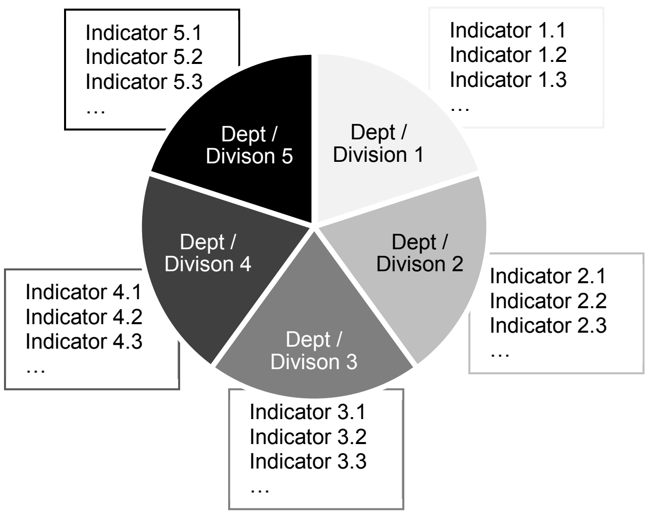
In a nutshell, there are five chronological main steps proposed in this study, at the end of which will allow the construction and implementation of a rational and optimal BSC: (1) gather historical data from the organization, (2) organize and prepare the final database, (3) ascertain and define the numbers of strategic perspectives and performance indicators connected to those, (4) assemble the cause and effect link between all strategic perspectives and, lastly, (5) employ and operate this management tool for long-term planning. As showed in Figure 3*, the first step* is associated with the collection of all historic key performance measures throughout the organization. Even though this seems a simple assignment, it actually entails a massive time gathering the metrics employed in the institution, particularly building a valid historic database. This exercise is crucial and will directly affect all of the following steps. Applying this step in the selected organization resulted in a total of 54 variables summarizing their evolution over 12 periods on a quarterly basis (3 years).

Taking into account the sizeable database of indicators, *the second step* is related to the final cleaning of the database (Table 1). As stated previously, the collected measures could contain errors and will potentially pollute the findings. Consequently, the variables should be characterized by (a) reliability and consistency, (b) same occurrence in time, (c) ability to capture a fraction of the organizational current strategy, (d) information singularity and (e) clarity and straightforwardness. This step is achieved through consistent analysis and intense top management consultations and will ensure that the retained performance indicators are the key drivers of the organization. After this step only 48 variables from the non-profit organization have finally been kept.

However, albeit this rational managerial selection has been employed, the company still has a large database, which is quite challenging to administer for the BSC construction. As illustrated in Figure 4, *the third main step* is to filter and congregate the variables within specific axes (or strategic perspectives) able to encapsulate a part of the organization's performance.There are three main attainments in performing this step: first is to generate the number of strategic axes summarizing an acceptable level of the total company's performance, second is to filter each axis and retain only the performance indicators that are highly correlated, disregarding any unnecessary and irrelevant information and, third is to label these assemblies of indicators by studying the nature of information that gravitates each strategic perspective or axis.

Several existing statistical methods are able to accomplish this classification. Both factor analysis and principal component analysis (PCA) can be applied for this step. Although different, the two techniques are often mixed up, though factor analysis becomes equivalent to PCA if the "errors" in the factor analysis model are supposed to all have the same variance. Principal component analysis can be used for dimensionality reduction in a dataset by preserving those characteristics of the data that influence most its variance and by keeping lower-order principal components and disregarding higher-order ones. Such low-order components regularly summarize the "most important" features of the dataset. Factor analysis on the other hand, is a statistical technique employed to describe variability among analyzed variables in terms of fewer unobserved variables called factors. Factor analysis assists in identifying "factors" that explain a diversity of results on distinct tests.

Figure 3: Identifying and Gathering Company's Performance Measures



Above figure shows an example of an organization with its various departments or divisions. After a careful analysis all performance measures will need to be identified and subtracted with the help of the main business owners.

Table 1: Example of Cleaning and Setting Up the Final Database

	Strategic Performance Indicators Database				
Time series	**Ind 1.1**	**Ind 1.2**	**Ind 1.3**	**…**	**Ind zz.yy**
Month 1	x	x	x		x
Month 2	x	x	x		x
Month 3	x	x	xxx		x
…		x	x		x
Month n		x	x		x

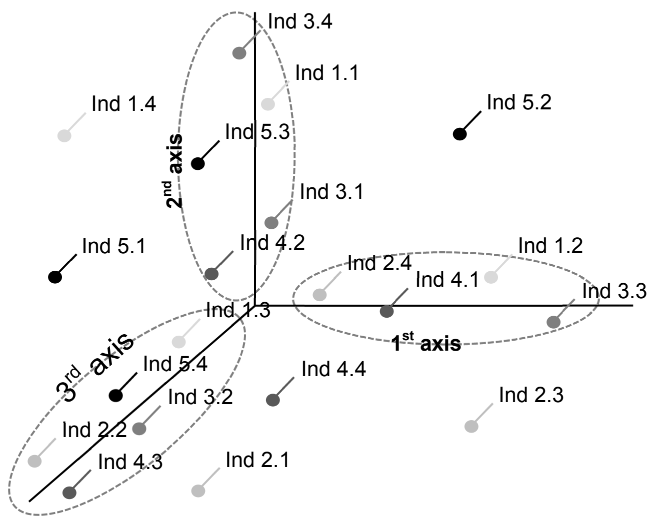
Missing variables

Unreliable variable

This table exemplifies the cleaning of the database, where one performance indicator contains several missing values and another one that have unreliable data (e.g. due to a change in the measurement or the re-definition of the variable). These kinds of indicators should either be corrected (if possible) or, otherwise, completely excluded from the final database.

As such, the PCA fits better this study requirement, as it is appropriate for a non-predefined experimental model, while factor analysis is righter for models that have already a standard. As the statistical technique applied (PCA) is handling historical data, the outcome of the actual research will subsequently be contingent on the data obtainable at the time of collection. Nevertheless, the purpose of this model is not to build the best indicators, which sometimes could lead to subjectivity and personal preference, but to actually emphasize the significance of the variables available.

Figure 4: Filtering the Performance Measures per Strategic Perspectives



Above figure illustrates the three main achievements in performing this third step: 1) generate the number of strategic axes (example shows 3 perspectives), 2) filter and retain only the performance indicators that are highly correlated (illustrated by the circles seizing only the relevant variables) and 3) label the groups of indicators by analyzing the information that gravitates each strategic perspective (for the sake of clarity the perspective names have been kept as 1st, 2nd and 3rd axis).

The software applied for the PCA calculation was SPSS. In the presented example, when this step is conducted over the whole variables, one can clearly observe that with four components, approximately 93% of the total organizational variance is explained (Table 2). This percentage can be interpreted as the influence of the axes on the total performance: the higher this percentage, the more explanation it provides on the company's performance.

Table 2: Extract of Total Variance Explained

Component	% of Variance	Cumulative %
1	24.26	50.53
2	11.97	75.46
3	5.78	87.51
4	**2.76**	**93.26**
5	1.37	96.12
6	0.80	97.79

This table shows the extract of the first six components cumulating a total of 97.8% of the organization's variance. However, with only four components and a total variance explained of 93% it is assumed to be sufficient to extrapolate to the total variance of the company.

The same PCA technique also provides the influence of the variables (indicators) against each of these four axes with the assistance of the component matrix establishing the correlation of all variables with each of these axes. Table 3 illustrates the correlation of the first 10 variables with each axis. The nearer a correlation is to zero, the less the corresponding variable influences the axis. Finally, the variables will be ranked and filtered with respect to the correlation is has upon the axes.

The first 10-15 indicators per axis are favored for selection, ranked by their correlation with the axis. First, these metrics offers a good outlook on the information clustered and second, because the indicators are sorted by correlation, their explanatory value will decrease when moving further in the ordered list. One may note that this straightforward selection will congregate the performance measures that are particular to one area of the company. To be precise, a simple mathematical clustering will distinguish the actual areas specific to the institution. The ranking and grouping of variables by axis will permit to label and define them strategically.

Table 3: Extract of the First 10 Indicators from Component Matrix

VAR no.	VAR name	1st axis	2nd axis	3rd axis	4th axis
VAR001	persofindetr	0.886	-0.259	0.324	-0.182
VAR002	persoju	0.765	-0.310	0.454	-0.257
VAR003	persoadmin	0.968	-0.153	0.092	-0.050
VAR004	arrivé	-0.021	-0.280	-0.098	-0.750
VAR005	départ	-0.192	0.134	-0.678	0.632
VAR006	agemoy	0.649	0.586	-0.109	0.288
VAR007	ho	0.902	-0.285	0.270	-0.073
VAR008	fe	0.799	-0.199	0.390	-0.348
VAR009	expeant	-0.221	0.273	-0.460	0.666
VAR010	formation	0.318	-0.521	0.567	-0.392

This table displays an extract of the first 10 performance indicators (out of the total 48 from the final database) with their respective correlation with each of the four components (or axis).

Statistically speaking, the top ranked indicators are highly correlated to the respective axis. However, after the PCA analysis, one still needs to do a rigorous analysis of the data and eliminate and/or replace those measures that would not adequately explain the definition of the perspective. While this procedure it is not mathematically validated, it is primarily aimed to clear out certain metrics that would violate the definition of the axis. The rejection or replacement of any indicator must be well justified in front of the strategy for defining the strategic axes. In any economic environment (which by definition is uncertain), it is improper to consider that all indicators correlated to the perspective in cause are also representative from a strategic viewpoint. Those indicators that do not describe the definition of the axis should not be selected in the final model as these might potentially corrupt the final result.

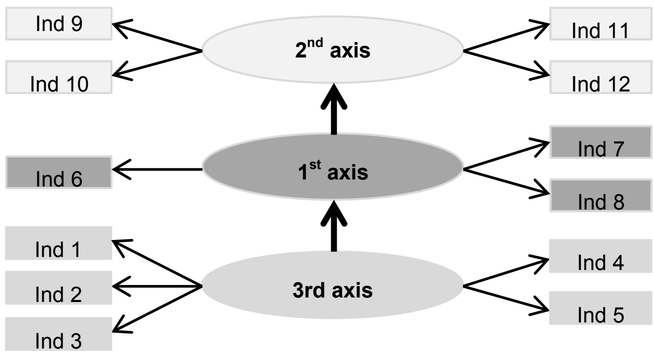
With the intention of better controlling and comprehending the final model and in order to maintain certain accuracy on the strategic perspectives, the final number of indicators per axis should rarely exceed 10. At the end of this third step, the organizational strategy from the presented example was acknowledged to gravitate along four perspectives: Regional Representation, Financial Perspective, Quality Perspective and International Law and Protection each of them containing 6 to 10 explanatory variables as described in the next step.

As exemplified in Figure 5, the *fourth major step* in ascertaining the actual strategy of the company is to employ a PLS Path Modeling regression on the final strategic perspectives. To determine the most viable cause-and-effect chain between the perspectives, all possible valid connections between these axes should be studied. The most stable PLS model from all possible combinations is regarded as the closed to the organization's current strategy. The stability of the PLS model could be assessed applying a bootstrap technique on each possible graph.

Applying this step to the specific example of this study, all possible valid connections between the four axes, that is to say a total number of 52'720 possibilities were examined with the in-house created software and the most stable PLS graph was chosen from all valid combinations represented in Figure 6. This assembly is the optimal structure of connection between the four axes and turns out to be more realistic than any other model - the closest to the actual organizational strategy.

This assembly is the optimal structure of connection between the four axes and turns out to be more realistic than any other model - the closest to the actual organizational strategic vision. This representation shows that the angular stone of the strategy is characterized by the Regional Programs, which, in turn, influence the financial health of the organization. The financial perspective affects at the same time the general quality of work as well as the whole of the "International Law & Protection" Program. In order to seize what these three bonds contain, we will study successively the causes suggested by the graph above. The objective is to briefly try to foresee what comes out from these causals connections.

Figure 5: Exemplification of a Cause-and-effect Chain Using PLS Path Modeling



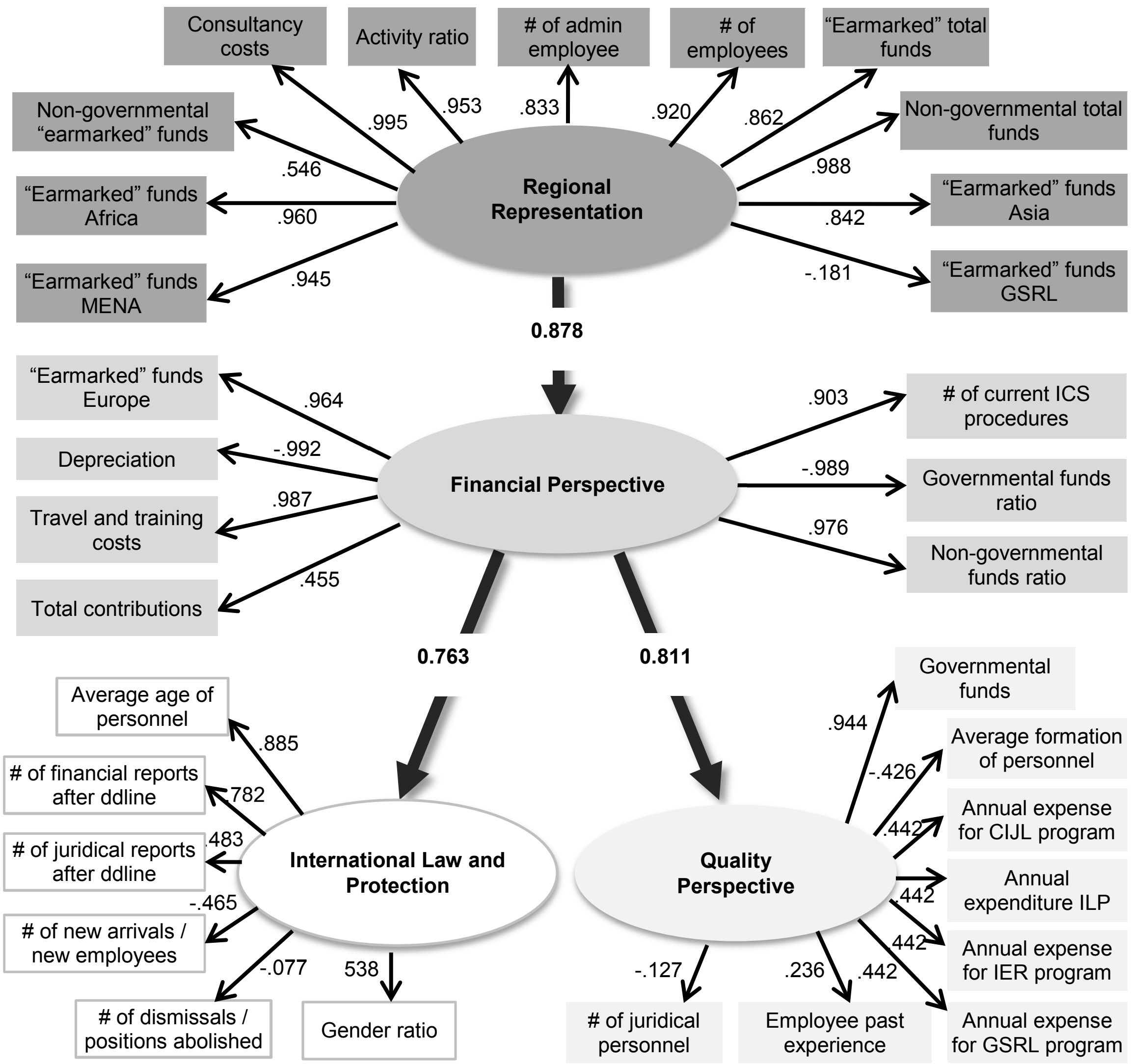
This figure illustrates 3 strategic perspectives together with their respective performance indicators linked in a cause-and-effect chain. The reason why the order of the axes is different is to show that after the bootstrap technique is finalized, the optimal model sequence might be altered.

The diagram emphasizes a capital element by spotlighting the Regional Programs. Indeed, we find among the variables which define this axis the nongovernmental funds under all its aspects: nongovernmental funds, nongovernmental restrictive funds (earmarked), total restrictive financing (earmarked), as well as the funds specifically intended for Asia, Africa and MENA. Consequently, we tend to believe that these programs are at the origin of the financial performance of the organization. In addition, since the causal links are one-way, activities of the regional programs can only be the subject of auto-financing and therefore the activities are not covered by any formed of organizational reserve.

Since the contributions for the Regional Programs are higher than the expenditure needed within the framework of their activities, it is perfectly obvious that are actually contributing to reserves of the organization. The reason why the Europe is attached to the Financial Perspective and not to the Regional Representation where one would see fit is that the principal activities as well as the headquarters are based in Geneva. This region is mainly seen as a support area rather than a "fundraiser" one.

Applying the logic further, the accumulated reserves can fund and support the International Program "ILP" as well as the Quality area. This is explained by the fact that the organization is characterized by a very high reputation and quality of the work. The education level of the personnel coupled with related expenditure is therefore essential. Contrary to the initial model of Kaplan and Norton (1992), the quality perspective does not influence the customer satisfaction, which, in fine, affects the financial area of the organization. This is indeed true as funds raised from various regional projects are not dependent on the overall outcomes of the organization. Or, in other words, the International Program "ILP" is financed in an organic way (bond between the financial health and the International Program), in order to provide a form of results which do not produce any "return on investment" (bond between the financial health and quality).This can be explained by two factors: 1) the quality of the work provided by the organization is already over and above the required standard and/or 2) the quality of the work is not important in the stakeholders' eyes (contributors). Whatever the cause, this last conclusion needs further investigation from the management side, especially that the current strategy is considered as problematic. It should be also noted that any management tool is usually needed to be implemented in a period of transition and important changes within the organization.

Figure 6: BSC's Cause-and-effect Chain Using PLS Approach (with 12 Quarterly Periods)



Above illustration represents the optimal structure of connection between the four strategic perspective and turns out to be the closest to the actual strategy of the organization. This final assembly has been selected from all possible connections using the bootstrap technique, being the most stable PLS graph.

When it comes to model validation from a statistical point of view (Table 4), the overall figures are assessing appropriately both measurement (outer) and structural (inner) model. As a general rule of thumb, in order to validate the outer model (measurement model), the Average Variance Explained (AVE) should be above 0.5 (Chin, 1998) and Composite reliability greater than 0.6 (Werts, Linn, and Jöreskog, 1974). Although all figures are exceeding the required threshold, one should note the borderline for Quality Perspective. While this perspective is perfectly validated, the low value will demand for a closer investigation together with the business of the measures that are building this block.

As for structural (inner) model validation, the best gauge to use is the R-square level. Values of 0.67, 0.33 and 0.19 are considered to be strong, moderate and respectively weak for the inner model valuation (Chin, 1998). The R-square have acceptable values for ILP Program as well as for the Quality Perspective, even very close to the highest acceptance threshold. Furthermore, for the Financial

Perspective one can remark a strong significance, materializing the conclusion that all values are validating in a satisfactory way our model.

Table 4: PLS Model Validation Criteria

	AVE	Composite	R-square	Redundancy index
Regional Representation	0.728	0.939		
Financial Perspective	0.834	0.821	0.770	0.641
Intl. Law and Protection	0.656	0.844	0.582	0.464
Quality Perspective	0.540	0.785	0.656	0.333

The table is summarizing several validation criteria for the selected PLS graph. The AVE and Composite reliability are used for the measurement model validation (or the outer model, that is to say the relationships between the latent variables with its observed variables) and the R-Square and Redundancy index are employed to validate the structural model (or the inner model, thus the relations between the endogen and exigent latent variables)

As stated in the beginning of this study, the inner and outer relations are based on structural equations. Hence, behind each PLS Path model lies equations that supports the relations between indicators and the corresponding axis (outer model equations) and between the axes or strategic perspectives themselves (inner model equations). The *fifth major step* is consequently based on applying these equations in order to study and forecast the relations for the long term. From a practical point of view, there are substantial advantages in doing that: a.) analyze the variance impact of one (or several) indicators to the whole model; b.) forecast the strategic changes by looking at the relationships between the axes; c.) visualize and manage both direct and indirect changes needed for an important change in the company‘s strategy; d.) simulate the impact of resources allocation decisions on the future performance, thus complementing the traditional budget approach;

However, one should keep in mind that an organization takes time in order to recalibrate to any change or crisis situation. Any change in the company’s strategy should be done in a pondered and controlled way. Moreover, it should be noted that a non-profit organization cannot be revolutionized or radically transformed as a commercially-driven company might be.

DATA AND METHODOLOGY

The data has been collected with the help of the Corporate Strategy Head ensuring high quality and reliable data. A total of 54 performance indicators have been gathered throughout the organization summarizing their evolution over 3 years on a quarterly basis. The crucial part in the proposed methodology is the selection of the number of axes and of the corresponding performance indicators. It is essential that the key performance indicators describe to a certain extent the strategy of the organization. Unquestionably, the strategy metrics differ among organization, especially among different sectors (e.g. profit vs. non-profit).The first cleaning of the initial database was jointly done with the business owners and under the guidance of the Corporate Strategy Head. After this first sift, only 48 key performance indicators have been kept in the final database.

In order to find the number of strategic perspectives and to filter all performance indicators per each axis, the principal component analysis (PCA) has been applied over the final database using SPSS software. After the final selection and grouping of indicators, in-house software (PLS Assistant) has been applied for the PLS Path Modeling. The software is capable of assessing the most stable PLS graph by applying the bootstrap technique to each possible arrangement and connection between the latest variables (strategic perspectives in our case). Finally, the data has been validated using several measures widely employed in the PLS specialized literature: AVE and Composite Reliability for the outer model validation and R-Square and Redundancy Index for the inner model validation.

FINDINGS

The main objective of this study was to put in debate the Kaplan and Norton BSC theory compared to a more pragmatic approach. Having founded the strategic research framework, we attempted to empirically validate the proposed model by developing a strategic map in the context of a Swiss nonprofit organization. The results obtained indicated that the BSC problems can be formalized in a more rigorous way. It is thus possible to reassess the notions progressed by Kaplan and Norton as exposed in the analysis of this case. The application of PLS Path Modeling translates the actual strategy into a cause-and-effect model that can be monitored and controlled using a handful of essential performance indicators. One might debate that by treating historical data, the model summarizes obsolete information by illustrating a picture that cannot be utilized to influence the future planning. While this assumption is legitimate, the model is actually identifying the actual strategy applied by the organization. Only by fully acknowledgement of the current situation one can plan for the period to come. As suggested in this paper, as the PLS regression is more suited for maximizing prediction, the model is also capable of portraying the forecast strategy of the company. Furthermore, this approach allows the simulation of the resource allocation impact on the company's overall performance.

Lastly, it should be noted that these management tools are applied in a moment of a significant need for strategic change in the organization. The use of this approach allows not only understanding the chain of causality between different strategic areas of the company's performance, but also reinforces the intuition with “a measure of the measures”.

It should be stressed that the necessary conditions are relatively constraining. It is essential to have an adequate number of indicators together with a consistent historical sample of data. Furthermore, the noted real value of BSC lies more in the diffusion and the comprehension of the strategy on all the levels within the company. Thus, this requires strong communication, interpretation and analytical skills.

Whereas we aimed and struggled to have the highest objectivity in our methodology, both for data collection and data analysis, it might be that some variables have been biased by personal views. Indeed our approach can be impartially applied, however in practical terms we noticed that a level of flexibility should be taken into consideration, level that cannot be mathematically proven or admitted. The threshold depends on the organization culture and the people one in interfering with at the time of the analysis.The Partial Least Square (PLS) technique will likely grow in usage in the upcoming period, as it is considerably less difficult to understand than the covariance-based techniques when it comes to identifying a model and explaining of results. However, disadvantages of PLS contain greater complexity of explaining the loadings of the independent latent variables and since the distributional characteristics of estimates are not acknowledged, the researcher cannot assess model significance with the exception of bootstrap induction. In addition, being quite a novel statistical technique, there are few universally accepted thresholds for the model validity and stability up to now. Nevertheless, we have applied the small number of tools available for PLS Path Modeling approach, tools commonly utilized in other PLS studies found in the specialized literature.

Based on the findings from our study, further research may aim for a much higher degree of both complexity and dynamism. The more insights that are gained into the “mechanics” underlying performance, the more the individual models in framework proposed can be developed.It would be beneficial to apply our research framework to other industries or countries. The framework could be particularly useful for analysis of other industries such as media, telecommunications or high tech. More and more industries are characterized by a truly changing and challenging environment. It is time, to replace simple tools with a more realistic approach to analyzing performance in such environments. A comparison of the results of such an analysis with the findings of the present study could conduce to a higher validity and generalizability of the approach.

Another interesting path to follow would be to apply the structural equation in order to predict the future trend of the company, at time T+1, T+2 and so on and so forth. This will complete the analysis in a full and comprehensive framework that will present ways to improve the company performance. We are convinced that this will provide the manager with the optimal tool to assist him in piloting the organization.To conclude, we believe that it is relevant to develop a more formal methodology in order to validate the company's strategy in a rational way, while using a simplified model. Indeed the PLS method suffers from a deficiency of theoretical foundation. Similarly, Kaplan and Norton's approach was strongly criticized in the specialized literature from this point of view as well. The difficulty with which future researchers will be challenged lies in the compromise between the pragmatism sought by the organizations and the need for the theoretical framework required by scholars.

CONCLUDING COMMENTS

The research aim of this paper was to elaborate and empirically validate an inclusive framework that channels Balanced Scorecard model with Structural Equation Modeling approach and endorses a modern comprehension of factors underlying the current strategy, in order to better manage and control the corporate performance.

The essential step towards this goal was the development of a general frame of reference that harmonized previously conflicting theoretical assumptions related to Balanced Scorecard as well as its ease of implementation. On this basis, the proposed framework is embracing several major concepts: 1.) addresses the issues of strategic vision of any organization and translates the actual strategy into an easy-to-use model for better integration, communication and long-term management; 2.) underlines the key performance indicators that have the ability to seize the most relevant information from the company, information that is strongly connected to the current objectives the organization is aiming for; 3.) compiles distinctive strategic perspectives that summarizes company information in a suitable way, in order to create a comprehensive illustration driving organizations in their road to success; 4.) determines the relationships between strategic perspectives in a cause-and-effect chain that highlights the interactions taking place at a strategic level, helping in spotlighting the company's advantages and weaknesses; 5.) overcomes the static feature of previous models revealing the dynamic evolution over time by employing mathematical PLS equations, refining the planning and control of the main constituents within an organization.

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