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Designing Strategy Maps of Balanced Scorecard by using Structural Equation Modeling

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Abstract

Through 1980s, management accounting researchers described the increasing irrelevance of traditional control and performance measurement systems. The Balanced Scorecard (BSC) is a critical business tool for a lot of organizations. It is a performance measurement system which translates mission and strategy into objectives. Strategy map approach is a development variant of BSC in which some necessary causal relations must be established. To recognize these relations, experts usually use experience. It is also possible to utilize regression for the same purpose. Structural Equation Modeling (SEM), which is one of the most powerful methods of multivariate data analysis, obtains more appropriate results than traditional methods such as regression. In the present paper, we propose SEM for the first time to identify the relations among objectives in the strategy map, and a test to measure the importance of relations. In SEM, factor analysis and test of hypotheses are carried out in the same analysis. SEM is known to be better than other techniques at supporting analysis and reporting. Our approach provides a framework which permits the experts to design the strategy map by applying a comprehensive and scientific method together with their experience. Therefore, this scheme is a more reliable method in comparison with the previously established methods.

Keywords : BSC; SEM; Strategy map.

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1 Introduction

Limitation of financial data as the basis for decision making in organizations has been recognized for a long time [8]. Furthermore, the utility of non-financial data to improve

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the decisions has been understood [22].

This information led the researchers of the management field to focus on the increasing irrelevance of traditional control and performance measurement systems. Many researchers have tried to find a comprehensive performance measurement system. Kaplan and Norton (1992) invented the Balanced Scorecard (BSC) that has become both well known and (in various forms) widely adopted [15]-[32]. According to the research study conducted by Kaplan and Norton in 1990, the BSC can act as a critical business tool for many organizations [27]. It is developed to communicate the multiple linked objectives that modern companies must achieve to compete on the capabilities. BSC has at least the following attributes (see [22], for details):

1. A mixture of financial and non-financial objectives [15].
2. Assigning measures to specific strategic objectives – usually illustrated in tables with one or more measures associated with each objective [15, 16].
3. A limited number of measures, numbering between 15-20 [16, 17].
4. Clustering objectives into the following list of four perspectives:
    (a) Financial
    (b) Customer
    (c) Internal process or internal business process
    (d) Innovation and learning or learning and growth [15, 16, 17, 18].
5. Representing causality [17, 18].

However, the last attribute of BSC is a little ambiguous, i.e., in Kaplan and Norton's work , the reader is referred to their earlier papers in 1992 and 1993 for the link between the above-mentioned perspectives [22] and they do not discuss these links in the text. In the mid-1990s, BSC documentations graphically revealed the relations among strategic objectives themselves (rather than the measures) and causality linking across the perspectives toward key objectives relating to financial performance [22]. The linkage as occurring among measures and strategic objectives is illustrated in [17, 18], respectively. At first, diagrams showing linkages among objectives were called "strategic linkage models," but more recently they have been called "strategy maps" [19, 20]. The strategy map enables managers at each level of the organization to specify scorecards that describe the strategy as a set of cause-and-effect relationships that can be tested and adjusted [1]. It has been emphasized that designing the strategy maps with clearly established causal links leads to cascading the understanding of strategy down through the organization. Therefore, all employees are aware of strategic intent and the impact of operational activities upon its delivery [10]]. To clarify the meaning of a causal model, in what follows, we examine an example which is given by Kaplan and Norton, 1996. Assume that we increase employee training in products, then they will become more knowledgeable about the full range of the products they can sell. If employees are more knowledgeable about products, then their sales effectiveness will improve, and if their sales effectiveness improves, then the average margin of the products they sell will increase. Such if-then rules can be considered by causal relations of a BSC mapping to tell the story of the strategy in a way that is meaningful.

Some researchers, such as Malmi [25], explicitly stated that measurement systems without cause-and-effect logic may also qualify as BSCs; however, a great number of authors consider cause-and-effect chains as a defining characteristic of the BSC concept [16, 23], e.g., Atkinson interpreted Kaplan and Norton's cause-and-effect logic as the ***essence*** of their approach [3]. Norreklit [28] writes: "The cause-and-effect chain is central to the BSC. The chain distinguishes the model from other approaches." Moreover, Hoque and James [12] argue: "The use of a BSC does not mean just using more measures; it means putting a handful of strategically critical measures together in a single report, in a way that makes cause-and-effect relations transparent."

In the past ten years, the BSC concept has successfully diffused all over the world. However, in practice, the implementation of BSC was not as successful as expected. For example, Lewy claims that 70% of scorecard implementations fail [23]. Criticisms of BSC were reported in different resources such as [25, 3, 28, 29]. Various studies on the adoption of BSC show that one problem encountered by many organizations is their inability to develop a causal model of their strategy [30]. Malmi found that the adopters of BSC in country-regionplaceFinland faced some difficulties in developing a causal model of their strategy and were unable to describe their model well. In fact, the weakness of the links claimed was the reason for this shortcoming [25]. Similar studies on BSC adoption in country-regionAustria and country-regionplaceGermany revealed that half of the companies considered did not develop a causal model of their strategy [33]. Davis and Albright's survey [7] of the literature on BSC shows that 77% of the companies that adopt BSC in the country-regionplaceUSA fail to develop a causal model of their strategy.

In spite of the importance of the causal model in BSC, there is no specific method to help organizations to develop such a causal model [25, 33]. Othman noticed that in order to implement BSC successfully, definition and development of causal links are of high priority [30]. According to his report, the problems experienced by those who did not develop a causal model of their strategy are more than the problems of those who did. Such a development improves the outcomes and facilitates BSC implementation.

It is important to note that the analyses and testing of casual relations are important parts of strategy maps designing. To this aim, experiences or mathematical models such as regression are usually used, see e.g., [5]. Structural Equation Modeling (SEM) is one of the most powerful methods of multivariate data analysis. SEM is an applicable statistical tool to test the relationships proposed in a parsimonious model. It has been proved that SEM functionality is better than other multivariate techniques including multiple regression, path analysis, and factor analysis [34].

Human and human related issues in management are very complicated issues and one dependent variable may be an independent variable in other dependence relationships. Therefore, a method that can simultaneously examine a series of dependence relationships helps to find complicated managerial and behavioral issues. Contrary to other statistical tools such as regression, SEM enables researchers to answer a set of interrelated research questions in a single, systematic, and comprehensive analysis. This method is based on modeling the relationships among multiple independent and dependent constructs simultaneously. This simultaneous analysis capability differs greatly from other methods such as linear regression, LOGIT, ANOVA, and MANOVA, which can analyze only one layer of linkages among dependent and independent variables at a time. Moreover, SEM permits complicated variable relationships to be expressed through hierarchical or non-hierarchical, and recursive or non-recursive structural equations to present a more complete picture of the entire model [6, 11].

SEM has been used in BSC to test the relations between perspectives, but to the best of our knowledge, there has been no published work which uses SEM as in this article. In fact, we will propose an approach which includes using SEM to understand, analyze and test the relations among the objectives of the strategy map. In section 2, the steps of strategy maps design are addressed. This section presents a framework which helps experts to design the strategy map by applying a comprehensive and scientific method together with their experience, which achieves a more reliable method. The effectiveness of the method is illustrated by an example. Section 3 will provide a description of our scheme including a given example. Finally, we will conclude our work in section 4.

2 Steps for designing strategy maps

The strategy map, which is composed of goals and related measures, is used to tell the story of a business unit strategy using some casual relations. To find such a strategy map, at first we should start our mission by a primary model design. Next, we use SEM indices to find wether our model fits collected data. If not, we should improve the measurement model and then enhance the structural model. However, in each step we decide what to do using SEM generated indices for the model. These steps are presented in figure 1. We will explain them in detail.

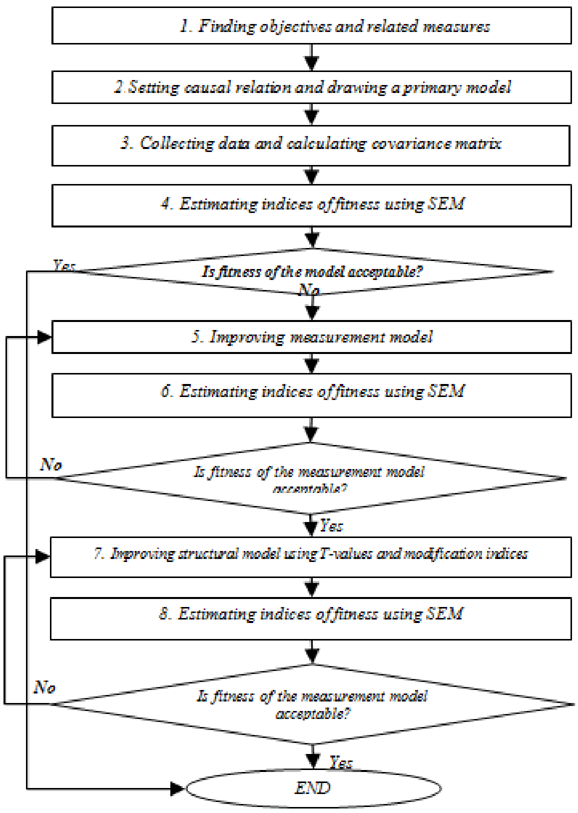

Fig. 1. Steps for designing strategy maps

2.1 Finding a primary model and collecting data

To establish a primary model, the recommendation of [16, 27] is to hold a meeting including senior managers. It is better to get an outside consultant or trained facilitator to manage the session. Before the session, a copy of the most recent versions of the mission, values, vision and strategy must be delivered to each participant. To have active participation for all members, it is better to start with small teams. After reviewing the various objectives generated in smaller groups, they brainstorm to come to consensus on what objectives they feel should comprise each perspective. The team should attempt to determine a strategy map in which objectives across the four perspectives appear to be linked in cause-and-effect relationships.

In the next step, we should test and modify the model using SEM. To do so, we must collect suitable data and estimate the covariance matrix. But, as Kaplan and Norton stated, it must be taken into account that gathering sufficient data to document significant correlation, relation, and causation among BSC measures can take a long time – months or years [18]-, especially in large organizations. Therefore, over short terms, managers' assessment of strategic maps may have to be based on subjective judgments.

2.2 Using Structural Equation Modeling

Latent variables are the key variables of interest in any structural study. We can observe the behavior of latent variables only indirectly and imperfectly. We consider our strategic objectives as latent variables and use manifest or observed variables– that are actual measures and scores– to ground our strategic objectives.

Figure 2 illustrates a simplified representation of a strategic map in which strategic objectives are represented as ellipses and their related measures are placed in rectangular boxes. The measurement model is the part which deals with strategic objectives and their indicators or measures, and the structural model specifies the structures that contain relationships among strategic objectives.

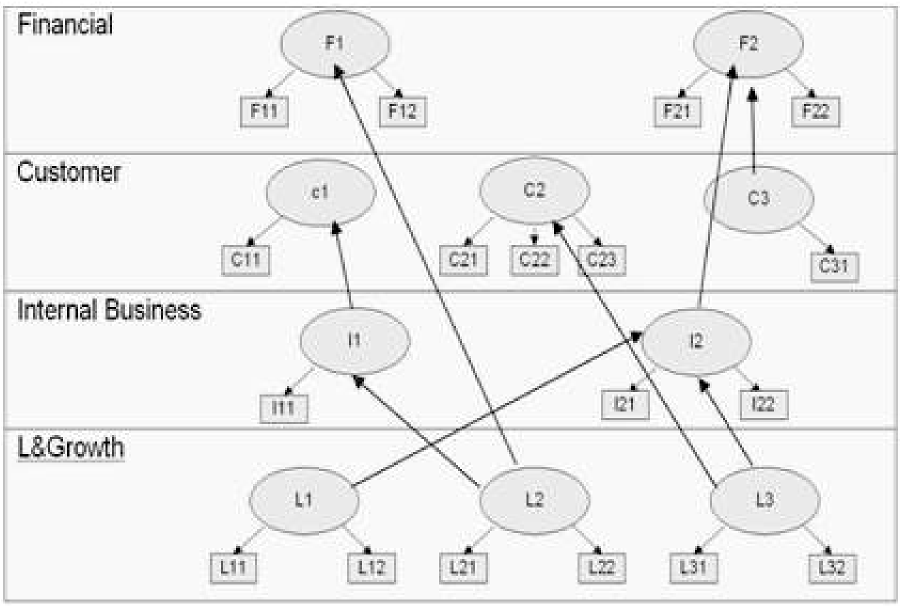

Fig. 2. Simplified representation of a strategic map

Unlike first generation regression tools, SEM not only assesses the structural model but, in the same analysis, also evaluates the measurement model. The combined analysis of the measurement and the structural model allows:

1. Measurement errors of the observed variables to be analyzed as an integral part of the model, and

2. Factor analysis to be combined in one operation with the hypotheses testing.

The result is a more rigorous analysis of the proposed research model and, very often, a better methodological assessment tool. Thus, SEM techniques provide more complete information about the extent to which the research model is supported by the data than regression techniques [11]. In the following two sections, we will propose some methods and indices that can be used in designing a strategy map.

2.2.1 Choosing a method

A variety of estimation methods have been used in SEM to indicate how closely the correlation or covariance matrix implied by a particular set of trial values conforms to the observed data, and thus to guide attempts to find best-fitting models. Each of these methods has its own advantages. Three standard methods that almost all SEM programs support are:

1. OLS (or ULS)

2. GLS

3. MLE

Various criteria, also known as discrepancy functions, can be considered as different ways of weighting the differences between corresponding elements of the observed and implied covariance matrices. In matrix terms, this may be expressed as:

$$F = (\underline{S} - \underline{C})'W(\underline{S} - \underline{C}) \tag{2.1}$$

where S and C refer to the non-duplicated elements of the observed and implied covariance matrices S and C, arranged as vectors, respectively. W is a weight matrix and its different versions yield different criteria. For example, if W is an identity matrix, the above expression reduces to:

$$F = (\underline{S} - \underline{C})'(\underline{S} - \underline{C}) \tag{2.2}$$

This expression may be simplified to other forms such as:

$$1/2\ \mathrm{tr}[(S - C)V]^2 \tag{2.3}$$

and

$$\ln|C| - \ln|S| + tr(SC^{-1}) - m \tag{2.4}$$

The larger the F, the worse the fit. An iterative model-fitting program will try to minimize F by seeking values for the unknowns which make the implied matrix C as much like the observed matrix S as possible (for more details see [24]).

The maximum likelihood estimation (MLE or ML) is the most common method that can be used for recursive and non-recursive models. But this method is not robust when data are ordinal or non-normal (very skewed). As ordinal variables are widely used in practice, it is helpful to note a rule of thumb that expresses discrete data (categorical data, ordinal data with values < 15) may be assumed to be normal if skewness or kurtosis is within the range of ± 1.0 (some use ± 1.5 or even 2.0) [35]. In this paper, we use ULS to estimate indices. As Joreskog [21] emphasized:
Although ULS is seldom used, it is quite robust (see Textsle, Balderjahn, 1985) and deserves more attention. It does not require any distributional assumptions. It can be used with small samples even when the number of variables is large and when the correlation matrix is not positive definite for other reasons (for example, this might be the case for a matrix of tetrachoric or polychoric correlations).

*2.2.*2 Fit indices

After estimating a measurement model, given a converged and proper solution, a researcher would assess how well the specified model accounted for the data with one or more overall goodness-of-fit indices [2]. The SEM program provides the probability value associated with the chi-square likelihood ratio test, the goodness-of-fit index, and the root-mean-square residual [14].

If the null hypothesis is supported, the assumption of multivariate normality holds, and sample size is reasonably large, then both GLS and ML criteria will yield an approximate χ^2using the following multiplication relation:

$$(N-1)F_{min} \tag{2.5}$$

The χ^2 test provides a useful basis for making decisions about the fitness of a model, or the relative fits of different models. In a satisfactory fit,$\chi^2 \approx df$ that means $p-value \approx 0.5$. RMSEA[1]is another index, which is relatively insensitive to sample size. If we rescale the noncentrality parameter, $\chi^2 - df$, by dividing it by N *-1*, we obtain a quantity d which we can use to define RMSEA:

$$RMSEA = \sqrt{d/df} \tag{2.6}$$

Browne and Cudeck [4] have suggested the following guidelines for interpreting RMSE:
" Practical experience has made us feel that a value of the RMSEA of about 0.05 or less would indicate a close fit of the model in relation to the degrees of freedom . . . . We are also of the opinion that a value of 0.08 or less for the RMSEA would indicate a reasonable error of approximation and would not want to employ a model with a RMSEA greater than .1."

RMSEA and χ^2 are overall fit indices that we can use to test the fitness of our model (strategy map).

We use another index, called t-value, to test the significance of individual paths. We can consider t-values higher than 1.96 to denote a strong causal relation among variables. Hence, we can consider those paths with t-values lower that 1.96 as weak paths which can be deleted if necessary.

[1] mean square error of approximation

If we conclude that the fitness of our model is not satisfactory, a reasonable strategy is to try to find out why the model does not fit, and then change it to fit better. We need to be a bit careful here since we are not only interested in fitting better to the current data set. In fact, we need a real improvement in measurement or theory, not just a procedure for decreasing chi-square (for more details see [24]).

2.3 Revising the model

When our model fits poorly to some collection of data, we should revise it. To do so, it is better to consider two steps. The first step that is nearly always worth considering is to ascertain to what extent the lack of fit resides in the measurement, and after modifying the model and finding a satisfactory measurement model, we should test the structural model (our strategy map) and modify it if necessary.

2.3.1 Improving the measurement model

Suppose that there are problems in the measurement part of the strategy map. Inspecting the results of the confirmatory factor analysis solution may give clues to the problem's nature. There are two main sources of difficulty in the measurement models. First, some indicators may fail to reflect the objectives they are supposed to measure. For example, they may have low factor loadings, or factor loadings of the wrong sign. One way of dealing with a variable which loads poorly is simply to remove it. However, the consequences should always be considered before taking such a step. One should determine if the remaining measures are conceptually adequate for defining the objective.

The second main source of measurement model misfit is that measures may, to some extent, reflect objectives other than the one they are intended to measure. If an indicator in fact reflects two objectives, but it is taken as a measure of one, and gives a zero path from the other, there will be a misfit. The model is now discrepant with respect to reality, since the correlations of this measure with others reflect both aspects of it, but the model assumes that only one aspect is present. Again, the choice of whether to omit such an ambiguous measure or to allow paths to it from both objectives will depend on such considerations as whether one has adequate measures of both without it (drop it) or not (probably keep it, although it may distort relations between the two objectives by bringing in a correlation due to the specific aspects of the measure) [24].

A final possible strategy is to decide whether the measurement model is good enough or not, despite a substantial χ^2, and go directly into the structural model. If one is in an exploratory mode, anyway, there is clearly no obligation that all measurement problems must be resolved completely before any structural problems can be addressed.

2.3.2 Improving the structural model

Changing a structural model is changing one's theory, and should always be done carefully. To improve the structural part of the strategy map, one can use the information provided by the fitting program to see whether existing paths are significantly different from zero. If not, for example if the t-value is lower than 1.96, experts might consider dropping some of them from the model. Experts can also use modification indices to improve the fitness of the model. SEM model-fitting programs provide diagnostic indicators that can be helpful in deciding which additional paths from objectives to measures or other objectives might improve the fit of the model. These are called Modification Indices. What they do for you is tell you roughly how much the χ^2 for the model will be improved by freeing each fixed path present in the model. One can look at modification indices to get an idea what the effects on the fit would be if one were to add particular paths. But modifications should not be made without careful consideration of their implications for the substantive theory that the model is intended to reflect. Such a caution was emphasized by a study by McCallum [26], who investigated the merits of a simple automatic model-improvement strategy as follows: If a model does not fit, make the single change that most improves its fit. Repeat as necessary until a non-significant %2 (desired fitness) is achieved. Then, test for and delete any unnecessary paths.

Table 1
Objectives and related measures

Perspective	*Objectives*	*Measures*
Financial	F1: Financing ratio F2: Return on sales F3:Return on financing (investment)	TR/F0: - Total revenue per amount of financing TR/F1: Total revenue per amount of financing AP/TR: Profitability per total revenue (from sales) AP/F Profitability per amount of financing
Customer	C1: Revenue generated by unique visitors (UV) C2: Marketing coverage C3: Penetration (market share)	TR/UV0 - Total revenue per UV0 TR/UV0 - Total revenue per UV0 MC - Marketing expenditure per unique visitors MS - Reach (% of users captured by a company)
Internal Business Processes	I1: Revenue generated by Marketing Expenditure I2: Employee Productivity1 I3:Employee Productivity2	TR/ME0 - Total Revenue per Marketing Expenditure. TR/ME1 - Total Revenue per Marketing Expenditure. EP1 - Revenue per Employee EP2 - Profitability per Employee
Learning and Growth	L1: Employee Development Revenue generated by development expenditure	EDC - Development Expenditure per employee TRADE - Total Revenue per development expenditure

3 Numerical example

In this section, we would like to illustrate the steps of the flowchart in Figure 1 in order to design the strategy map related to the data presented in [9]. In the first step, we must find our objectives and measures which are illustrated in Table 1. In step 2, we introduce a primary strategy map, which experts suggest through brainstorming. After calculating the covariance matrix of the given data in step 4, we test the model. The model has been estimated by unweighted least square method using LISREL 8.51.

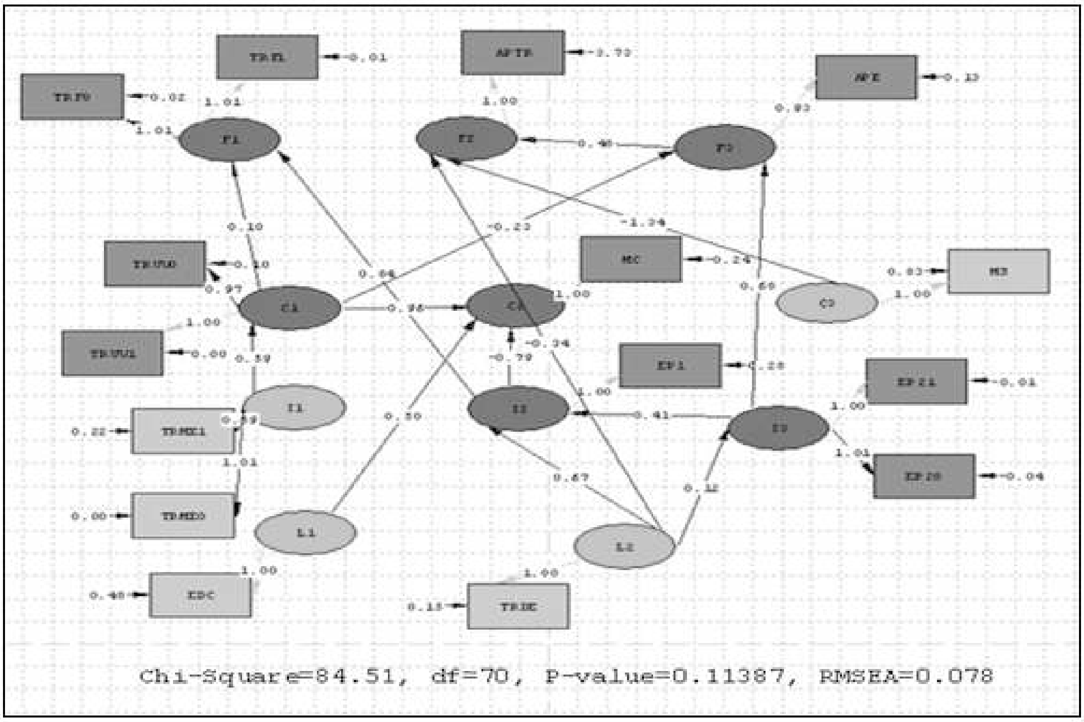

Fig. 3. A primary model

Figure 3 shows the primary model and its corresponding indices. $RMSEA = 0.07$ and $p - value = 0.11$ show that our primary model does not fit.

Each objective has at most 2 measures; therefore, as was stated , we skip steps 5 and 6 and go to step 7, and try to find the problems in the structural part of our strategic map. At first, we should compare the corresponding t-value for each relation against 1.97 to find statistically non-significant relations. The corresponding t-value for the relation between F1 and C1 is 0.96, which is relatively low. Therefore, we can remove it. To test the model in step 7, we run LISREL again. The revised model does not still fit the data. Looking at the corresponding t-value of the relations, we can see that all of them are statistically significant.

Therefore, we use modification indices to add (a) path/path(s) between some relations. As was emphasized before, this must be done carefully with the aid of experts. In each step, we add only one relation and, if necessary, we will add another in the next step. Looking at modification indices, we can see the path from $L1$ to $I2$ is logically acceptable. In step 8, we test the revised model. The RMSEA value and other indices of the model show that the model is acceptable but there is a problem with the t-value of a relation. The corresponding t-value of the relation between $L2$ and $F2$ is -1.5, which does not satisfy the acceptable criteria. We can remove this relation from the model by considering both theory and experience.

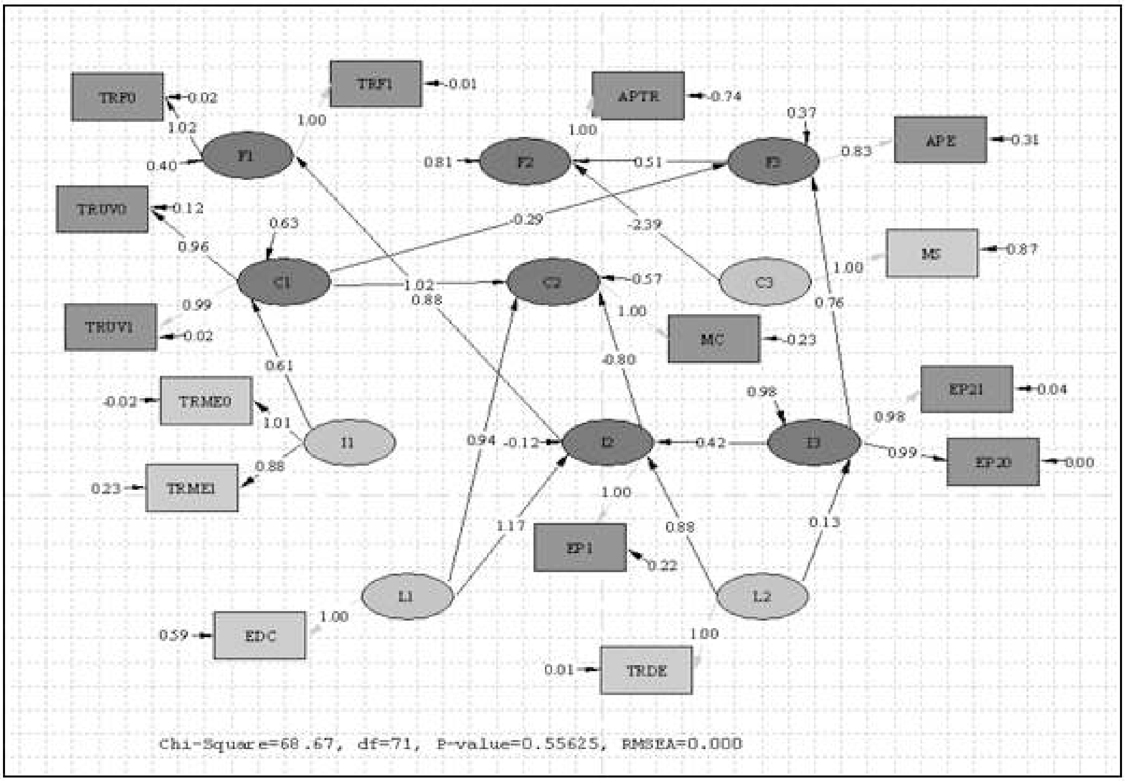

Fig. 4. Final strategy map and related indices

The final model is shown in figure 4. Test results show that this model fits the data quite well. The RMSEA of the model is 0.0, which indicates the acceptable fit of the model. The $\chi^2 = 68.67$ with degree of $freedom = 71$ and $p - value = 0.55$ suggest that the model cannot be rejected. SEM also provides some other helpful indices each of which has some priority over others. As has been shown in Table 2, the corresponding values of these indices make us more certain about the fitness of the model.

The t-values of relations have been shown on arrows in Figure 5. As we can see, all t-values are between -1.97 and 1.97 and the model, therefore, reports on the strength of the relations among objectives. Considering Figure 1, we are now in the final step and this is the time when experts can handle this model – which is statistically acceptable – in using BSC in the organization.

Table 2
Fit indice

Indices	IFI	CFI	NFI	NNFI	RMSR	AGFI	RMSEA
Value of the Model	1.00	0.93	1.00	0.90	0.13	0.87	0
Acceptable Value	≥ 0.9	≥ 0.9	≥ 0.9	≥ 0.8	≥ 0.0	≥ 0.9	≤ 0.05

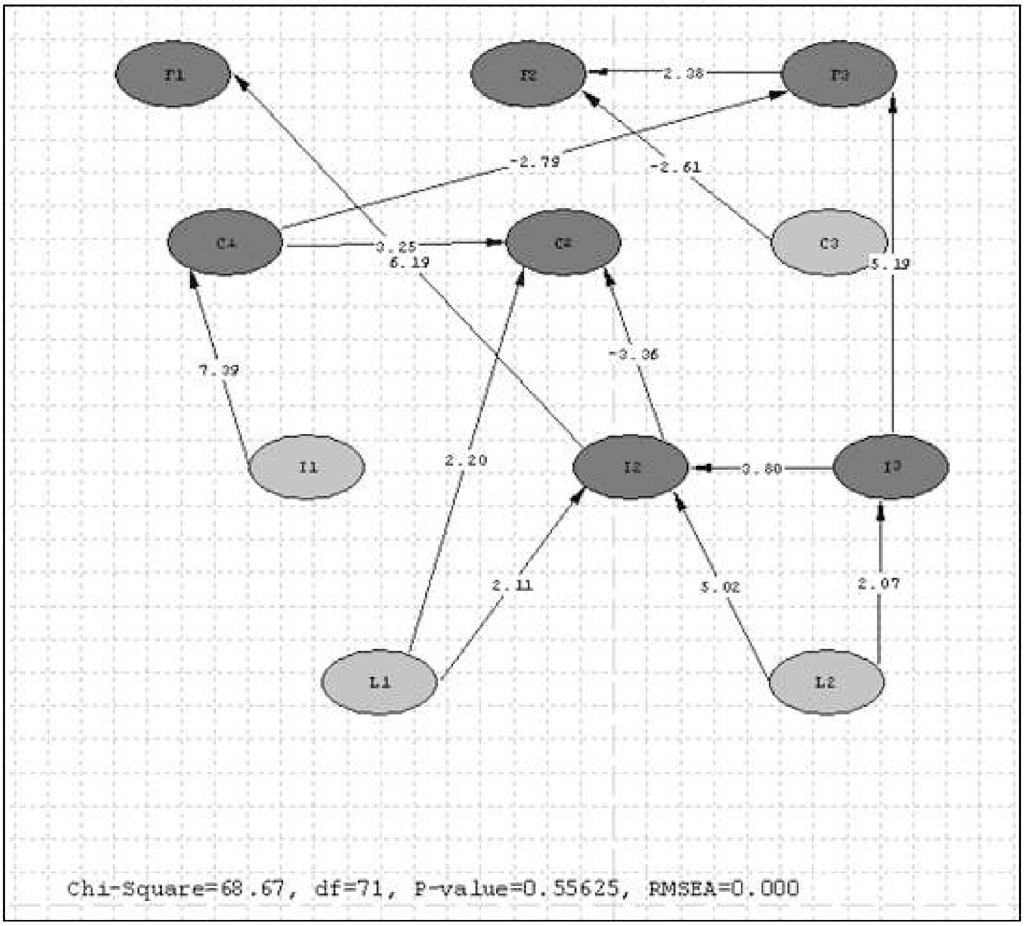

Fig. 5. Final map and t-values among objectives

4 Conclusion

Recent studies have revealed that finding the causal relation among objectives and testing them have a critical role in strategic map design. In this paper, we suggested the use of SEM in designing strategy maps. In our proposed method, both factor analysis and hypotheses testing were examined in the same experiment.

In comparison with previous techniques, the proposed method provides more accurate and precise information. Moreover, as organization managers have recognized that they need to manage a shift from objective methods to subjective ones, our proposed method would act better than previous methods used to test or even find strategy maps.

In the first step of our road map, the most vital objectives and their related measures should be declared, then we try to propose a basic model in which there are causal relations among some objectives. Next, using SEM, we generate some indices which help us to analyze the model. If the model does not fit the data, we will try to determine the problem in the measurement part of the model and refine the measures, if necessary. In the next step, the structural part of the model would be analyzed and, if necessary, the relations among objectives will be revised. In this step, one can use t-values to find the corresponding weak relations. The final model, whose fitness is statistically acceptable, can be used to implement BSC in the target organization.

SEM-based techniques require a greater number of data to generate more appropriate results; i.e., we need to collect more data before using these techniques. Nonetheless, the advent of information era forced organization leaders to provide enough data to prove their quality enhancement. As a result of this process, data requirements of SEM-based techniques would be satisfied.

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