Simultaneous Equation Model based on the generalized maximum entropy for studying the effect of management factors on enterprise performance

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Simultaneous Equation Model based on Generalized Maximum Entropy for studying the effect of the Management's Factors on the Enterprise Performances

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The aim of this paper is to study the effect of management factors on enterprise performance, considering a survey that the University Consortium in Engineering for Quality and Innovation has led. The relationships between management factors and enterprise performance are formalized by a Simultaneous Equation Model based on the generalized maximum entropy (GME) estimation method. The format of this paper is as follows. In Section 2, the data collected, the questionnaire evaluation, and the management model analytical formulation are introduced. In Section 3, the GME formulation is specified, showing the main characteristics of the estimation method. In Section 4, the results and a comparison among GME, partial least squares (PLS), and maximum likelihood estimation (MLE) is shown. In Section 5, concluding remarks are discussed.

Keywords: *generalized maximum entropy, human resources, leadership, maximum likelihood estimation, partial least squares, performance, Simultaneous Equation Model, strategic planning*

1. Introduction

A sample of Italian manufacturing companies was selected in order to verify the abilities to manage the human resources effectively, the spreading level of an effective and aware leadership, and the ability of strategic planning according to a correct identification of the objectives.

The generalized maximum entropy (GME) estimation method is used for analysing the data collected, where the relationships were formalized by a simultaneous equation statistical model. The GME is a suitable and flexible method, widely used in linear modelling, where no parametric assumptions are necessary, and a global measure of fit is available.

A comparative study is made with partial least squares (PLS) and maximum likelihood estimation (MLE) methods.

2. The Data Collected and the Model for Evaluating the Management's Factor

Data were collected from a sample of Italian manufacturing companies and represents the answers of 120 enterprises. The sample is based on an analysis of the Italian manufacturing structure, with the reference to D economic section, of the Italian Statistics Institute Ateco 2002[1] classification system. The sector is characterized by

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[1] http://www.istat.it/strumenti/definizioni/ateco/.

mostly small and medium enterprises (93%) and the remaining part by enterprises with more than 100 employees. From an economic point of view, the big enterprises cover 50% of the production of the whole sector and employ 40% of the workforce. In order to respect the structure of the Italian manufacturing sector, the sample was selected as a weighted random sample where each company was assigned sampling weights according to the company size. Based on 120 selected companies, the percentage of the enterprises selected follows the below proportions:

- 42%, with less than 50 employees;
- 14%, between 50 and 100 employees;
- 44%, with more than 100 employees.

To measure the impact of the management factors on the enterprises' performances, a questionnaire subdivided into four evaluation areas was used (Table 1). Questionnaire data related to 35 statements were gathered through telephone interviews with the leaders of the selected companies. Respondents were asked to evaluate each statement on an ordinal scale with variation from 1 (disagree) to 2 (neither disagree nor agree) to 3 (agree). Table 1 shows all the variables used and formulated as positive statements.

A short description of the latent variables (LVs) may help to make the discussion easy. For Leadership, the statements (the manifest variables) selected highlights the character of the leader, managerial capability in long-term planning, orientation towards innovation, increasing the value of own collaborators, and having a good relationship with the stakeholders. In the Human Resource area, the necessity to have employees who are skilful to bring the enterprise towards excellence has been the focus. The statements are about promotions, re-conversions, careers, training, and recognition of improvements. Strategic Planning may be the backbone for excellence. The focus is to measure and analyse if managers jointly work with all members of the enterprise through planning, doing follow up activities driven by management, using systematic methodologies to support and evaluate decisions taken. Performance is the objective measure of company health where statements about market share and economic indexes such as Return of Investment or profit level measure the efficiency of the company.

2.1 The questionnaire evaluation

The first step before the analysis of the model has been quantification of the data analysed, for transforming the scale from an ordinal scale to a quasi-cardinal scale, in order to improve the mathematical properties of the scale. The quantification process has been conducted as otherwise it is not possible to analyse the data by using statistical methods based on a metric. The modalities of the questionnaire are referred only to a 'verbal expression', so the three numbers are just mathematical symbols, without any continuum between each response.

The method used is the Thorgerson method, based on the Thurstone approach [24], whose main idea is that the criterion of the choice of each interviewee follows a LV with a normal distribution.

Table 1. The variables used in the Management Factor Model.

Manifest Variables

I. Performance
1. The market share has been improved during the last three years.
2. The revenue has increased during the last three years.
3. The percentage of Profit has increased.
4. The percentage of Return of Investment has increased during the last three years.
5. The total trend of the company's performance has improved.

II. Leadership
6. Leadership values are well defined.
7. The leadership styles of governance depend on employee characteristics.
8. Management is open when communicating with employees.
9. Management participates in formative events.
10. Management is involved in setting employee rewards.
11. Management evaluates its leadership style when compared with other company managers.
12. Management listen to considerations from employees.
13. Management promotes programs for improving the Society and the Environment.
14. Management involves the employees in setting objectives.
15. Management has negotiation capacity in critical situations.

III. Human Resource
16. The personnel's careers are based on specific plans.
17. The company has invested in Research & Development.
18. Job satisfaction is being evaluated.
19. Personal skills are being evaluated.
20. People's merits are recognised and rewarded.
21.Work groups are used for specific themes.
22. The employees have decision autonomy.
23. The employees identify themselves with the companies.
24. Middle management has decision autonomy.

IV. Strategic Planning
25. Systematic analyses are made for customer expectations and market potentiality.
26. Performance indexes are used for medium and long-term plans.
27. The strategies consider competitor analysis.
28. Medium- and long-term plans are used for resource allocation.
29. The strategies are periodically re-evaluated.
30. A structured process defines the objectives and their diffusion.
31. The various operative groups conform to the main objectives.
32. Each employee knows his objectives and results.
33. The employees are involved in the definition of objectives.
34. New planning documents are developed for new projects.
35. Documents for the annual operative planning are developed.

In this way it is possible to transform the original ordinal scale to a scale that has a metric which follows the normal distribution. This approach can be explained by the following three simple steps:

1. For each modality, of each variable X_j, is calculated the number of respondents (absolute frequency), in this case there are 3 modalities (1, 2, 3) and 35 variables.
2. The cumulative relative frequencies is calculated, representing the estimation of the cumulative density function $F_j(i)$, of the normal distribution.
3. The $\Phi^{-1}[F_j(i)]$ represents the inverse function of the normal standard distribution to compute quantile τ_j of the function.

The choice to use the normal distribution is based on the observation that the distribution of the modalities response is almost symmetric, that means the evaluation don't fall in the extreme values.
The index, used for evaluating the distribution of the modalities frequencies, has been defined by Portoso [14] as follow:

$$W = \sum_{i=1}^{S} f_i \cdot (2 \cdot i - S - 1)/(S - 1) \qquad (1)$$

where S is the number of modalities (S = 3) and f_i is the relative frequency. The normalized index assumes values in the range of −1 to +1. When the index assumes value −1, all the frequencies are associated with the first modality 1 (disagree); when the index assumes the value +1, the frequencies are allocated to the last modality 3 (agree); when the value is 0, then the frequencies are balanced in a symmetrical way around the central value 2 (neither disagree nor agree).
The Portoso's Index calculated on the data is equal to 0,173, showing that the frequencies are almost balanced around the central value.
Moreover, in order to verify the sensitivity of the quantification process, a comparative study has been made by considering three different [13] inverse function $\Phi^{-1}[F_j(i)]$: The *first one*, with a symmetric distribution, by using the normal distribution; The *second one*, with a asymmetric negative distribution, by using a negative exponential distribution; The *third one*, with a asymmetric positive distribution, by a positive exponential distribution. The results are in the table 2:

Table 2. The Quantification Process Sensitive Analysis.

Ordinal Scale	**Normal Distribution**	**Negative Exponential Distribution**	**Positive Exponential Distribution**
1	1.000	1.000	1.000
2	1.832	1.579	1.437
3	2.679	1.758	2.473

The table 2 shows that the normal distribution's estimated values, are symmetric in term of distance among the quantified modalities. The negative exponential distribution gives more importance to the left tail of the modalities, whereas the positive exponential distribution evidences that the right modality is far from the first and the second one.
The Portoso's index result (W=0,173) and the sensitivity analysis (Table 2) lead us to chose the normal distribution, that stores a constant distance among the quantified modalities.
After the quantification two main analyses are developed to evaluate the quality of the questionnaire: a factorial analysis for unidimensionality and for selecting the relevant manifest variables; an internal coherence study, by the Cronbach's Alfa index.
Based on the results of the principal component analysis, some variables have been deleted because they were not relevant on the formation of the LVs.
Table 3 reports only the manifest variables selected. The two main factors were chosen by considering the scree-test method. As can be seen from Table 3, the factors underlie the following theoretical construct: the first axis represent ***Management Factors***, the second one, represent ***Performance***.

Table 3. Principal components Loadings.

Latent variables	Manifest variables labels	F1	F2
Performance	*Variable 1*	0.119	**0.809**
	Variable 2	0.141	**0.895**
	Variable 4	0.054	**0.818**
	Variable 5	0.153	**0.744**
Leadership	*Variable 12*	**0.569**	-0.007
	Variable 13	**0.553**	0.074
	Variable 14	**0.522**	-0.146
Human Resource Management	*Variable 16*	**0.636**	0.003
	Variable 18	**0.582**	-0.044
	Variable 19	**0.558**	0.048
	Variable 20	**0.484**	0.094
	Variable 21	**0.538**	0.168
Strategic Planning	*Variable 26*	**0.602**	-0.027
	Variable 28	**0.615**	-0.088
	Variable 29	**0.592**	-0.006
	Variable 30	**0.627**	-0.086
	Variable 32	**0.509**	-0.103
	Variable 33	**0.636**	0.003
	Variable 34	**0.728**	-0.237
	Variable 35	**0.604**	-0.214

By considering only the manifest variables selected, an analysis of internal coherence has been conducted to evaluate the degree of reliability of each LV to express the theoretical concept which they measure.

Table 4. Internal Coherence and manifest variables selected.

Latent variables	Cronbach's alfa Index	Manifest variables
Performance	0.680	1. The market dimension has been improved during the last three years. 2. The revenue has increased during the last three years. 4. The percentage of Return Of Investment has increased during the last three years. 5 The total trend of the company's performance has improved.
Leadership	0.680	12. Management listen to considerations from employees 13. Management promotes programs for improving the Society and the Environment 14. Management involves the employees in setting objectives.
Human Resource Management	0.807	16. The personnel's careers are based on specific plans. 18. Job satisfaction is being evaluated. 19. Personal skill is being evaluated. 20. The merits are recognised and rewarded. 21. Work groups are used for specific themes
Strategic Planning	0.853	26. Performance indexes are used for medium and long term plans. 28. Medium and long term plans are used for resource allocation. 29. The strategies are periodically re-evaluated. 30. A structured process defines the objectives and their diffusion. 32. Each employee knows his objectives and the results 33. The employees are involved in the definition of objective resources. 34. New planning documents are developed for new projects. 35. Documents for the annual operative planning are developed

Table 4 reports the values of Cronbach's Alfa index for each LV. As is possible to read, the values are almost equal to 0,7, the target value, for Performance and for Leadership, whereas, for Human Resource and for Strategic Planning, Cronbach's Alfa is bigger than 0,8. From this analysis, it is possible to conclude that the process of the selection and validation of the questionnaire shows good results in terms of reliability of the LVs.

2.2 The Management Factor Model

The Management Factor Model is shown as a path diagram in figure 1. The latent variables are estimated by using the average of the manifest variables belonging to the respective LV.
The model considers as dependent variables (endogenous variables) Performance, Human Resources, and Strategic Planning; and as independent variable (exogenous variable) Leadership.

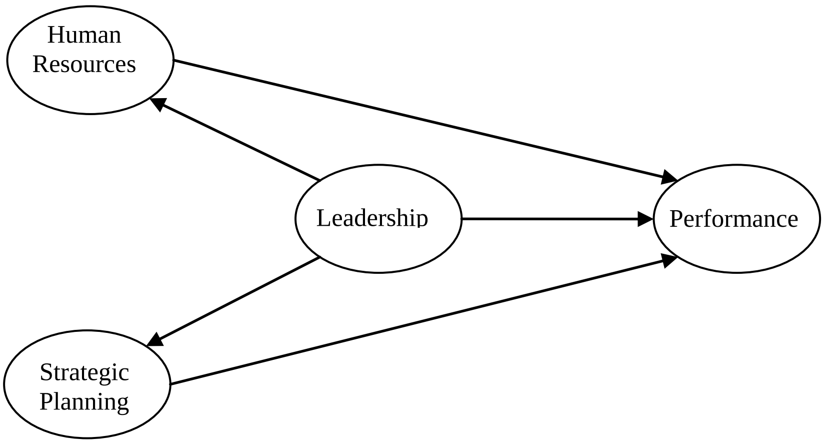

Figure 1. The Management Factor Model.

The path model reported in the figure 1 can be expressed by an analytical representation, considering a simultaneous equation linear statistical model, formalized by the following matrix formulation:

$$\begin{bmatrix} \mathbf{Y}_1 \\ \mathbf{Y}_2 \\ \mathbf{Y}_3 \end{bmatrix} = \begin{bmatrix} \mathbf{X}_1 & 0 & 0 \\ 0 & \mathbf{X}_2 & 0 \\ 0 & 0 & \mathbf{X}_3 \end{bmatrix} \cdot \begin{bmatrix} \boldsymbol{\beta}_1 \\ \boldsymbol{\beta}_2 \\ \boldsymbol{\beta}_3 \end{bmatrix} + \begin{bmatrix} \boldsymbol{\varepsilon}_1 \\ \boldsymbol{\varepsilon}_2 \\ \boldsymbol{\varepsilon}_3 \end{bmatrix} \tag{2}$$

The dependents vectors $\mathbf{Y}_1$, $\mathbf{Y}_2$ and $\mathbf{Y}_3$, represent respectively the variables Performance, Human Resource and Strategic Planning. The predictor matrix is a diagonal block matrix where each diagonal element is a matrix of 120 rows (the observations) specified as follows: The matrix $\mathbf{X}_1$ has 3 columns representing the variables Leadership, Human Resource and Strategic Planning; the matrices $\mathbf{X}_2$ and $\mathbf{X}_3$ have one column which both refer to the variable Leadership.
The vector of the beta coefficients represents the linear impact of each block independent variables on the own dependent variable.
The covariance matrix $\boldsymbol{\Phi}=E(\boldsymbol{\varepsilon\varepsilon}')$, is a diagonal matrix reported in the following formulation:

$$\mathbf{\Phi} = \begin{bmatrix} \varphi_{11} & & \\ 0 & \varphi_{22} & \\ 0 & 0 & \varphi_{33} \end{bmatrix} \tag{3}$$

There is no distribution assumption on the error term and no restrictions are considered about the correlation between the predictor variables and the error term, which means that the X variables are considered non exogenous in the model with the exception of X_3, the Leadership variable.
The statistical method used to estimate the measure of the relationship is known as GME.

3. The Generalized Maximum Entropy Estimation Method

Golan *et al.*[8] proposed a semi-parametric method that performs well with small and possibly ill-behaved, noisy data.
The method, called GME, is based on the re-parameterization and re-formulation of a general linear model, to estimate the parameters within the Maximum Entropy Principle (MEP) framework developed by Jaynes [10 11].
Considering the following regression model with n observations and m explanatory variables:

$$\mathbf{y}_{(n,1)} = \mathbf{X}_{(n,m)} \cdot \boldsymbol{\beta}_{(m,1)} + \boldsymbol{\varepsilon}_{(n,1)} \tag{4}$$

The regression parameters, coefficients ($\boldsymbol{\beta}$) and error terms ($\boldsymbol{\varepsilon}$), can be re-parameterized as a convex combination of expected value of a discrete random variable.
The GME method, therefore, estimates the parameters and the error terms, by recovering the probability distribution of a discrete random variables set. The model (4) can be re-formulated as follows:

$$\mathbf{y}_{(n,1)} = \mathbf{X}_{(n,m)} \cdot \mathbf{Z}_{(m,m\cdot M)} \cdot \mathbf{p}_{(m\cdot M,1)} + \mathbf{V}_{(n,n\cdot N)} \cdot \mathbf{w}_{(n\cdot N,1)} \tag{5}$$

The matrices **Z** and **V** are diagonal and the generic kth element is represented respectively by the vectors:

$$\mathbf{z}_k^{'} = [-c \quad -c/2 \quad 0 \quad c/2 \quad c], \qquad \mathbf{v}_k^{'} = [-b \quad -b/2 \quad 0 \quad b/2 \quad b], \tag{6}$$

of dimensions M and N. These vectors define the support variables, called fixed points (FPs), usually uniformly and symmetrically chosen around zero with equally spaced distance discrete points. However, if we know the possible values of the parameters from the theory then we specify them accordingly.
Golan *et al.* [7] carried out Monte Carlo experiment for computing the number of FPs (M and N), and showed a substantial decrease in the Mean Squared Error of the estimates occurs when FPs increases from 2 to 3; based on Al-Nasser [1] and Golan *et al.* [7] it appears that the greatest improvement in precision comes for using 5 support points.

The choice of **v,** clearly depends on the observed sample as well as any conceptual or empirical information about the underlying error. However; if such conceptual or empirical information does not exist, then **v** may be specified to be uniformly and symmetrically distributed around zero.
Chebychev's inequality may be used as a conservative means of specifying sets of error bounds as v_1=-dσ and v_n=-dσ, or these bounds can be obtained by 3σ rule [15].
The vectors **p** and **w** are the probabilities associated respectively to the **β** regression coefficients and the **ε** error terms. The generic k^{th} element is represented respectively by the following vectors:

$$\mathbf{p}_k^{'} = [p_{k1} \quad p_{k2} \quad p_{k3} \quad p_{k4} \quad p_{k5}], \qquad \mathbf{w}_k^{'} = [w_{k1} \quad w_{k2} \quad w_{k3} \quad w_{k4} \quad w_{k5}] \tag{7}$$

reported with dimensions M=N=5. The objective is to estimate these probabilities by the maximization of the following Shannon's entropy function (1948):

$$H(P,W) = -\mathbf{p}_{1,m\cdot M}^{'} \cdot \ln \mathbf{p}_{m\cdot M,1} - \mathbf{w}_{1,n\cdot N}^{'} \cdot \ln \mathbf{w}_{n\cdot N,1} \tag{8}$$

subjected to the consistency constraints, that represent the information generated from the data:

$$\mathbf{y}_{(n,1)} = \mathbf{X}_{(n,m)} \cdot \mathbf{Z}_{(m,m\cdot M)} \cdot \mathbf{p}_{(m\cdot M,1)} + \mathbf{V}_{(n,n\cdot N)} \cdot \mathbf{w}_{(n\cdot N,1)} \tag{9}$$

and, adding up the normalization constraints:

$$(\mathbf{I}_{m,m} \otimes \mathbf{1}_{1,M}') \cdot \mathbf{p}_{m\cdot M,1} = \mathbf{1}_{m,1} \tag{10}$$
$$(\mathbf{I}_{n,n} \otimes \mathbf{1}_{1,N}') \cdot \mathbf{w}_{n\cdot N,1} = \mathbf{1}_{n,1} \tag{11}$$

where **I** is the identity matrix, of order *m* for the variables and *n* for the observations; **1,** is a vector of ones of m-dimension and n-dimension respectively for the variables and for the observations; the symbol $\otimes$ is the Kronecker's product.
The non-linear programming system is solved by the formulation of the Lagrangian function and the first order conditions which provides the basis for the solution. The estimates will not be in closed form and to get the final values, a numerical optimization technique (successive quadratic programming method) may be used to compute probabilities.
The GME has several desirable properties [7], which can be briefly summarized in the following points:

- The GME approach uses all the data points and does not require restrictive moments or distributional error assumptions.
- Thus, unlike the MLE estimator, the GME is robust for a general class of error distributions.
- The GME estimator may be used when the sample is small, where there are many covariates, and when the covariates are highly correlated.
- Moreover, using the GME method, it is easy to impose nonlinear and inequality constraints.

Therefore the GME works well in case of ill-behaved data, where the MLE cannot proceed.
A good alternative, in this is case, is represented by the PLS method [18, 19, 23] where the estimation method provides a good option, solving the problem of multicollinearity and also because this method has no distributional assumptions.
A drawback of PLS is that the method finds optimal local solutions by a series of interdependent OLS regression [6], minimizing residual variance under the so called FP method [20, 21].
That means, it doesn't optimize any global scalar function, so that, it doesn't provide an index for evaluating the global validation of the model.
However, a global criterion called Goodness of Fit (GoF) index has been recently proposed [2], as geometric mean of the average communality index and the average R^2 value, respectively of each LV. Nevertheless, the GoF index represents an operational solution to this problem, because it is based on local measures (Communality and R^2 are referred to the single latent variable) not on a global criterion of fit.
The GME provides the measure of the normalized entropy measure [7, 9] that quantifies the level of information in the data, giving a global measure of the goodness of relationships, hypothesized in the simultaneous equation linear model. The normalized entropy measure can be expressed by the following formulation:

$$S(\tilde{p}) = \frac{-\mathbf{p}' \cdot \ln \mathbf{p}}{K \cdot \ln M} \tag{12}$$

This normalized index is a measure of the reduction in uncertainty information, where $-\mathbf{p}' \cdot \ln \mathbf{p}$, is the Shannon's entropy function as shown in Equation (8), defined only for the predictor probabilities; K is the number of the predictors; M is the number of the FPs.
The quantity $K \cdot \ln M$ represents maximum uncertainty. If $S(\tilde{p})$=0, there is no uncertainty; and if $S(\tilde{p})$=1, it means total uncertainty.
The normalized entropy measure can be used also as a method for the selection of the explicative variables. In fact, it is possible to calculate the Shannon Entropy function for one predictor, as: $-\mathbf{p}_k' \cdot \ln \mathbf{p}_k$, so the information of each explicative variable is the following:

$$S(\tilde{p}_k) = \frac{-\mathbf{p}_k' \cdot \ln \mathbf{p}_k}{K \cdot \ln M} \tag{13}$$

Additionally, it is possible to define the log-likelihood ratio statistic:

$$W(ME) = 2K \ln(M)\left[1 - S(\tilde{P})\right] \tag{14}$$

Which, under the null hypothesis that all the parameters are zero, converges in distribution to a χ^2 with k degrees of freedom, where the degrees of freedom are the number of constraints imposed [9]. Moreover a Pseudo-R^2 can be defined as:

$$R^2 = 1 - S(\tilde{P}) \tag{15}$$

The R^2 is a measure to derive a Goodness of Fit of the model, where the value 0 implies no informational value of the data, and 1 implies perfect certainty or perfect in-sample prediction. This measure, is the same as the information index in Soofi [17].

4. Analysis of the Results

4.1 Estimation Results and Comparative Study

The GME, PLS and MLE methods are used for estimating the relationships (path coefficients or impact scores) and significance via bootstrap, reported in Table 5. Figure 2 shows the Path Diagrams with the results of the GME estimation method.

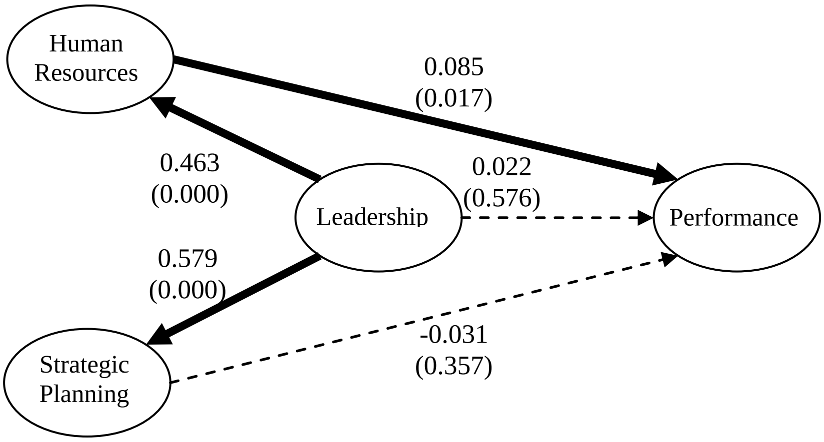

Figure 2. Results of the GME estimation.

Figure 2 shows the estimated coefficients, where the significant relationships have been highlighted by a bold line, and non significant relationships are shown by broken lines. The numbers in brackets are the *P*-values. The significance of the variables is calculated via bootstrap re-sampling, considering 100 samples of dimension 120.
Table 5 gives support for evaluating the differences in the empirical results obtained by using the various estimation methods.

Table 5. Comparing the GME – PLS – MLE estimation methods.

Relationships	**GME(*P*)**	**PLS(*P*)**	**MLE(*P*)**
Leadership → Performance	0.022 (0.576)	-0.025 (0.733)	-0.02(0.841)
Human Resource → Performance	**0.085** (0.017)	**0.148** (0.031)	**0.15**(0.041)
Strategic Planning → Performance	-0.031 (0.357)	0.040 (0.568)	0.04(0.682)
Leadership → Human Resource	**0.463** (0.000)	**0.459** (0.000)	**0.46** (0.000)
Leadership → Strategic Planning	**0.579** (0.000)	**0.445** (0.000)	**0.45** (0.000)

It is seen, from Table 5, that there are differences in the size of the impact scores but the methods show the same results with respect to significant relationships.
The estimated coefficients suggest that Human Resource is the only variable having a significant and positive direct impact on Performance. The variables Leadership and Strategic Planning have no significant direct impact on Performance, but the impact of Leadership on Human Resources and Strategic Planning are significant.

For giving also an empirical evaluation of the GME performance, Table 6 shows a comparison in terms of Mean Squared Error for the three dependent variables:

$$MSE(\hat{y}) = n^{-1} \cdot \sum_{i=1}^{n} \left(\hat{y}_i - y_i\right)^2 \qquad (16)$$

where small improvement for the GME compared with PLS and MLE is noted, except Human Resources.

Table 6. The MSE comparison between GME, PLS and MLE.

Variables	MSE (GME)	MSE (PLS)	MSE (MLE)
Performance	0.0084483	0.008537	0.008418
Human Resource	0.0071092	0.006654	0.006654
Strategic Planning	0.0053539	0.005788	0.005777

The results reported in the Table 6 do not suggest a practical way to chose one of these methods, because no assumptions about the error structure are made by considering the Quantile-Plot (Q-Plot) of standardized residuals (Appendix 1). In case of no distribution assumption, the MLE method cannot be used and its χ^2 loses the inferential meaning of global measure for evaluating the goodness of the model.
The PLS, representing a good alternative in case of non parametric approach, has the drawback that it does not solve a global optimization problem for parameter estimation, indicating that there exists no single and unique criterion to determine model parameter estimates [22].
The GME, instead, provides the normalized entropy measure, that is a valid tool for giving a global evaluation on the phenomenon studied, measuring the goodness of relationships based only on the degree of information explained by the model.
The values of the normalized entropy measure $S(\tilde{p})$ and the related indices are reported in the Table 7. The $S(\tilde{p})$=0.19 means that there is a reduction in the uncertainty of about 80%, which is a good result with respect to the criterion of selection suggested by Golan *et al.* [7].
Additionally, the $\text{PseudoR}^2 = 0{,}81$ gives a good result in the fitting of the model. The log-likelihood ratio statistic is $W(ME) = 13{,}036 > \chi^2_{(5)} = 9.5$, that means to reject the null hypothesis at the significance level of 5%, that the parameters are zero, under the limiting χ^2 distribution.

Table 7. Model Statistics.

Entropy Ratio, $S(\tilde{p})$	**Goodness of Fit, R^2**	**Chi-Square, χ^2**
0.19	0.81	13.036

Moreover, the results reported in Table 7 can be further supported by other comparative simulation studies [3, 7], showing that GME is over-performing PLS in case of strongly correlated variables and more general in cases of the ill-posed problems.

4.2 A Sensitivity Analysis of the GME Estimates

Given the estimated results, it is useful and recommended [8], to verify the support spaces on the parameters and to measure the sensitivity of results across support space specifications.

Table 8. Results of the Sensitivity Analysis.

Vector of Fixed Points	**Parameters** $\beta_{LP}^{(N)}$	$\beta_{HP}^{(S)}$	$\beta_{SP}^{(N)}$	$\beta_{LH}^{(S)}$	$\beta_{LS}^{(S)}$	**Entropy Ratio**
[-100 -50 0 50 100]	0.0224	0.0852	-0.0317	0.4635	0.5786	0.223
[-50 -25 0 25 50]	0.0224	0.0852	-0.0317	0.4635	0.5786	0.221
[-10 -5 0 5 10]	0.0224	0.0852	-0.0317	0.4635	0.5786	0.195
[-3 -1,5 0 1,5 3]	0.0224	0.0852	-0.0317	0.4635	0.5786	0.190
[-1 -0,5 0 0,5 1]	0.0224	0.0852	-0.0317	0.4635	0.5786	0.190
[-100 0 100]	0.0224	0.0852	-0.0317	0.4635	0.5786	0.247
[-50 0 50]	0.0224	0.0852	-0.0317	0.4635	0.5786	0.239
[-10 0 10]	0.0224	0.0852	-0.0317	0.4635	0.5786	0.206
[-3 0 3]	0.0224	0.0852	-0.0317	0.4635	0.5786	0.201
[-1 0 1]	0.0224	0.0852	-0.0317	0.4635	0.5786	0.198

Table 8 shows the results of the sensitivity analysis for the FPs. It has been considered in the first five rows, the number of FPs equal to 5, in the second five rows, a number equal to 3. Moreover has been chosen the values of the constant '*c*' (*supra* § 3) that goes from 100 to the value 1.

The parameters in the table are so defined: β_{LP}, β_{HP}, β_{SP}, are the causal coefficients respectively of the Leadership, Human Resource and the Strategic Planning, on the Performance; β_{LH}, is the causal coefficient between the Leadership and the Human Resource; β_{LS}, is the causal coefficient between the Leadership and the Strategic Planning. The coefficients significant are reported with an (S) in the brackets and the non significant relationships report the (N) in the brackets.

The last column reports the normalized entropy measure $S(\hat{p})$ to measure the informational content of the estimates with 1 reflecting uniformity (complete ignorance) of the estimates and 0 reflecting perfect knowledge (*supra* § 3).

The support on errors is based on a three sigma rule symmetric around 0. Sigma is the empirical standard deviation on the dependent variables, that are centered and standardized. The estimated parameters show to be robust in terms of estimated values, although the entropy ratio is variable to the choice of number support values, reaching a stable and good value with [-3 -1.5 0 1.5 3] and [-1 -0.5 0 0.5 1].

4.3 The interpretation of the results for helping Decision Makers

For improving the interpretation of the results and for giving a valid support to the decision makers, Table 9 reports the estimated values of the LVs, obtained as the average value of the manifest variables.

Table 9. Estimated Values of the Latent Variables.

LVs	**Performance**	**Leadership**	**Human Resource**	**St. Planning**
Values	2.072	2.290	2.054	2.200

The exogenous LVs were categorized into two groups of agreement level, where the variables in the first group have a relative high level of agreement with the positive statements, and the variables in the second group have a low level of agreement. The level of agreement is in this case recognised as high when the agreement value is 2.60 or higher and low when the level of agreement is below 2.60.
By using this categorization it became possible to construct an interventions matrix, by combining the information of the path coefficients and the average agreement reached, in order to group the variables according to importance and agreement, as reported in the following Table 10.

Table 10. Interventions Matrix.

		Agreement	
		Low	**High**
Importance	**Low**		Strategic Planning
	High	Human Resource	Leadership

The 'message' of the interventions matrix is that improvements should be prioritised to variables where importance is high and agreement low. Hence the general message of Table 10 is that Italian industrial companies are relatively weak on Human Resources and they should first of all improve the Human Resource aspects. This message is based on the fact that Human Resources were the only variable with a significant impact on Performance, and the level of agreement reached was smaller than for the other management factors of the model.

Table 11. Average Scores of the Manifest Variables.

Latent variables	LV Mean	Manifest variables	MV Mean
Performance	2,072	1. The market dimension has been improved during the last three years.	1,993
		2. The revenue has increased during the last three years.	2,096
		4. The percentage of Return Of Investment has increased during the last three years.	1,971
		5 The total trend of the company's performance has improved.	2,227
Leadership	2,290	12. Management listen to considerations from employees	2,401
		13. Management promotes programs for improving the Society and the Environment	2,137
		14. Management involves the employees in setting objectives.	2,331
Human Resource	2,054	16. The personnel's careers are based on specific plans.	2,012
		18. Job satisfaction is being evaluated.	1,749
		19. Personal skill is being evaluated.	2,283
		20. The merits are recognised and rewarded.	2,207
		21. Work groups are used for specific themes	2,019
Strategic Planning	2,200	26. Performance indexes are used for medium and long term plans.	2,158
		28. Medium and long term plans are used for resource allocation.	2,241
		29. The strategies are periodically re-evaluated.	2,428
		30. A structured process defines the objectives and their diffusion.	2,040
		32. Each employee knows his objectives and the results	2,311
		33. The employees are involved in the definition of objective resources.	2,186
		34. New planning documents are developed for new projects.	2,068
		35. Documents for the annual operative planning are developed	2,165

Table 11 shows the average scores for each manifest variable. Regarding Human Resource aspects the variables with the lowest scores were 'job satisfaction is being evaluated' and 'the personals' careers are based on specific plans'.

For Leadership, the variables with the lowest scores were ‘management promotes programs for improving the Society and the Environment’ and ‘management evaluates its leadership style compared with other company managers’.
Under Strategic Planning we have the lowest scores related to ‘a structured process defines the objectives and their diffusion’ and ‘new planning documents are developed for new projects’.
Regarding Performance we can see that most of the average scores were relatively low indicating that there has not been a positive trend in Italian industrial companies’ performance during the last 3 years.

5. Concluding Remarks

This paper has focused on a study of the relationships between Leadership, Human Resources and Strategic Planning, and the impact of these LVs on Performance. The data analysed were collected by telephone interviews with leaders from 120 Italian industrial companies.
The analysis has been formalized by simultaneous equation linear statistical model and the estimation has been conducted by considering the GME, the PLS and the MLE methods. It has been shown how these methods demonstrated the same interpretative overall results, but also showed a little improvement of the GME on the PLS in terms of MSE.
The limitations of the parametric MLE and non parametric PLS estimation methods are highlighted in this application, where no distributional assumption or unique global measure are to be satisfied. The GME performs well in both well-posed and ill-posed data sets, under-determined problems, high levels of co-linearity, and gives a very suitable measure of fit called normalized entropy measure and its related indexes.
The analysis of the survey data showed interesting and unexpected results regarding the non significant relationship between Leadership and Performance. What does that mean? Doesn’t good Leadership influence enterprises’ performance?
The answer to this question is that even if there is no direct relationship between the two variables, the effect of Leadership is obtained by an indirect relationship through Human Resources. The combination of Leadership and Human Resources has hence been identified as the variables which have the highest impact on the performance of Italian industrial companies. This result is totally in accordance with the findings and suggestions by Dahlgaard & Dahlgaard [4, 5] and Martens *et al.* [7] in their “4P” model for business excellence. The message from this model is that a general strategy for improving performance is to improve ‘the 4P’ – People, Partnerships, Processes, and Products – in this order. And because the foundation of ‘the 4P’ is Leadership improvements always starts with Leadership. Without Leadership no sustainable improvements, and improvements of ‘the 4P’ go through Leadership. The statistical analyses shown in this paper support this strategy.
Another interesting and unexpected result was that there was no significant impact of Strategic Planning on Performance. It seems that the leaders of Italian industrial companies have not understood that good strategic planning is a necessary condition for achieving excellence. It seems that they have not understood what excellent companies have learned during the last decades that good strategic planning with effective policy deployment is the backbone of Total Quality Management and Business Excellence.
So another improvement area, which was not highlighted by the interventions matrix, is in fact Strategic Planning. This area should have the highest priority and highest

responsibility of any top management team and the focus should include how to establish a strong relationship between strategic planning and performance. If statistical data analyses, as shown in this report, show now correlations between strategic planning and performance, then we have a strong indication that something is wrong. It is not enough that Leadership is doing Strategic Planning – Leadership is also about studying and following up on results in order to assure impacts on performance. This link seems to be missing in Italian industrial companies (as indicated in figure 2).

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APPENDIX 1. Quantile-Plot of standardized residual

Quantile-Plot (Q-Plot) consists in plotting the residual from the sample, to evaluate the assumption of normality or other distribution.
The following Q-Plot reports on the *x-axis* the standardized residual and on the *y-axis* the expected values in case the residuals follow a Normal Distribution with mean 0 and variance 1. If the standardized residual lie roughly on a line, then they follow a Standard Normal Distribution.

Q-Plot of standardized residual