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THE ANALYSIS OF THE PASSENGER SATISFACTION AS A FORMATIVE SECOND-ORDER CONSTRUCT

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SUMMARY

The aim of the paper is to define a new concept of global measure for the Passenger Satisfaction (PS), conceived as second-order latent variables (Henseler and Chin, 2010), and a new estimation approach to its measurement. This idea arises from theoretical and methodological limits of the existent models in correctly capturing the construct of satisfaction and the relationships with its sub-dimensions. The two main approaches to the estimation of higher-order constructs through the Partial Least Squares Path Modeling (PLS-PM) are presented: the so called Repeated Indicators and the Two-Step approaches. Some criticisms of these methodologies are highlighted and a solution to the issue of the identification of formative second-order constructs is suggested through the adoption of a Hybrid Two-Step approach for solving the presented PS case study. Three ways of modeling PS are then compared: a Base Model, where PS is measured as a traditional first-order construct, and two second-order models estimated, respectively, through the Repeated Indicators and the Hybrid Two-Step. Results are discussed.

Keywords: *Passenger Satisfaction, Second Order Latent Variables, Partial Least Squares Path Modeling, Hybrid Two-Step Approach.*

1. INTRODUCTION

Passenger Satisfaction is a specific variant of the broader issue of the Customer Satisfaction (CS) measurement in the context of the transport services. A great variety of methods and theoretical perspectives for understanding and measuring CS has been adopted by different disciplines, such as economics, marketing, psychology and sociology. Each of these domains studies the construct using different premises about key-constructs such as ‘‘consumption’’, ‘‘satisfaction’’, ‘‘consumer behavior’’ and so on. As stated by Fine (1997), ‘‘for economists, consumption is used to produce utility; for sociologists, it is a means of stratification; for anthropologists, it is a matter of ritual and symbol; for psychologists, it is the means by which to satisfy or express physiological and emotional needs; and for business, it is a way of making money’’. Despite of the radical diversity among disciplines, many customer/ consumer related issues have been addressed from interdisciplinary and multidisci-

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plinary points of view. A set of methods and tools is thus shared by those different research fields dealing with consumer behavior and customer satisfaction with products and/or services.

The Kano model (Kano, Seraku, Takahashi and Tsuji, 1996), the Service Quality model (Grönroos, 1982), the SERVQUAL model (Parasuraman, Zeithaml and Berry, 1985), are only the major frameworks for studying and evaluating CS. Particularly, the whole literature about CS in the field of services has been influenced by the SERVQUAL model and its subsequent changes and developments (especially its reduced version, SERVPERF, which is a performance only based scale). These models are general enough to be employed in most fields of the service industry, despite many criticisms on the conceptual as well as the practical side (an overview of the difficulties with SERVQUAL is provided by Van Dyke, Kappelman and Prybutok (1997) and Van Dyke, Prybutok and Kappelman (1999). Anyway, we do not focus on an exhaustive summary of all the difficulties with the existent models, but we rather underline in what circumstances they are not sufficient in evaluating CS and, in the specific case, Passenger Satisfaction, and a higher-order level of abstraction is needed. As an example, consider the SERVQUAL five dimensions of service quality: Reliability, Assurance, Tangibles, Empathy and Responsiveness; from a theoretical point of view, it seems more correct considering them as formative aspects, rather than predictive aspects, of an overall evaluation of the service. In other words, customers can aggregate their evaluations on first-order constructs (the SERVQUAL dimensions) to form their perceptions on the second-order dimension (the overall service quality and, indeed, the overall satisfaction about the service received).

Moreover, conceptualizing general satisfaction as a second-order construct leads to an important practical advantage: the possibility of deriving a global measure of satisfaction when it is not provided by the model itself.

Different procedures have been proposed in literature in order to model second (and higher) order constructs. The approaches to second-order modelling and some of their limits are shown in Section 2 and the development of a new approach for the estimation of formative second-order construct is presented as well. In the following Section 3 a model in which PS can be thought as second-order construct is described. The results of a comparison among different ways of modelling PS is finally presented in the Section 4. In the last section some conclusions and discussions are reported.

2. PLS PATH MODELING AND THE HIGH-ORDER ESTIMATION METHODS

In this paragraph it is showed the classic PLS estimation algorithm for the Path modeling and then the high order methods and the proposed approach are reported in the successive sub-paragraphs.

PLS Path Modelling (PLS-PM) is the most suitable tool for the investigation of models with a high level of abstraction. Proposed for the first time by Herman Wold to be used in multivariate analysis, the basic PLS algorithm was subsequently extended for its application in the Structural Equation Modelling (SEM) in 1975 by Wold himself. An extensive review on PLS approach is given in the Handbook of PLS (Esposito Vinzi, Chin, Henseler, Wang, 2010).

The model-building procedure can be thought of as the analysis of two conceptually different models. The measurement (or outer) model specifies the relationships of the observed variables with their (hypothesized) underlying (latent) constructs; the structural (or inner) model specifies the causal relationships among latent constructs, as posited by some theory. The two sub models' equations are the following:

$$\boldsymbol{\xi}_{(m,1)} = \mathbf{B}_{(m,m)}\boldsymbol{\xi}_{(m,1)} + \boldsymbol{\tau}_{(m,1)}$$
$$\mathbf{x}_{(p,1)} = \boldsymbol{\Lambda}_{(p,m)}\boldsymbol{\xi}_{(m,1)} + \boldsymbol{\delta}_{(p,1)}$$

where the subscripts m and p are the number of, respectively, the latent variables (LVs) and the manifest variables (MVs) in the model, while the letters $\boldsymbol{\xi}$, $\mathbf{x}$, $\mathbf{B}$, $\boldsymbol{\Lambda}$, $\boldsymbol{\tau}$ and **d** indicates LV and MV vectors, the path coefficients matrices linking the LVs, the factor loadings matrix linking the MV to the LV, and the errors terms vectors of the model.

The parameters estimation (Ciavolino and Al-Nasser, 2009) follows a double approximation of the LVs ξ_j (with $j = 1, ..., m$). The *external estimation* of ξ_j, $\mathbf{y}_j$, is obtained as the product of the block of MVs $\mathbf{X}_j$ (considered as the matrix units for variables) and the *outer weights* $\mathbf{w}_j$ (which represent the estimation of measurement coefficients, $\boldsymbol{\Lambda}$). The *internal estimation* of ξ_j, $\mathbf{z}_j$, is obtained as the product of the external estimation and the *inner weights* e_j.

According with the relationship among MVs and LVs hypothesized, outer weights are computed as:

$$\mathbf{w}_j = \mathbf{X}_j'\mathbf{z}_j$$

for Mode A (reflective relationship), and:

$$\mathbf{w}_j = \left(\mathbf{X}_j'\mathbf{X}_j\right)^{-1}\mathbf{X}_j'\mathbf{z}_j$$

for Mode B (formative relationship). The *inner weights* $e_{j,i}$, are calculated for each LV in order to reflect how strongly the other LVs are connected to it. For each pair of $\mathbf{y}_j$ and all the $\mathbf{y}_i$ (with *ij*) directly related to it, inner weights can be computed by following three different schemes:

- the sign of the correlation between each pair of external estimations $\mathbf{y}_i$ and $\mathbf{y}_j$ (centroid scheme);
- the correlation between each pair of $\mathbf{y}_j$ (factorial scheme);
- the multiple regression coefficient among $\mathbf{y}_j$ (path weighting scheme).

The PLS algorithm starts by initializing outer weights to one for the first MV of each LV; then, the parameters estimation is performed, until the convergence, by iteratively computing:

1. *external estimation*, $\mathbf{y}_j = \mathbf{X}_j \cdot \mathbf{z}_j$;

2. *internal estimation*, $\mathbf{z}_j = \sum_{j \neq i} e_{j,i} \, \mathbf{y}_i$;
3. *outer weights estimation*, with Mode A or B.

The causal paths among LVs (the coefficients in the **B** matrix) are obtained through Ordinary Least Squares (OLS) method or Partial Least Squares regression.

2.1 *Second-order LVs with PLS-PM*

Lohmöller (1989) proposed a procedure for the case of hierarchical constructs, the so-called *Hierarchical Component Model* or *Repeated Indicators Approach*, which is the most popular approach when estimating higher-order constructs through PLS. The procedure is as follow: ‘‘a second-order factor is directly measured by observed variables for all the first-order factors. While this approach repeats the number of MVs used, the model can be estimated by the standard PLS algorithm’’ (Reinartz, Krafft and Hoyer, 2004). The manifest indicators, measuring each first-order LV, are simply repeated in order to represent the higher-order construct. The Repeated Indicators approach is applied when all the first and second-order measurement relationships are modelled as reflective (Rajala and Westerlund, 2010).

Another way of building a higher-order model is the *Two-Step Approach*: the LV scores are initially estimated in a model without the second-order construct (Agarwal and Karahanna, 2000). Once the first-order LV scores are computed, they are subsequently used as manifest variables in a separate higher-order structural model analysis. Such an approach may offer advantages when estimating higher-order models with formative indicators (Diamantopoulos and Winklhofer, 2001; Reinartz *et al.*, 2004). The implementation is not one simultaneous PLS run; this implies that any second-order construct, investigated in stage two, is not taken into account when estimating LV scores at the first stage. Moreover, since we consider at second step the estimated scores as manifest variables, the method doesn’t take into account the measurement errors (Carpita and Ciavolino, 2012; Ciavolino, Carpita and Al-Nasser, 2012), which could affect the estimations at second steps. The two approaches are illustrated in Figure 1.

2.2 *Formative second-order construct with the Hybrid two-step approach*

A special case in which a second-order LV results to be not identified arises when the relationships with its sub-dimensions are modelled as formative and it does not have links with further variables in the model (Diamantopoulos, Riefler and Roth, 2008). This the case of a formative second-order LV estimated through the Two-Step approach, when any causal link is provided from the second-order to any other variables.

In this case the outer weights cannot be estimated because of the equality between internal and external estimation of the LV (respectively, **z** and **y**).

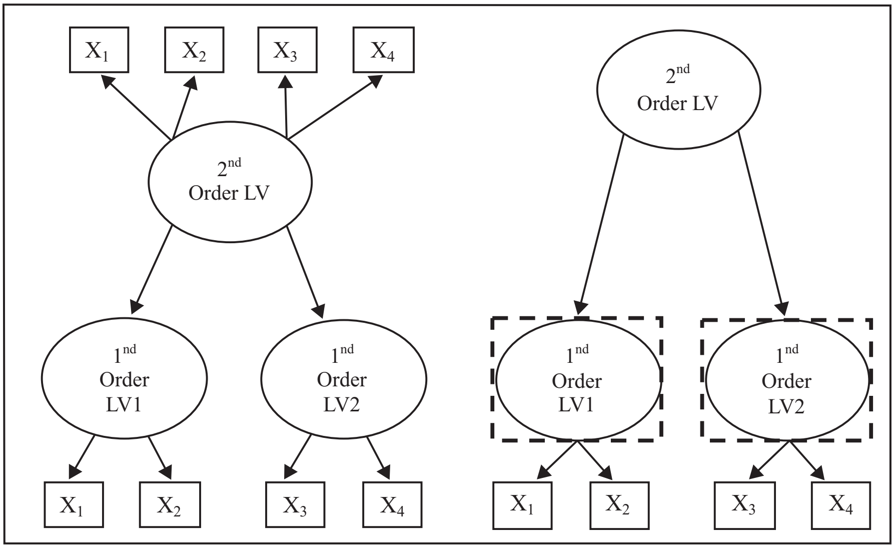

FIGURE 1. - *Model building: Repeated indicators and two-step approaches*

Within the Mode B (formative), the outer weighting estimation ($\mathbf{w}_j$) is realized as the multiple regression of the internal estimation $\mathbf{z_j}$ on the MVs $\mathbf{X}$ related to the same LV, so that:

$$\mathbf{w}_j = (\mathbf{Z}_j'\mathbf{X}_j)^{-1}\mathbf{X}_j'\mathbf{z}_j \tag{1}$$

Following the PLS algorithm, indeed, the internal estimation $\mathbf{z}$ is computed as:

$$\mathbf{z}_j = \sum_{j \neq i} e_{j,i}\mathbf{y}_i$$

where $e_{j,i}$ is the inner weight as above showed. Then, in a model with only one , internal and external estimation will coincide. By substituting $\mathbf{z}$ with $\mathbf{y}$ in the equation 1 we obtain:

$$\mathbf{w}_j = (\mathbf{X}_j'\mathbf{X}_j)^{-1}\mathbf{X}_j'\mathbf{y}_j = (\mathbf{X}_j'\mathbf{X}_j)^{-1}(\mathbf{X}_j'\mathbf{X}_j)\mathbf{w}_j = \mathbf{X}_j$$

so that weights do not change through iterations.

The proposed method to overcome this problem is the adoption of a hybrid approach (Ciavolino and Nitti, 2013) in which the estimation of the second-order LV is performed in two steps, according to the following procedure:

1. the first-order reflective constructs are estimated as uncorrelated factors;
2. the LV scores obtained in the first step are used as reflective indicators of the second-order construct. The model is then re-estimated by relating, formatively, the first-order LVs to the second-order one, as shown in Figure 2(c).

In this way, the higher-order LV has reflective indicators, represented by the factor scores of the lower-order LVs computed in the first step. The construct is used, within the second step, as a LV caused by the whole set of first-order variables.

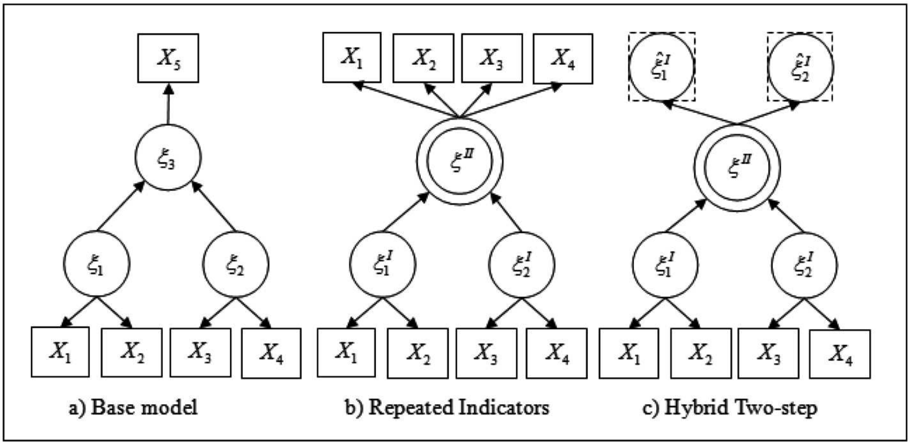

FIGURE 2. - *First-order and second-order models*

In the next section we compare three different way of modeling PS:

- Model *a* is the Base Model proposed by Ciavolino *et al.* (2007), in which PS is a first-order LV reflectively measured by a single questions about the overall satisfaction. In this case, PS is measured by its own item (i.e. a specific question on the global level of satisfaction) and no distinctions can be made about the degree of abstraction of the constructs in the model.
- Model *b* uses the Repeated Indicators approach for the estimation of PS as a second-order construct which is formatively related to first-order dimensions and reflectively measured by its MVs (which are the whole set of indicators of first-order constructs).
- Finally, the Hybrid Two-Step approach is applied to the estimation on PS in Model *c*. The same links between first and second-order LVs and between second-order LV and its indicators of the previous model hold. As above explained, the indicators used are the factor scores of the LV estimated at stage one. Relationships at the first level are posited as reflective for all models.

3. PASSENGER SATISFACTION AS SECOND-ORDER LATENT VARIABLE

The case study analyzed (Ciavolino, D'Ambra and De Franco, 2007) is based on a survey committed by AMTS, which is a Local Transport Company operating in Benevento, a little town in the South of Italy. The aim of the survey was to measure the level of satisfaction of the passengers and to identify the aspects of the transport service have to be improved.

The study is realized by using a self-administered questionnaire, to a sample of AMTS regular customers, which has a size dimension equal to 400.

Formative aspects of the PS have been determined by decomposing the whole transport service into five dimensions of the process, characterized by a set of activities involved in reaching a goal. These dimensions concern:

a) *service accessibility*, in terms of availability of information on routes and timetables, tickets, shelters;

b) *staff,* professionality and kindness;

c) *vehicles conditions*, in terms of comfort and cleanness;

d) *safety on board*;

e) *transport service conditions*, such as regularity and punctuality of the transport.

Overall Passenger Satisfaction would result from the evaluation of each of the dimensions described. The questionnaire has been validated and the items selected by means of the Simple Component Analysis (Rousson and Gasser, 2003); the items used are listed in the Table 1. An ordinal scale, from 1 (minimum rating) to 10 (maximum rating) has been administered to respondents, and then quantified through the Thurstone method (Zanella, 2001). The conceptual model hypothesized by the authors is represented in Figure 3.

TABLE 1. - *Latent variables and corresponding items*

Latent Variables (LVs)	**ID-LVs**	**Manifest Variables (MVs)**	**ID-MVs**
Access	ξ_1	*Timetable availability*	X_1
		Info on timetable	X_2
		Ticket availability	X_3
		Bus access	X_4
		Invalid services	X_5
		Bus shelters	X_6
Staff	ξ_2	*Staff behaviour*	X_7
Vehicles	ξ_3	*Bus cleaning*	X_8
		Travel comfort	X_9
		Environmental impact reduction	X_{10}
Safety	ξ_4	*Travel safety*	X_{11}
		Safety on board	X_{12}
Transport	ξ_5	*Punctuality*	X_{13}
		Regularity	X_{14}
		Connections with other transports	X_{15}

PS, which has been measured by a single question, represents the effect of customer evaluations about different components of the transport service. Our idea is that, since PS results from the composition of the five aspects, it could be conceptualized as a formative second-order construct.

In this sense, it could be interpreted as a composite indicator which synthesizes complex and multidimensional facets of the service. As MacKenzie, Podsakoff and Jarvis (2005) pointed out, ''this model posits that the measures jointly emanates from the measures to the construct in the sense that the full meaning of the composite latent construct is derived from its measures''. In the case here analysed, the ''measures'' are not observable variables but latent reflective variables and then the overall satisfaction would be a construct at a higher level of abstraction.

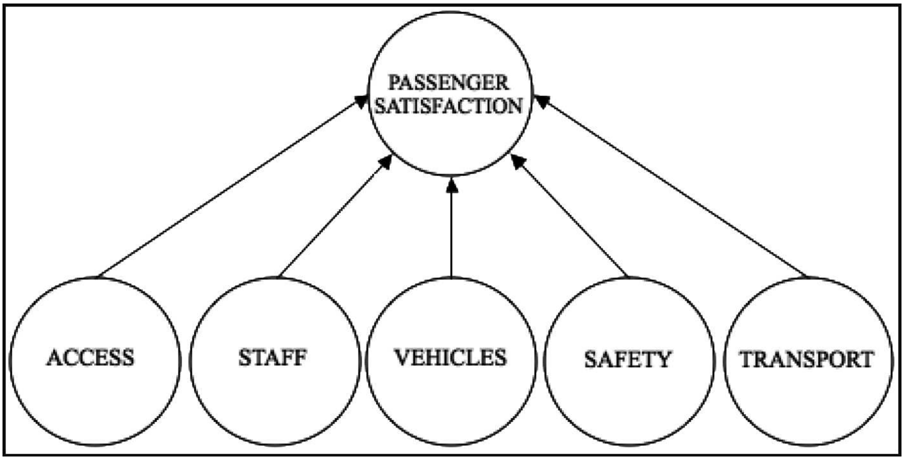

FIGURE 3. - *The Passenger Satisfaction Path Model*

4. RESULTS

The three PS models have been estimated with AMTS data by using a tailor-made algorithm developed in MATLAB. Table 2 reports the main quality measures of the three models. The assessment of a structural model estimated with PLS approach involves inner as well as outer model measures of quality.

Since the first-order LVs are reflectively related to their indicators, traditional measures of reliability and unidimensionality can be used for assessing the quality of the measurement model. Internal consistency of each construct, assessed through Composite Reliability (CR) and Cronbach's *a* indexes, is the most commonly used quality criterion for the measurement model. This implies that a single common construct should underlie its related observed variables. Furthermore, another widely used index in PLS literature is represented by the *communality* index, which measures the amount of MVs variability explained by the corresponding LV.

As concerns the second-order construct PS (as modeled with the Repeated Indicators and the Hybrid Two-Step approaches), while having reflective indicators, it is multidimensional in nature and thus internal consistency perspective is inappropriate for assessing the suitability of the construct.

It is worth to notice, however, that reliability cannot be verified for constructs with only one item (this is the case of STAFF, and, for the Base Model, PS).

TABLE 2. - *Reliability and Unidimensionality*

	Access	Staff	Vehicles	Safety	Transport	PS		
						Base Model	***Repeated Indicators***	***Two-step Hybrid***
Cronbach's alpha	0.680	-	0.711	0.502	0.774	-	0.857	0.796
Composite Reliability	0.791	1.000	0.838	0.798	0.869	1.000	0.883	0.860
Communality	0.390	1.000	0.634	0.665	0.689	1.000	0.342	0.552

Composite reliability is higher than 0.7 for all constructs, while communality is far below the commonly accepted threshold of 0.7, among the first-order LVs, only for the ACCESS dimension.

Discriminant validity is also used to test the possibility to discriminate between different constructs. A common way of examining discriminant validity is comparing the correlations between any two constructs against their individual root square of the average variance extracted (AVE). Discriminant validity is verified if the square root of each construct's AVE is higher than the correlation between LVs. Furthermore, according to MacKenzie *et al.* (2005), correlations lower than 0.71 occur between independent constructs; on the contrary, higher correlations indicate that the variance shared by the two constructs is bigger than 50%, which implies a matter of re-specification of the constructs involved. As shown in Table 3, PS dimensions exhibit a good discriminant validity.

TABLE 3. - *Discriminant validity: Correlation among PS dimensions (Square root of AVE on diagonal)*

	Access	Staff	Comfort	Safety	Transport
Access	*0.625*	-	-	-	-
Staff	**0.346**	*1.000*	-	-	-
Comfort	**0.559**	**0.494**	*0.796*	-	-
Safety	**0.427**	**0.368**	**0.523**	*0.815*	-
Transport	**0.394**	**0.395**	**0.506**	**0.440**	*0.830*

The significance of the structural parameters linking dependent and independent LVs in the model is considered for the evaluation of the relationships hypothesized. In order to assess the significance of path coefficients, *t*-values have been computed by bootstrapping (200 samples; *t*-values >1.96 significant at the 0.05 level).

Table 4 reports values and significance of the structural coefficients linking quality dimensions to PS.

TABLE 4. - *Bootstrap means, standard error and t-statistics of the path coefficients per approach (non-significant parameters are marked in bold)*

	Base Model			Repeated Indicators			Two-step Hybrid		
	Mean	SE	t-stat	Mean	SE	t-stat	Mean	SE	t-stat
Access–>PS	0.140	0.126	**1.114**	0.319	0.147	2.170	0.271	0.022	12.502
Staff–>PS	0.038	0.108	**0.351**	0.138	0.024	5.759	0.235	0.042	5.627
Vehicles–>PS	0.216	0.124	**1.739**	0.334	0.036	9.143	0.291	0.048	6.099
Safety–>PS	0.153	0.103	**1.483**	0.216	0.028	7.772	0.254	0.042	6.051
Transport–>PS	0.355	0.089	4.002	0.259	0.033	7.869	0.255	0.068	3.749

In the model where PS is a first-order construct, only the parameter linking TRANSPORT to PS results to be significant, differently from the two second-order models, where all path t-statistics are higher than 1.96. Differences in the intensity of the links may seem remarkable when comparing the Repeated Indicators and the Hybrid Two-Step approach; despite the differences in the absolute values, however, the sorting of the coefficients is the same for the two approaches. VEHICLES is the most important dimension in building up the satisfaction, while STAFF results to be the less influent among all the facets. The greater discrepancy between the estimates concerns the relationship STAFF PS, and this is maybe due to the fact that STAFF is a single-item LV. To overcame this effect, a proposal could be the introduction of the measurement errors as proposed by Carpita and Ciavolino (Carpita and Ciavolino, 2012; Ciavolino *et al.*, 2012).

TABLE 5. - *Goodness of fit index*

	Base Model	Repeated Indicators	Two-step Hybrid
R^2	0.494	0.987	0.741
Gof	0.546	0.673	0.755

Table 5 reports the global measure of goodness of fit (Gof) proposed by Amato *et al.* (2005). This index is constructed in order to take into account the quality of both the measurement and the structural model as it results from the geometric mean of the average communality index and the average R^2 computed on each regression in the model. Applied to the case study proposed, the highest Gof value is that obtained by the Hybrid Two-Step approach (0.755), indicating a better fit of this model to the data. All the three indexes, however, can be considered acceptable, but it's worth to remember that PS, as measured in the base model, has a communality equal to one and this could have inflated the Gof value, which is still lower than the other two models.

Once the parameters in the model and the factorial scores have been estimated, they could be usefully related in order to plan future interventions on each different dimension of the service quality, where needed. Figure 4 is the representation of the

Performance (on the *y*-axis) obtained by the company on each facet (that is the average of the factorial scores, for each of the LVs) and the Impact (on the *x*-axis) of every dimension on the overall satisfaction (as resulting by the structural coefficients estimated). The origin of the axes has been fixed to the medium values of Performance and Impact.

The approach considered for the construction of the intervention map is the Hybrid Two-Step, which leads to the highest value the Gof index.

The interpretation of the graph starts from the consideration that the ideal condition, for a company, is the customers' highest satisfaction on the most important dimensions of the service provided. This condition of excellence is represented by the quadrant I on the plane. The points falling in that section indicate facets of the service which the company have to feed and foster for satisfying the passenger. In our model, SAFETY obtains the highest performance, but its improving is not of primary importance since its impact on PS is lower than other dimensions. The behavior of the STAFF, although it is rated well by the passengers, does not play an important role in forming their satisfaction.

VEHICLES, which is of greatest importance in determining satisfaction, receives a low appreciation (under the medium value of 5.7) by the customers. Great efforts of the company in increasing the level of cleanness and comfort of the vehicles, and more attention to issues of environmental impact is then suggested by the matrix. The same considerations apply, to a lesser extent, for ACCESS.

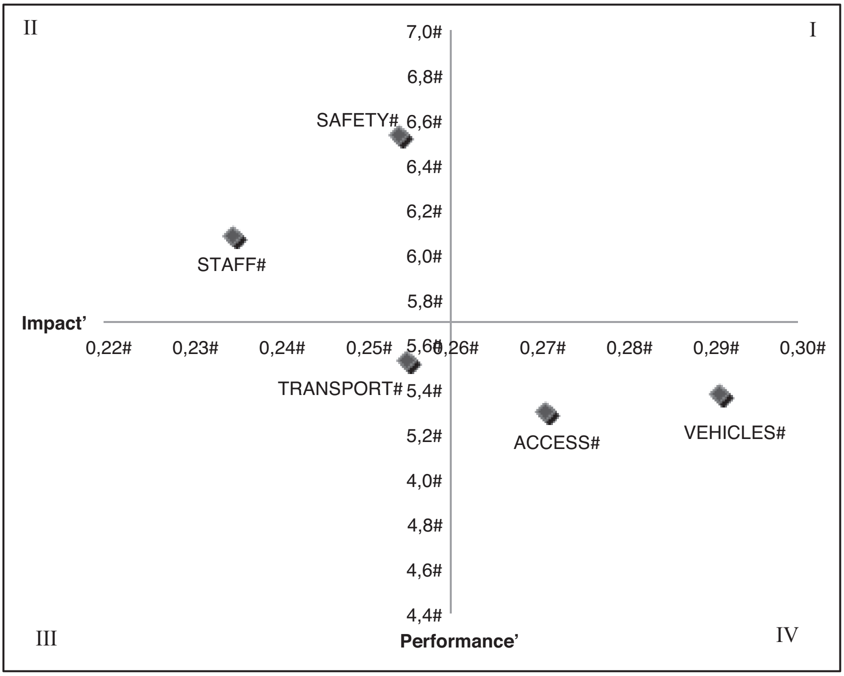

FIGURE 4. - *Intervention Map*

Ratings for TRANSPORT are just above the medium value, showing that passengers do not comply about punctuality and regularity of the service neither the degree of connection with other transports. Interventions on such dimension, which still represents the main aspect within the whole transport service process, are not a priority compared with the ACCESS and VEHICLES facets.

5. CONCLUSIONS AND DISCUSSION

The proposal to model PS as second-order LV stems from the consideration that some limits exist, both in the research design (as in the case of SERVPERF and SERVQUAL models) and in the theoretical definition of the construct.

The main issue concerns the degree of complexity of the construct considered: if the primary focus of the study is the PS, the researcher would be interested in clearly distinguish between the different facets of satisfaction, and then accurately measure these facets with multiple items. In such cases, the researcher may develop multi-item scales to measure each of the sub-dimensions of the overall satisfaction. The resulting PS construct would be necessarily higher-ordered, as it is measured by a set of LVs, and multidimensional, as its sub-dimensions are different from each other.

The matter of the specification of the relationships between the PS construct and its facets (both at first and second level of abstraction) is also treated: the proper definition of formative rather than reflective relations collides with identification problems which need to be solved.

Finally, according with the approaches to the construction of second-order LVs, satisfaction can be derived, given certain conditions, in models where its measurement is not provided. As a matter of fact, many studies about the quality of a product/service do not provide a global measure of satisfaction; in most cases, satisfaction is calculated as the mean of the constructs which are supposed to cause or reflect it.

Two main approaches have been proposed in literature for facing the high-order modeling issue, the Repeated Indicators and the two-step. As pointed out by Jarvis, MacKenzie and Podsakoff (2003) in his review study, only second-order constructs reflectively measured by first-order dimensions have been recognized in the literature (which they call Type I and Type III models).

A correct specification of the measurement model, both at first and second level of abstraction, is not a secondary problem, but hypothesizing formative relationship is not always possible because of model identification matters.

The case study analyzed shows why Passenger Satisfaction could be seen as a formative second-order construct and how the problem of identification of formatively measured higher-order LV could be solved, through a hybrid two-step approach. The proposed approach, by using the factor scores of the first-order LVs as reflective manifest indicators of the second-order construct, is an attempt to solve the identification problem in case of formative relationships.

The results of three models, one in which PS is measured by a single item about the overall satisfaction, and two second-order models estimated through the Repeated Indicators and the hybrid two-step approaches, have been compared.

Comparisons based on the quality of the outer model, in terms of internal consistency of the PS constructs, are not of great importance since a second-order construct is multidimensional in its definition. The three models show the same discriminant validity, so demonstrating that different and separate dimensions of the whole satisfaction exist and thus a formative relationship with the second-order construct is suitable.

Remarkable differences arise from the analysis of the structural models obtained. While in the base model only one dimension of the quality significantly affect the PS, in the two second-order models all the considered dimensions have, proportionally, the same impact on the overall satisfaction. Furthermore, a poor local goodness of fit characterizes the causal relationships from the predictors to PS in the base model in this application. The Gof values clearly indicates the Hybrid two-step as the best approach in terms of global goodness of fit.

REFERENCES

Agarwal R., Karahanna E. (2000). Time flies when you're having fun: Cognitive absorption and beliefs about information technology usage, *MIS Quarterly*, **24**(4), 665-694.

Ciavolino E., Carpita M. and Al-Nasser A.D. (2012). A Job Satisfaction Structural Equation Model Obtained Combining Rasch Analysis and Generalized Maximum Entropy Estimation (January 27, 2012). Available at SSRN: http://ssrn.com/abstract=1993102 or http://dx.doi.org/10.2139/ssrn.1993102.

Carpita M., Ciavolino E. (2012). Using the GME estimator with the Rasch analysis in the multigroup SEM. *Quaderni di Statistica*, **14**, 61-64.

Ciavolino E., Nitti M. (2013). Using the Hybrid Two-Step estimation approach for the identification of second-order latent variable models. *Journal of Applied Statistics*, **4**(3), 508-526.

Ciavolino E., Al-Nasser A.D. (2009). Comparing generalised maximum entropy and partial least squares methods for structural equation models. *Journal of Nonparametric Statistics*, **21**(8), 1017-1036.

Ciavolino E., D'Ambra L., De Franco D. (2007). Massima Entropia Generalizzata e Simple Component Analysis per l'analisi della Customer Satisfaction nel Trasporto Pubblico Locale: L'Esperienza dell'Azienda AMTS di Benevento. *Rivista di Economia e Statistica del Territorio*, **3**, 201-221.

Diamantopoulos A., Riefler P., Roth K. (2008). Advancing Formative Measurement Models. *Journal of Business Research*, **61**(11), 1203-1218.

Diamantopoulos A., Winklhofer H.M. (2001). Index construction with formative indicators: An alternative to scale development. *Journal of Marketing Research*, **38**(2), 269-277.

Esposito Vinzi V., Chin W.W., Henseler J., Wang H. (2010). *Handbook of Partial Least Squares. Concepts, Methods and Applications*. Springer Handbooks of Computational Statistics, New York.

Fine B. (1997). Playing the Consumption Game. Consumption. *Markets and Culture*, **1**(1), 7-30.

Grönroos C. (1982). Strategic management and marketing in the service sector. Helsinkis, Swedish School of Economics, Research report 0357-5764, 8.

Henseler J., Chin W.W. (2010). A comparison of approaches for the analysis of interaction effects between latent variables using partial least squares path modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, **17**(1), 82-109.

Jarvis C.B., MacKenzie S.B., Podsakoff P.M. (2003). A Critical Review of Construct Indicators and Measurement Model Misspecification in Marketing and Consumer Research. *Journal of Consumer Research*, **30**, 199-218.

Kano N., Seraku N., Takahashi F., Tsuji S. (1996). Attractive Quality and Must-be Quality. *The Best on Quality*, **7**(165).

Lohmöller J.B. (1989). *Latent Variable Path Modeling with Partial Least Squares*. Physica-Verlag, Heidelberg.

MacKenzie S.B., Podsakoff P.M., Jarvis C.B. (2005). The problem of measurement model misspecification in behavioral and organizational research and some recommended solutions. *Journal of Applied Psychology*, **90**(4), 710-30.

Parasuraman A., Zeithaml V., Berry L.L. (1985). A conceptual model of service quality and its implications for future research. *Journal of Marketing*, **49**, 41-50.

Rajala R., Westerlund M. (2010). Antecedents to consumers' acceptance of mobile advertisements - a hierarchical construct PLS structural equation model. The 43rd Hawaii International Conference on System Sciences (HICSS), Jan 5–8, 2010.

Reinartz W., Krafft M., Hoyer W.D. (2004). The customer relationship management process: Its measurement and impact on performance. *Journal of Marketing Research*, **41**(3), 293-305.

Rousson V., Gasser Th. (2003). Simple component analysis. *Journal of the Royal Statistical Society*, **53**(4), 539-555.

Van Dyke T.P., Kappelman L.A., Prybutok V. (1997). Measuring information systems service quality: Concerns on the use of the SERVQUAL questionnaire. *MIS Quarterly*, **21**(2), 195-208.

Van Dyke T.P., Prybutok V.R., Kappelman L. (1999). Cautions on the use of the SERVQUAL measure to assess the quality of information systems services. *Decision Sciences*, **30**(3), 877-892.

Wold H. (1975). Path models with latent variables: The NIPALS approach. In H.M. Blalock (Ed.), *Quantitative Sociology* (pp. 307-357). Seminar Press, NewYork.

Zanella A. (2001). Measures and models of customer satisfaction: the underlying conceptual construct and a comparison of different approaches, Sixth TQMWorld Congress, Saint Petersburg.